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Geospatial Analytics for Environmental Pollution Modeling

Analysis, Control and Management

Springer

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Dedicated to beloved parents

Preface

Environmental Pollution may threaten the prospects of environmental sustainability. This issue needs to be addressed comprehensively as India's economic development is moving at a very fast pace. It is therefore important to perform investigations for mitigating environmental risks. Hence, in recent years, effective control of environmental pollution such as water, air, soil, and noise has become one of the top work priorities at global level. This may help coming generations in addressing the challenges of environmental deterioration. Industrialization, urbanization, agriculture, forest fires, desert dust, and inadequate waste management have intensified environmental health risks and pollution, especially in developing countries.

Pollution is the largest environmental cause of disease and premature death. Pollution causes more than nine million premature deaths (16% of all deaths worldwide). That's three times more deaths than from AIDS, tuberculosis, and malaria combined and 15 times more than from all wars and other forms of violence. Global health crises, such as the COVID-19 pandemic, further highlight the need for continued action in addressing environmental pollution. For instance, water, an essential resource for all life on Earth, if contaminated due to pollution can lead to health issues in humans such as cholera, diarrhoea, dysentery, hepatitis A, typhoid, polio, cancer, or cardiovascular conditions. On the other hand, contamination of soil with anomalous concentrations of toxic substances harbours a broad spectrum of negative consequences that affect plants, animals, humans, and the ecosystem as a whole. Examples of health hazards related to contaminated soil includes diseases of the central nervous system, immune system diseases, cancer, and birth defects. Not only water and soil, air pollution, exposure to lead and other chemicals, and hazardous wastes including exposure to improper e-waste disposal cause debilitating and fatal illnesses, create harmful living conditions, and destroy ecosystems. Noise pollution impacts millions of people on a daily basis. The most common health problem it causes is noise-induced hearing loss (NIHL). Exposure to loud noise can also cause high blood pressure, heart disease, sleep disturbances, and stress. These health problems can affect all age groups, especially children.

Pollution stunts economic growth and exacerbates poverty and inequality in both urban and rural areas. Poor people, who cannot afford to protect themselves from the negative impacts of pollution, end up suffering the most. It is critical to address pollution because of its unacceptable toll on health and human capital, as well as associated GDP losses. Pollution management can also make substantial contributions to climate change mitigation through actions, such as reduction of black carbon emissions, which contribute to both air pollution and climate change.

This book demonstrates the geospatial technology approach to data sampling, analysis, modelling, assessment, visualization, impacts of pollution, laws, legislations, and strategies in different aspects of environmental pollution. The book has 15 chapters that aim to provide a comprehensive study on construing various aspects of environmental pollution dynamics. Especially, the utility of geospatial technology would be demonstrated for accurate and effective study on environmental pollution, as space and location are very important for effective environmental health surveillance. The application of geospatial technology in environmental health investigations is a practice for decades and recently WHO also suggested that GIS technology is well suited in the above-mentioned field. Moreover, different types of pollution are explained in detail and its relationship with space-time aspects is also discussed in detail.

We express our gratitude to all the authors who have diligently contributed to this publication, completing their documents in a short time frame and making it an enlightening and valuable resource. We believe that this book will serve as a valuable reference for professionals and researchers in various fields, including Ecologists, Environmental Scientists, Hydrologists, Geospatial Scientists, Remote Sensing and GIS experts, and those studying environmental pollution and its management. Additionally, we anticipate that this publication will be beneficial to research scholars, environmentalists, and policymakers.

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Thank you so much Dr. Majid Farooq, Dr. Alok Bhushan Mukherjee, and Dr. Mili Ghosh Nee Lala for being integral part of this project as co-editors. Dr. Fayma Mushtaq would like to acknowledge the Department of Ecology, Environment & Remote Sensing, Srinagar, India, for providing the logistic support and infrastructure facilities. Thanks to LeadsConnect management and Department of Remote Sensing, Birla Institute of Technology, for allowing Dr. Mukherjee and Dr. Ghosh to be a part of this book project as co-editors.

Each and every author is the heart and soul of this book project. We are really thankful to them for the ways they responded to the requirements. With the blessings of Almighty and parents, we have stayed in this journey with all energy, focus, and passion. We wish and pray that their blessings always stay with us so that we can keep contributing to the scientific fraternity and society.

Thank you everyone who shouldered in this journey!!

Disclaimer

The responsibility for ideas, views, data, figures, and geographical boundaries presented in each chapter of this book lies solely with the respective authors of those chapters. The publisher, editor, and authors of forewords, preambles, or other chapters have not endorsed these contents in any way. It should be noted that the views expressed in this book do not necessarily represent the views of the organizations, to which the authors belong.

Contents

About the Editors

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Chapter 1
Types of Environmental Pollution and Its Effects on the Environment and Society

Rasiq Ahmad Mir, Afaan Gulzar Mantoo, Zubair Ahmad Sofi, Darakshan Ayub Bhat, Affreen Bashir, and Saba Bashir

Abstract Environmental pollution from human activities such as urbanization, industrialization, mining, and exploration is a severe worldwide problem posing a threat to the well-being of the general population and the natural surroundings. Despite stringent regulations for protecting the environment, both developed and developing nations contribute to pollution. Pollutants can be found in air, water, soil, and other sources, such as chemical substances, noise, heat, and light. There are seven types of pollution, namely, air pollution, water pollution, soil pollution, noise pollution, thermal pollution, light pollution, and radiation pollution. Pollution has a significant impact on morbidity and mortality rates globally. To combat pollution, comprehensive strategies are needed, including addressing the causes and effects of pollution, reducing greenhouse gas emissions, enhancing energy efficiency, and advocating for the adoption of renewable energy sources. Different sectors, such as governments, industries, and individuals, must collaborate for the lasting success of pollution control. It is essential to prioritize efforts to reduce pollution and promote a sustainable future for generations to come.

Keywords Environment · Pollution · Effects of pollution · Types of pollution · Mitigation

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1.1 Introduction

The term "pollution" may be described as "infiltration of vitality or substances into the environment by either natural or anthropogenic means that may compromise human health, decimate ecosystems and living beings, wreak havoc on social amenities, or interfere with the environment's ability to be utilized for its intended purposes" (Holdgate, 1979). These harmful substances are referred to as pollutants or contaminants. Two primary categories of pollutants exist, namely, primary pollutants and secondary pollutants. Primary pollutants are harmful in their original form, while secondary pollutants are generated through chemical reactions of relatively benign precursor substances present in the environment (Alloway & Ayres, 1997; Daughton, 2005). Although highly toxic substances are responsible for a significant portion of environmental pollution (Baudouin et al., 2002), sometimes even seemingly harmless materials can cause pollution if they exist in excessive quantities or are located at inappropriate spatial–temporal conjunction, which can create difficulties in defining pollution (Dales, 2002; Siddiqua et al., 2022).

Pollution is a global problem (Wilkinson et al., 2022). Even though urban regions are usually more polluted than rural areas, the impact of pollution can reach far-off places where no human habitation exists (Fenger, 1999; Mihai et al., 2022; Nicholls et al., 2020; Satterthwaite, 2003). Pollution not only hinders economic development (Bastola & Sapkota, 2015) but also worsens poverty and inequality in both urban and rural regions (Liu et al., 2020). Moreover, pollution significantly contributes to climate change (Eguiluz-Gracia et al., 2020). Individuals living in poverty, who lack the financial means to safeguard themselves from the detrimental effects of pollution, often bear the brunt of its consequences (Denton, 2002).

Environmental pollution is the primary cause of illnesses and untimely fatalities, resulting in over nine million early mortalities every year (Fuller et al., 2022; Landrigan et al., 2018; Lelieveld et al., 2015). The majority of pollution types are imperceptible to the naked eye and manifest in various ways (Boyes et al., 1999). There are essentially seven types of pollution: air pollution, water pollution, soil pollution, noise pollution, thermal pollution, light pollution, and radiation pollution (Khopkar, 2007; Lindop & Rotblat, 1971; Narisada & Schreuder, 2013). These types of pollution are discussed in this chapter.

1.2 Air Pollution

Air pollution (also known as atmospheric pollution) refers to the exceeding of predetermined concentrations of certain substances in the atmosphere that result in a harmful phenomenon for the ecological system and disrupt normal conditions for human existence and development (Bai et al., 2018). The substance responsible for this contamination is referred to as an atmospheric pollutant/contaminant that can be any gaseous or particulate matter that, when present in sufficiently elevated concentrations, has the potential to cause harm to living organisms, natural surroundings, and/or physical assets (Brusseau et al., 2019). The source of this contaminant can be either natural or anthropogenic or both (Lee et al., 2018). Currently, the main contaminants recognized as posing a risk to health primarily include particulate matter (PM) that is dispersed in the air and gaseous impurities such as sulfur dioxide (SO_2), ozone (O_3), carbon monoxide (CO), as well as nitrogen oxides such as nitrogen dioxide (NO_2) and NOx (Okokpujie et al., 2018). The unit of measurement for the concentration of atmospheric contaminants is parts per million (ppm) or $\mu g/m^3$. A contaminant may be primary or secondary, depending on the source of its release. Primary contaminants are released directly into the atmosphere, while secondary contaminants are produced when the primary contaminant reacts with other atmospheric chemicals (Tiotiu et al., 2020). Numerous natural origins, such as wildfires or volcanic eruptions, contribute to atmospheric pollution; however, the industrialization period caused atmospheric contamination to become a worldwide issue (Mayer, 1999). The expansion of urban areas coupled with changes in land use patterns resulting from growing urban populations are likely significant factors contributing to atmospheric pollution issues (Harlan & Ruddell, 2011; Mayer, 1999).

Air pollution has a significant impact on the atmosphere through its emission of various anthropogenic compounds (such as PM, NOx, and SO_2) (Kampa & Castanas, 2008; Manisalidis et al., 2020). These pollutants are known to alter the atmospheric composition and radiative balance, leading to changes in atmospheric stability and circulation patterns (Ramanathan et al., 2005). Air pollutants can interact with cloud formations, leading to changes in cloud albedo and precipitation patterns, ultimately impacting the hydrological cycle (Tao et al., 2012). Furthermore, these emissions contribute to acid rain and ground-level ozone formation (Shammas et al., 2020). As per the United States Environmental Protection Agency (US EPA) (2020), the air quality in developed nations has shown a positive trend, whereas the levels of air pollution in developing nations have been increasing gradually. The World Health Organization (WHO) established standards for measuring air pollution by creating air quality guidelines for various pollutants. As per the statistics provided by the WHO, the majority of the global population, i.e., 90%, is subjected to atmospheric contamination above permissible thresholds. Among the population residing in urban settlements, which are closely monitored for air pollution levels, over 80% of them experience air quality below the recommended limits specified by the WHO. Figure 1.1 represents the global average concentrations of major air pollutants as reported by the WHO and highlights the concerning extent of air quality issues faced by urban populations. Furthermore, approximately 3 billion individuals face severe indoor air pollution issues due to the usage of biomass, kerosene, and coal as fuel for cooking and heating purposes, leading to a substantial occurrence of respiratory disorders.

The WHO reports that in 2012, 6.5 million individuals across the globe died as a result of air pollution. Approximately three million of these fatalities were caused by outdoor air pollution; however, the incidence of air pollution-related deaths varied considerably across different regions. The Democratic People's Republic of Korea recorded the highest rate of air pollution-induced fatalities, at 238.4 deaths

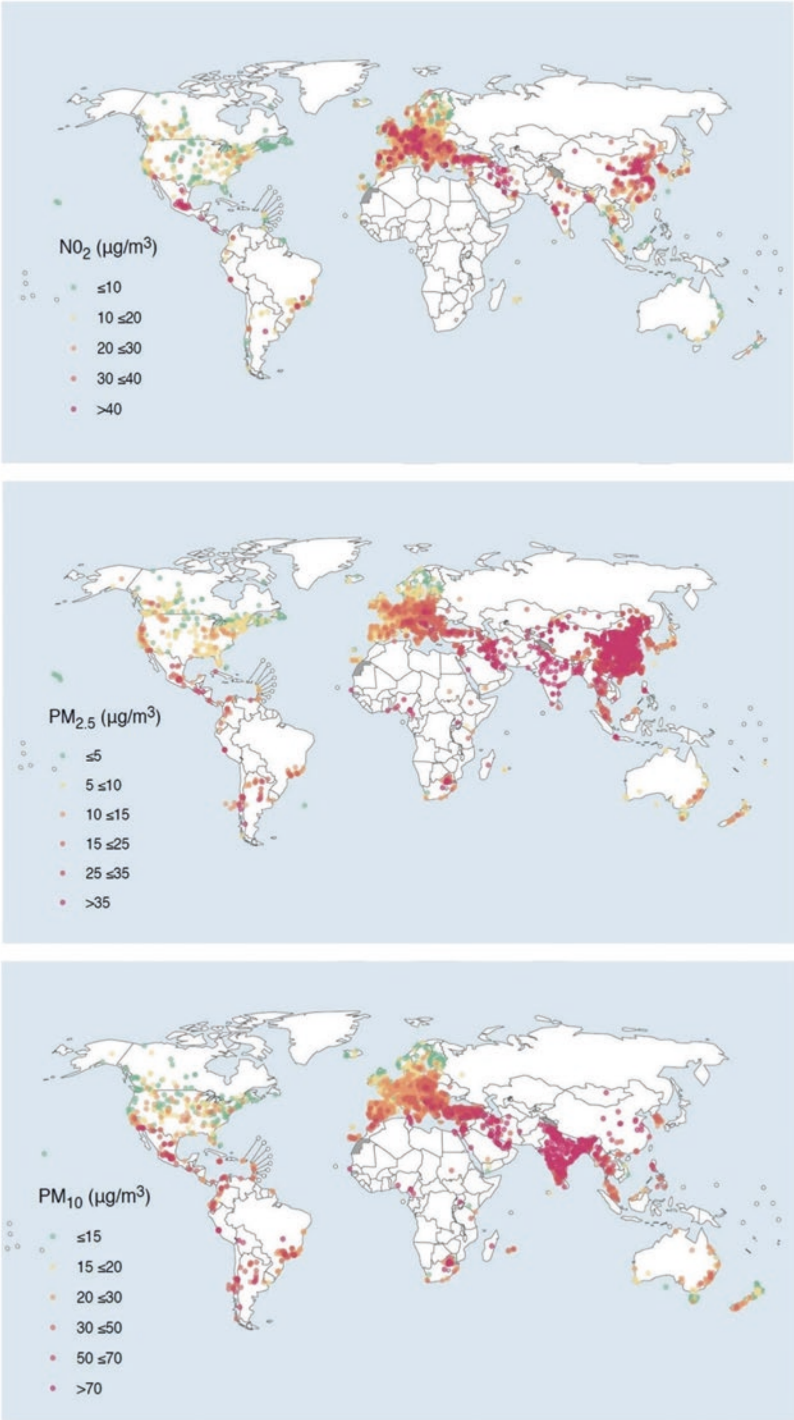

Fig. 1.1 Global average NO_2, $PM_{2.5}$, and PM_{10} concentrations. (Source: WHO. https://cdn.who.int/media/docs/default-source/air-pollution-documents/air-quality-and-health/who-air-quality-database-2022%2D%2D-v7.pdf?sfvrsn=c6d52e7b_7anddownload=true)

Table 1.1 Major air pollutants, their emission sources, and health impacts

Pollutant	Emission sources	Health effects
Carbon monoxide (CO) and nitrogen oxides (NOx)	Combustion of fossil fuels, industrial processes, vehicle exhaust	Headaches, dizziness, nausea, impaired vision and cognitive function, respiratory problems, and increased risk of heart disease
Sulfur dioxide (SO_2)	Burning of fossil fuels, mining and smelting operations	Respiratory problems and increased risk of heart disease
Particulate matter (PM)	Dust and debris generated by construction, industrial processes, transportation, and natural sources such as wildfires	Respiratory and cardiovascular problems, and lung cancer
Ozone (O_3)	The photochemical reactions occurring in the presence of sunlight between nitrogen oxides and volatile organic compounds	Respiratory problems and decreased lung function
Lead (Pb)	Lead-based paint, industrial processes, gasoline	Neurotoxicity, decreased cognitive function, and increased risk of heart disease
Volatile organic compounds (VOCs)	Solvents, paints, cleaning products, and industrial processes, vehicle exhaust	Respiratory problems and cancer
Polycyclic aromatic hydrocarbons (PAHs)	Combustion of fossil fuels, industrial processes, and wildfires	Cancer and DNA damage

Sources: Abdel-Shafy and Mansour (2016), Afroz et al. (2003), Das (2022), Gregoris et al. (2014), Huang et al. (2014), Manisalidis et al. (2020), Thepanondh et al. (2011) and WHO (2006, 2021)

per 100,000 individuals, while Brunei had the lowest recorded rate (0.2 per 100,000 population). In low- and middle-income countries of Southeast Asia, Central Africa, and Western Pacific regions, where exposure to outdoor (ambient) air pollution is more severe, a disproportionate burden of premature deaths, accounting for 91% of the 4.2 million deaths in 2016, has been observed (WHO, 2020). Numerous studies have established a correlation between air pollution and a significant number of cardiovascular fatalities occurring before their expected time, reaching tens of thousands each year (Anderson, 2009; Makri & Stilianakis, 2008; Schwartz, 2001). The respiratory systems of children and individuals with weakened immune systems are at a heightened risk of being adversely affected by air pollution, owing to their lung developmental stage and potentially compromised endogenous mechanisms for combating inhaled contaminants (Kulkarni & Grigg, 2008). Table 1.1 showcases the key air pollutants, their origins, and their detrimental effects.

Air pollution can be mitigated through the adoption of proper measures. Some important action points for controlling air pollution include the following:

(i) Implement strict emission standards for industries and transportation, such as those set by organizations such as the US EPA and the European Commission.

(ii) To lessen reliance on non-renewable energy sources, such as fossil fuels, encourage the adoption of sustainable energy alternatives, including wind, solar, and hydropower.
(iii) Encourage public transportation, cycling, and walking through investments in infrastructure and incentives for individuals.
(iv) Increase energy efficiency in buildings through measures such as insulation and the use of sustainable energy-efficient heating and cooling systems.
(v) Foster the development and adoption of clean technologies, such as electric vehicles and carbon capture and storage systems.
(vi) Implement regulations on agricultural practices to minimize ammonia emissions from fertilizer and manure application.
(vii) Control open burning and ensure proper waste management to reduce emissions of particulate matter and hazardous air pollutants.
(viii) Implement early warning systems and contingency plans to mitigate the impacts of air pollution episodes, such as heat waves and bushfires.
(ix) Encourage active public participation in air quality monitoring and management through initiatives such as citizen science programs.
(x) Strengthen international cooperation and coordination on air pollution control through mechanisms such as the United Nations convention on long-range transboundary air pollution.

1.3 Water Pollution

Water pollution is defined as the presence of substances in water bodies that change their chemical, physical, or biological properties and can have adverse effects on living organisms and their environment (Bilotta & Brazier, 2008; Verma & Ratan, 2020). It occurs when contaminants, such as chemicals, microorganisms, or waste are introduced into water systems beyond a level that is safe for consumption by humans and the health of any ecosystem (Kim & Aga, 2007). Water pollution is caused by various contaminants, such as chemical pollutants (pesticides and heavy metals) (Jayasiri et al., 2022), microbiological pollutants (bacteria and viruses) (Akpor et al., 2014), nutrient pollutants (nitrogen and phosphorus) (Puckett, 1995), thermal pollution and waste products (sewage and industrial waste) (Singh & Gupta, 2016). The measurement of water pollution is typically expressed as the concentration of the contaminant in milligrams per litre (mg/L) or parts per million (ppm) (Weiner, 2010). Water pollution can have both natural and anthropogenic causes. Natural causes include algae blooms and runoff from agricultural fields (Hudnell, 2008; Mushtaq & Nee Lala, 2017; Mushtaq et al., 2022), while anthropogenic causes include discharge from factories and sewage treatment plants, as well as waste products such as sewage and industrial waste (Pang & Abdullah, 2013). These pollutants can harm aquatic species, disrupt food webs, and cause harm to human health (Ali et al., 2019).

Water pollution has far-reaching impacts on the environment and ecosystems, affecting not only water quality but also the health and survival of plants and animals (Barnes et al., 2019). Water pollution can disrupt the food web and cause declines in the populations of species that depend on healthy water ecosystems for survival (Ali et al., 2019; Henley et al., 2000). An overabundance of nutrients, particularly nitrogen and phosphorus, may infiltrate aquatic ecosystems and cause excessive growth of algae and plants, leading to eutrophication. This can deplete the oxygen in the water, causing significant harm to aquatic life (Carpenter et al., 1998; Lushchak, 2011). In addition, water pollution can also have significant economic impacts, as it can lead to a decrease in the accessibility of potable water, as well as water for agricultural and other purposes (Goel, 2006). This can increase the cost of providing clean water and harm the economies of communities that rely on water for their livelihoods (Nicol, 2000).

Water, as a universal solvent, presents a significant risk for infection transmission. According to the WHO, 80% of diseases are waterborne and a significant portion of the potable water available worldwide fails to comply with the regulations and guidelines set forth by the WHO (Khan et al., 2013). Approximately 3.1% of deaths occur annually due to poor water quality and unhygienic conditions (Pawari & Gawande, 2015). Several health agencies, such as the Indian Council of Medical Research (ICMR) (1962), US Public Health Service Drinking Water Standards (USPHS) (1962), and WHO (1992) have established water quality standards (Lester, 1969). Water pollution can have serious impacts on human health. Contaminants, including heavy metals, toxic organic compounds, and pathogens, can enter the water supply, causing a range of health problems, including gastrointestinal illnesses, skin infections, and damage to the nervous, immune, and reproductive systems (Afroz et al., 2003; Das, 2022; Gregoris et al., 2014; Huang et al., 2014; Manisalidis et al., 2020).

Nearly 2.2 billion individuals lack access to improved sources of fresh water for proper usage, including drinking. According to the WHO, contaminated water is responsible for more than 500,000 deaths each year, primarily in developing countries. The most common waterborne diseases that cause death are cholera, typhoid, and diarrhoea, which are all caused by consuming water contaminated with fecal matter (Qadri & Faiq, 2020). Moreover, exposure to toxic chemicals such as lead, mercury, and arsenic in contaminated water leads to serious health issues and even death in some cases. In underdeveloped nations, where there is limited availability of hygienic water and rudimentary sanitation facilities, water contamination has an especially detrimental effect on human health (Järup, 2003). Table 1.2 summarizes the key water pollutants, their origins, and their detrimental effects. Figure 1.2 provides insights into the state of water quality across various regions based on a global water quality risk map prepared by analyzing the biochemical oxygen demand, nitrogen content, and salinity measurements spanning from 2000 to 2010.

The adoption of appropriate measures can help reduce water pollution. To control water pollution, the following measures can be implemented:

Table 1.2 Major water pollutants, their contamination source and health impacts

Pollutant	Contamination sources	Health effects
Nitrogen and phosphorus	Agriculture, human and animal waste, and fertilizers	Algae blooms, low oxygen levels, and fish kills
Bacteria and viruses	Human and animal waste, agricultural runoff, and malfunctioning septic systems	Gastrointestinal illness, infections, and sepsis
Heavy metals (lead, mercury, and cadmium)	Industrial and mining operations, agricultural runoff, and sewage disposal	Damage to the nervous system, kidneys, reproductive system, and increased risk of cancer
Oil and petroleum	Oil spills, urban runoff, agricultural runoff, and industrial discharges	Smothered aquatic life, suffocation, damage to fur and feathers of birds and mammals, and disrupts the food chain
Chlorine	Industrial discharges, runoff from cleaning agents, and sewage	Irritation of eyes and skin, respiratory problems, and damage to aquatic life
Pesticides	Agricultural operations, urban runoff, and industrial discharges	Damage to aquatic life, contamination of fish and other seafood, potential human health risks
Detergents	Urban runoff, residential, and commercial use	Damage to aquatic life and decreased water clarity
Pharmaceuticals	Human and animal waste, agricultural runoff	Endocrine disruption and development problems
Polychlorinated biphenyls (PCBs)	Industrial discharges and leakage from landfills	Cancer and damage to reproductive and immune systems

Sources: Abdel-Shafy and Mansour (2016), Afroz et al. (2003), Das (2022), Gregoris et al. (2014), Huang et al. (2014), Manisalidis et al. (2020), Thepanondh et al. (2011) and WHO (2006, 2021)

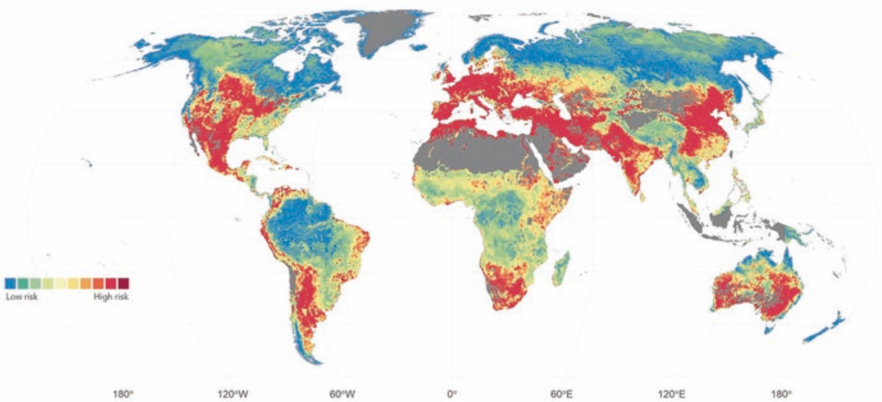

Fig. 1.2 Global water quality risk map determined by analyzing biochemical oxygen demand, nitrogen content, and salinity measurements spanning from 2000 to 2010. (Source: World Bank. https://www.globalwaterintel.com/news/2019/34/agencies-plead-for-global-action-on-water-pollution)

(i) Implement best management practices (BMPs) in agriculture: This can include planting cover crops, constructing filter strips, and implementing precision agriculture techniques to reduce the amount of agricultural chemicals and nutrients entering water bodies.
(ii) Enhance the wastewater treatment facilities: Augmenting the functionality of the prevailing wastewater treatment facilities and erecting novel facilities to guarantee compliance with the prescribed water quality benchmarks for discharging effluent.
(iii) Control industrial discharge: Regulating industrial discharge through the implementation of discharge permits, which specify limits on the amount and type of pollutants that can be released into water bodies.
(iv) Developing and enforcing water quality standards: Developing water quality standards for pollutants and enforcing them to safeguard human health and the environment, is imperative to shield against deleterious agents, which include heavy metals, organic chemicals, and bacterial entities, commonly referred to as pollutants.
(v) Monitor and manage stormwater runoff: Implementing stormwater management techniques such as green roofs, permeable pavements, and bioretention systems to reduce the number of pollutants and sediment that enter water bodies during storms.
(vi) Implement land use planning: Encouraging sustainable land use practices, such as preserving wetlands and floodplains, and managing development to mitigate the effects of alterations in land utilization on the quality of water, measures are taken to reduce the extent of damage caused.
(vii) Promote conservation practices: Encouraging conservation practices, such as reducing water usage and managing groundwater resources to minimize water withdrawals and protect water quality.
(viii) Increase public education and outreach: Disseminating information to the general public regarding the origins and ramifications of water contamination and encouraging them to take action to prevent it, such as reducing the use of household chemicals and properly disposing of hazardous waste.
(ix) Use of innovative technologies: Adopting innovative technologies, such as constructed wetlands and other natural treatment systems, to treat contaminated water and restore degraded water bodies.
(x) Enforce penalties for noncompliance: Enforcing penalties for noncompliance with water quality regulations, such as fines and criminal penalties for intentional pollution, to deter illegal activities that contribute to water pollution.

1.4 Soil Pollution

Soil pollution pertains to the infiltration of noxious substances into the composition of the soil, leading to detrimental consequences on the environment and human health (Cachada et al., 2018; Yong, 2000). This phenomenon is typically initiated by anthropogenic activities such as industrial processes, agricultural practices, and improper disposal of hazardous waste materials (Barbieri, 2016). The presence of contaminants in the soil can result in significant soil degradation and decreased fertility, negatively affecting the growth and viability of vegetation, fauna, and microorganisms (Pimentel, 2006). Additionally, soil pollution may result in leaching of contaminants into the underlying groundwater aquifers, leading to widespread contamination and posing a potential hazard to human and animal well-being through the transmission of adverse effects along the food chain (Abrahams, 2002; Mishra et al., 2019).

Soil pollution has a detrimental impact on the environment as well as the atmosphere. The presence of hazardous contaminants in the soil can result in decreased soil fertility, degradation of soil structure, and alterations to the soil–plant–atmosphere continuum (Lehmann & Joseph, 2015; Nieder & Benbi, 2003). The release of VOCs and other pollutants from contaminated soil can contribute to air pollution and the formation of harmful atmospheric species such as ozone and particulate matter (Kampa & Castanas, 2008; Manisalidis et al., 2020). Furthermore, soil contamination can lead to the percolation of pollutants into adjacent water bodies, leading to water pollution and negatively impacting aquatic ecosystems (Tiwary, 2001). Soil contamination possesses the capacity to perturb the soil-microbial consortium and modify the dynamics of nutrient cycling and greenhouse gas emissions (Bisht & Chauhan, 2020). Contaminants present in polluted soil can leach into groundwater, leading to widespread contamination of drinking water sources and affecting human health (Azizullah et al., 2011; Evanko & Dzombak, 1997; Holt, 2000). Additionally, the presence of pollutants in the soil can give rise to the build-up of hazardous compounds in agricultural produce and livestock, thereby inducing contamination within the food chain and presenting a potential hazard to human well-being (Khan et al., 2015). According to the WHO, soil pollution is linked to various human health impacts, including cancer, neurological disorders, and respiratory problems. The presence of toxic substances in soil can also result in decreased biodiversity, as contaminated soil can significantly impede the growth and viability of plants, animals, and microbes (Geisen et al., 2019). The United Nations Environment Programme (UNEP) has estimated that soil pollution affects over 33% of global croplands, leading to decreased agricultural productivity and food security. Soil pollution also results in significant economic losses, with the United Nations estimating the cost of soil degradation and pollution at US $400 billion per year. In addition, the remediation of contaminated soil can be complex and expensive, requiring significant investment in technology and resources. Quantifying or measuring soil pollution is a multidisciplinary task that employs diverse analytical methodologies to ascertain the existence and abundance of pollutants within soil specimens (Garrett et al., 2008). The methods used for quantifying soil pollution include chemical and physical analysis techniques, such as X-ray fluorescence (XRF), gas chromatography–mass spectrometry (GC–MS) and inductively coupled plasma–mass spectrometry (ICP–MS) (Ali & Jain, 2004). Additionally, bioassay techniques can also be used to determine the toxicity of soil and the impact of contaminants on soil biota (Terekhova, 2011). To accurately measure soil pollution, it is necessary to consider

Table 1.3 Major soil pollutants, their contamination source and health impacts

Pollutant	Contamination sources	Health effects
Lead	Industrial activities, batteries, and fuel additives	Neurological disorders, decreased IQ in children, anaemia, and kidney damage
Cadmium	Fertilizer application, industrial activities, and sewage sludge	Kidney damage, anemia, weakened bones, and decreased reproductive capacity
Mercury	Industrial activities and coal-fired power plants	Neurological disorders, developmental problems in children, and decreased immune system function
Arsenic	Agricultural activities, wood preservatives, and pesticide application	Skin lesions, cancer, cardiovascular disease, and developmental problems in children
Polychlorinated biphenyls (PCBs)	Industrial activities and improper disposal of electrical equipment	Cancer, developmental problems in children, hormonal imbalances, and decreased immune system function
Dioxins	Industrial processes and burning of waste materials	Cancer, developmental problems in children, decreased immune system function, and hormonal imbalances
Polycyclic aromatic hydrocarbons (PAHs)	Improper disposal of petroleum products and burning of fossil fuels	Cancer, developmental problems in children, and decreased immune system function

Sources: Fisher (1999), Genchi et al. (2020), Khan et al. (2021), Papanikolaou et al. (2005), WHO (2019), Xu et al. (2015) and Zahir et al. (2005)

the spatiotemporal variability of soil characteristics, in addition to the nature and concentration of the contaminants present. The measurement of soil pollution should also be conducted in accordance with established protocols and quality assurance/quality control procedures to ensure accurate and reliable results (Brookes, 1995; Kowalska et al., 2018). Table 1.3 summarizes the major soil pollutants, their origins, and their detrimental effects, and Fig. 1.3 shows the soil contamination status across the globe.

The control and mitigation of soil pollution require a multifaceted approach incorporating both preventative and remedial measures. Some key strategies for controlling soil pollution include the following:

(i) Regulating hazardous waste management: Effective regulation and enforcement of hazardous waste management practices is critical in preventing soil pollution. This includes implementing strict regulations for the disposal of hazardous waste, ensuring the proper management of underground storage tanks, and enforcing regulations regarding the storage and handling of hazardous substances.

(ii) Implementing best management practices in agriculture: Agricultural activities can contribute significantly to soil pollution, and implementing best management practices, such as reducing pesticide and fertilizer use and promoting conservation tillage, can help minimize soil contamination.

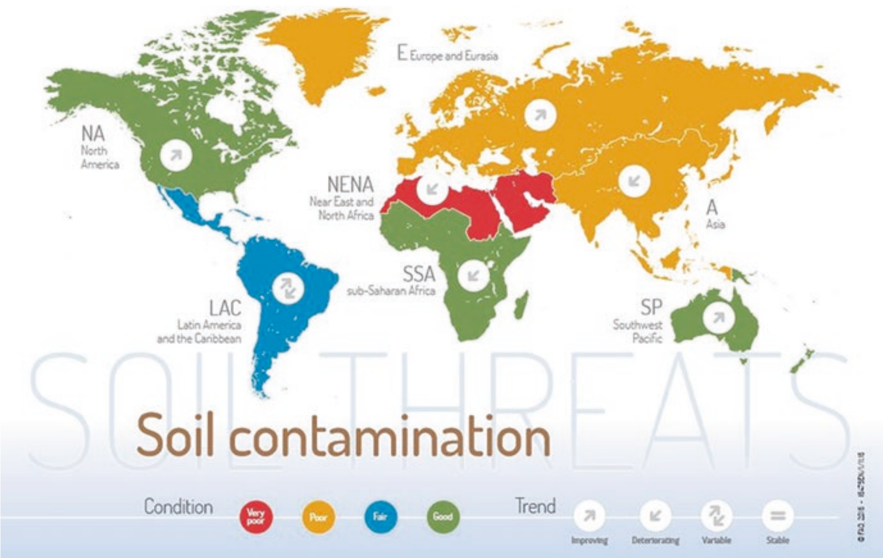

Fig. 1.3 Global map of soil contamination. (Source: FAO. https://www.fao.org/3/cb4894en/online/src/html/chapter-03-6.html)

(iii) Promoting sustainable industrial practices: Industries have the potential to incorporate sustainable methodologies aimed at mitigating soil pollution, including the curtailment of hazardous chemical usage and the establishment of efficient wastewater management systems.

(iv) Implementing soil remediation technologies: In cases where soil pollution has already occurred, various remediation technologies can be employed to mitigate the effects and restore soil quality. These include physical, chemical, and biological methods such as soil washing, bioremediation, and phytoremediation.

(v) Conducting regular soil monitoring and assessment: Regular monitoring and assessment of soil quality can help identify contamination hotspots and inform targeted remediation efforts. This can include using geospatial technologies, such as remote sensing and GIS, to identify areas of concern and prioritize remediation efforts.

(vi) Encouraging public education and awareness: Raising public awareness and education about the dangers of soil pollution and promoting best practices for minimizing soil contamination is critical in reducing the risk of soil pollution and promoting environmental sustainability.

1.5 Noise Pollution

Noise pollution, also known as anthropogenic noise, pertains to the amplification of inherent background noise levels caused by human activities that produce sound. This auditory disturbance can have adverse effects on both humans and animals, potentially leading to detrimental consequences (Slabbekoorn, 2019; Tripathy, 2008; Weilgart, 2018). Certain auditory stimuli are intentionally generated and desired, such as melodic compositions, emergency sirens, seismic investigation acoustics, or military echolocation systems. Conversely, the majority of anthropogenic acoustic disturbances are unintended side effects, including the clamour of vehicular traffic or the resonances emitted by power generators, as well as abrupt sonic emissions originating from pile driving activities and explosive detonations, among others (Potter, 2007; Spiga et al., 2012).

Noise pollution, characterized by excessive sound levels that disrupt normal activities, has severe negative impacts on both human beings and various species (Basner et al., 2014; Passchier-Vermeer & Passchier, 2000). According to the WHO, being subjected to noise pollution can give rise to a range of health complications, including hypertension, sleep disruption, and cardiovascular ailments. Specifically, prolonged exposure to noise levels surpassing 55 decibels (dB) is linked to an augmented susceptibility to heart disease (Münzel et al., 2020). Rapidly escalating, noise pollution has become a pressing issue in urban centres globally, with a visual representation (Fig. 1.4) highlighting countries grappling with the most severe noise

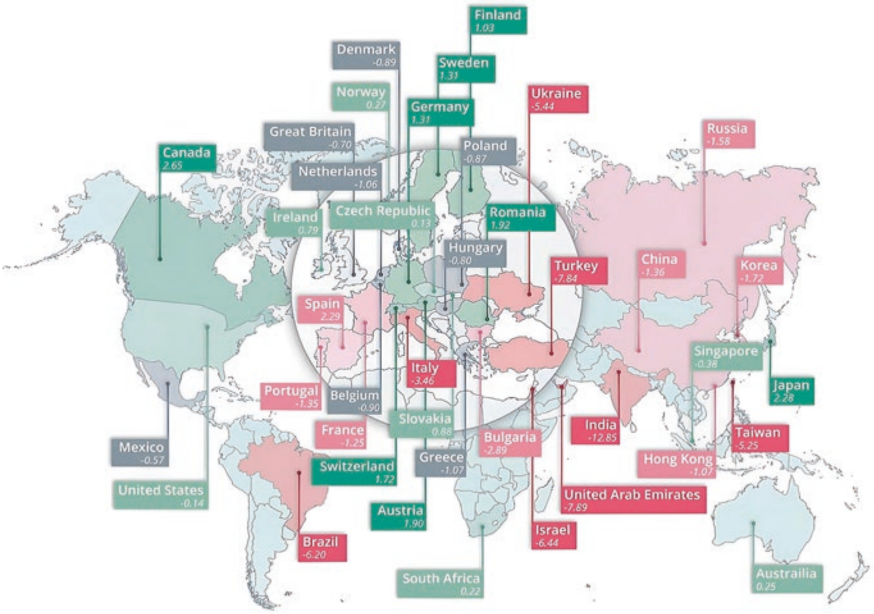

Fig. 1.4 Map depicting countries with the worst noise pollution. (https://knops.co/magazine/noise-pollution-worst-countries/)

Table 1.4 Major sources of noise pollution and their health impacts

Pollutant	Contamination sources	Health effects
Transportation noise	Road, air, and railway traffic	Sleep disturbance, stress, cardiovascular disease, and hearing loss
Industrial noise	Manufacturing processes, construction sites, and heavy machinery	Sleep disturbance, stress, hearing loss, and decreased cognitive function
Recreational noise	Loud music, fireworks, and sporting events	Sleep disturbance, stress, and hearing loss
Residential noise	Neighbourhood and urban noise, such as barking dogs, traffic, and air conditioning units	Sleep disturbance, stress, and hearing loss

Sources: Basner et al. (2014), Berglund et al. (1999), Gupta et al. (2018), Münzel et al. (2021) and WHO (2015)

pollution levels. In the United States, the US EPA estimates that the number of individuals subjected to noise levels, posing a threat to their well-being, exceeds 100 million. Additionally, research conducted by the European Environment Agency (EEA) reveals that over 50% of European Union (EU) residents experience road traffic noise levels surpassing 55 dB.

Studies by the UNEP reveal that noise pollution not only affects humans but also has adverse effects on animals. It can disrupt communication, feeding patterns, and mating habits of various species (Francis et al., 2009; Lowry et al., 2013). For instance, cetaceans such as whales and dolphins depend on acoustic signals for the purposes of orientation, social interaction, and sustenance acquisition. Anthropogenic noise such as ship noise and sonar can cause acoustic trauma to these mammals and lead to mass strandings and deaths (Cox et al., 2006; Hildebrand, 2005). Table 1.4 summarizes the major causes of noise pollution, their origin, and their detrimental effects.

Controlling noise pollution can be achieved through various strategies, some of which are as follows:

(i) The use of noise barriers and sound insulation materials can significantly reduce the transmission of noise from the source to the surrounding environment. These materials include double-glazed windows, acoustic panels, and concrete barriers.

(ii) Urban planners and policymakers can implement noise control measures, such as zoning regulations, to limit the creation of noise in residential areas. This includes reducing the number of sources of noise, such as highways, airports, and industrial sites in close proximity to residential areas.

(iii) The development of quieter technologies and machinery can significantly reduce noise pollution from various sources, such as transportation, construction, and industrial activities. For instance, electric vehicles and hybrid engines produce lower levels of noise than traditional internal combustion engines.

(iv) Disseminating knowledge to the general population regarding the deleterious repercussions of noise pollution and advocating for the adoption of noise mitigation measures can effectively mitigate the extent of noise pollution exposure. This includes encouraging the use of headphones or earplugs in noisy environments and reducing unnecessary noise such as loud music in public spaces.
(v) The enforcement of noise pollution regulations and guidelines by authorities can deter businesses and individuals from generating excessive noise. This includes imposing fines and penalties for noise violations and setting up monitoring systems to measure noise levels.
(vi) Technological advancements, including the utilization of artificial intelligence (AI) and machine learning, have the potential to facilitate the detection and mitigation of noise pollution. For example, AI-powered noise sensors can detect and locate sources of noise pollution, while machine learning algorithms can optimize noise reduction strategies based on real-time data.

1.6 Thermal Pollution

Thermal pollution is the harmful alteration of water or air temperature caused by human activities, such as the discharge of heated water from industrial processes or the use of cooling systems in power plants (McMichael et al., 2006; Verones et al., 2010). This temperature variation can have detrimental effects on the natural ecosystem by inducing a reduction in dissolved oxygen concentrations, an elevation in the metabolic rates of aquatic organisms, and modifications in the dynamics of the overall ecosystem (Altieri & Gedan, 2015; Ficke et al., 2007; Sheridan & Bickford, 2011). Particularly, thermoelectric power plants play a pivotal role in aggravating global river thermal pollution, intensifying concerns about elevated water temperatures and environmental ramifications (Fig. 1.5).

Thermal pollution possesses the potential to engender adverse impacts on the well-being of both human and animal populations, as it alters the natural environment in which they live (Anju et al., 2010). According to the US EPA, exposure to water temperatures above 90 °F can lead to heat exhaustion, heatstroke, and other heat-related illnesses in humans. In addition, elevated water temperatures can affect the growth and survival of fish, causing declines in fish populations and disrupting food webs (Breitburg, 2002; Yamamuro et al., 2019). The National Oceanic and Atmospheric Administration (NOAA) reports that thermal pollution can also trigger harmful algal blooms capable of generating toxins that present a substantial peril to both human beings and wildlife. Furthermore, elevated water temperatures can reduce the solubility of oxygen in water, leading to hypoxic (low oxygen) conditions that can cause fish and other aquatic organisms to suffocate (Hobbs & McDonald, 2010; Shepherd et al., 2017). A study by the US Fish and Wildlife Service found that the emission of excess heat generated by power plants can result in substantial reductions in populations of thermally vulnerable fish species, including salmon and trout, and can also alter their behaviour, reproduction, and migration

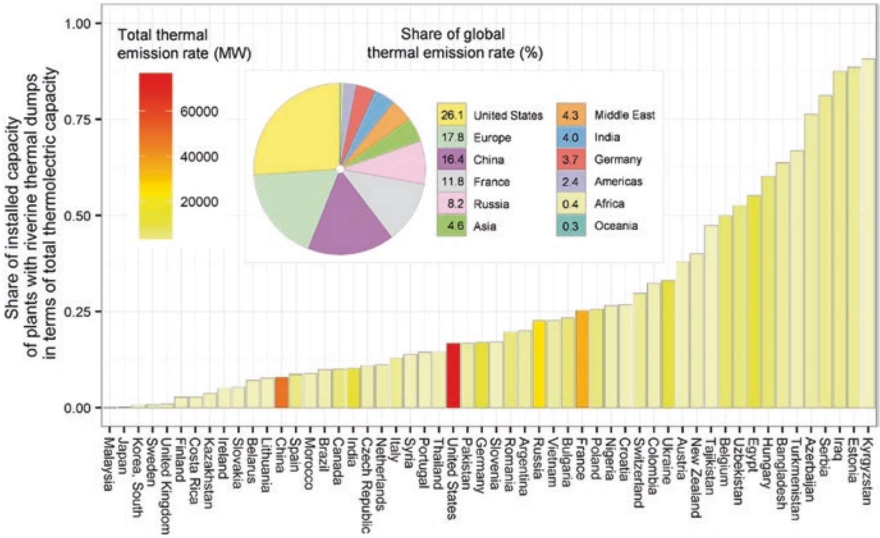

Fig. 1.5 Contribution of thermoelectric power plants to the global thermal pollution of rivers. (Source: Raptis et al., 2016. https://iopscience.iop.org/article/10.1088/1748-9326/11/10/104011)

patterns. Additionally, investigations have revealed that thermal pollution exerts a detrimental influence on the biodiversity and population density of various aquatic taxa, including insects, and amphibians (Swer & Singh, 2004; Van Dijk et al., 2013). Table 1.5 summarizes the major causes of thermal pollution, their origin, and their detrimental effects.

Managing thermal pollution necessitates the deployment of efficient and environmentally sound measures that can alleviate the adverse ramifications arising from excessive heat transfer in water or air systems. Some technical methods that can be implemented to control thermal pollution are as follows:

(i) Use alternative cooling systems: One of the most efficacious methodologies to control thermal pollution is by using alternative cooling systems that do not rely on the discharge of heated water. For example, dry cooling systems, which use air instead of water to cool industrial processes, can significantly reduce thermal pollution. In addition, closed-loop cooling systems, which recycle water instead of discharging it, can also help to mitigate thermal pollution.
(ii) Implement regulations and guidelines: Governments possess the capacity to exert substantial influence and impact in controlling thermal pollution by implementing regulations and guidelines that limit the amount of heated water that can be discharged into the environment. For example, the Clean Water Act in the United States establishes standards for the temperature of water discharged from power plants and other industrial facilities.
(iii) Increase efficiency of industrial processes: Another approach to controlling thermal pollution is to enhance the operational efficacy of industrial procedures,

Table 1.5 Major causes of thermal pollution, their source of origination and associated health impacts

Pollutant	Contamination sources	Effects
Heavy industries (water as a coolant)	Power, chemical, nuclear, and manufacturing industries	Plants and animals can suffocate due to low oxygen levels giving rise to anaerobic conditions. The density and viscosity of water increase affecting food supplies. Nuclear power plants release water that is slightly radioactive into natural systems causing an increase in toxicity
Domestic and industrial effluents	Drainage from hospitals, research institutions with minimum, or no treatment	Reduction in fish population and drop-in reproduction rate
Urban stormwater runoff due to paved surface	Pavements hinder groundwater recharge as less amount goes into the soil	Negative impact on the growth of vegetation and food supplies
Deforestation	Removal of forests/trees resulting in lack of shade and sunlight falling directly on rivers, canals and ponds	Spread of zoonotic diseases
Soil erosion	Soil erosion and sedimentation make it directly exposed to sunlight	Loss of biodiversity
Geothermal activities	Geothermal activities and volcanoes	Suffocation; infectious diseases, such as conjunctivitis; acute and chronic respiratory diseases from falling ash and breathing gases and fumes; burns and traumatic injuries, such as lacerations from falling rock; eye and skin irritations from acid rain

Sources: Chowdhary et al. (2020), Costa (1997), Fosmire (1990), Gade (2015), Haefliger et al. (2009), Kravchenko and Lyerly (2018) and WHO (2019)

which can reduce the amount of heat generated in the first place. This can be achieved through the use of energy-efficient technologies, process optimization, and waste heat recovery systems.

(iv) Improve wastewater treatment: Effective wastewater treatment can also help to control thermal pollution, as it can reduce the temperature of water before it is discharged into the environment. Advanced treatment technologies, such as membrane filtration and reverse osmosis, can effectively remove heat from wastewater while also reducing the levels of pollutants.

(v) Encourage conservation and awareness: Finally, controlling thermal pollution also requires the participation of individuals and organizations in conserving energy and raising awareness about the issue. Encouraging energy conservation through initiatives such as green building design and energy-efficient appliances can help to reduce the demand for energy and, consequently, the amount of heat generated. Similarly, educating the public about the impacts of thermal pollution and ways to mitigate it can increase awareness and encourage action.

1.7 Light Pollution

Light pollution refers to the human-caused modification of the ambient light levels present in the natural environment caused by the excessive and poorly designed use of artificial light sources (Gaston et al., 2013; Riegel, 1973) (Fig. 1.6). This results in the over-illumination of the night sky and the surrounding landscape, causing a variety of negative effects on the astronomical, ecological, physiological, and sociological aspects of the environment (Chepesiuk, 2009; Pothukuchi, 2021). The three main components of light pollution are skyglow, glare, and light trespass, which collectively contribute to the deterioration of the ecological integrity of the nocturnal habitat and the perturbation of the circadian rhythms of organisms (Cleary-Gaffney, 2022; Elsahragty & Kim, 2015; Gaston et al., 2012; Mizon, 2012).

The phenomenon of light pollution has been scientifically demonstrated to exert diverse detrimental impacts on both human beings and various biological species (Gaston et al., 2012). Studies by the WHO and the American Medical Association have linked exposure to artificial light at night with disruptions in circadian rhythms, which can increase the risk of chronic diseases such as cancer, diabetes, and cardiovascular disease. Additionally, exposure to light at night has been linked to sleep disorders, depression, and impaired cognitive function in humans (Crowley, 2011; Xie et al., 2017). In terms of species, light pollution can disrupt the behaviour and physiology of animals, leading to changes in migration, foraging, and reproduction

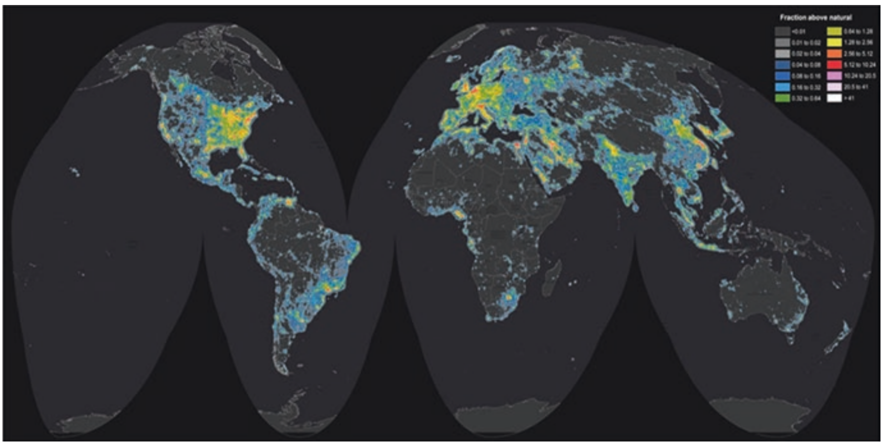

Fig. 1.6 The contemporary global compendium on artificial nocturnal sky luminance. (Source: Falchi et al., 2016. https://www.science.org/doi/10.1126/sciadv.1600377)

Table 1.6 Major causes of light pollution, their source of origination and associated health impacts

Pollutant	Contamination sources	Health effects
Skyglow	Artificial lighting from cities and towns	Circadian rhythm disturbances, heightened susceptibility to chronic conditions such as malignancies, diabetes, cardiovascular disorders, sleep dysregulation, depressive symptoms, and compromised cognitive capabilities
Glare	Poorly shielded light fixtures	Decreased visibility, increased risk of accidents, discomfort, and headaches
Light trespass	Excessive or misplaced outdoor lighting	Disruption of circadian rhythms, sleep disorders, reduced visibility, disturbance to wildlife, and increased energy waste
Over-illumination	Excessive lighting for aesthetic or security purposes	Wasted energy, light pollution, increased greenhouse gas emissions, and increased costs for lighting and maintenance
Flicker	Inconsistent lighting sources	Migraine headaches, photosensitive epilepsy, visual discomfort, and decreased visual performance

Sources: Conlon et al. (2001), Kabir et al. (2022), Kumar et al. (2019), Rajkhowa (2014), Zielinska-Dabkowska and Bobkowska (2022)

(Lennox et al., 2016; Longcore & Rich, 2004). The International Dark-Sky Association reports that up to 1 billion birds are killed annually in North America alone due to collisions with artificial light sources, while sea turtle hatchlings are often disoriented by beachfront lighting, causing them to head in the wrong direction and reducing their chances of survival. Furthermore, the disruption of natural light cycles caused by light pollution can also have cascading effects on ecosystems, such as changes in predator–prey interactions and altered plant growth patterns (Grubisic et al., 2018; Horváth et al., 2009; Oro et al., 2013). Therefore, it is crucial to tackle the problem of light pollution by enacting efficient lighting regulations and advocating for conscientious lighting practices to safeguard the well-being of both human populations and biodiversity. Table 1.6 summarizes the major causes of light pollution, their origin, and their detrimental effects.

Light pollution is a complex problem that requires a multidisciplinary approach to mitigate its effects and preserve the natural darkness of the environment. Some of the points that can be followed to control light pollution are as follows:

(i) Implementing lighting regulations: Governments can create and enforce regulations on outdoor lighting to limit light pollution. These regulations can include guidelines on light fixture design, light colour, and intensity, as well as curfews and restrictions on the use of certain types of lighting.
(ii) Using energy-efficient lighting: Replacing traditional lighting sources with energy-efficient options such as LEDs can help reduce light pollution and energy consumption. These technologies often offer better colour rendering and directional lighting, reducing light trespass, and skyglow.
(iii) Promoting responsible lighting practices: Disseminating information to the general populace regarding the adverse effects of light pollution and the

advantageous outcomes resulting from adopting conscientious lighting methodologies can effectively heighten consciousness and instigate modifications in conduct. This can include encouraging the use of motion sensors, timers, and dimmer switches, as well as proper light fixture installation and maintenance.

(iv) Encouraging the use of shields and filters: Shields and filters can be used to direct light downwards, reducing glare and light trespass. Additionally, specialized filters can be used to reduce the amount of blue light emitted by outdoor lighting, which can disrupt circadian rhythms and impact wildlife.

(v) Supporting dark sky preservation: Maintaining the integrity of natural darkness in regions characterized by minimal levels of light pollution can yield advantageous outcomes for human well-being, biodiversity conservation, and the field of astronomy. This can be achieved through the establishment of dark sky parks and reserves, as well as the use of responsible lighting practices in rural and remote areas.

1.8 Radiation Pollution

Radiation pollution refers to the existence of ionizing or nonionizing radiation within the surrounding environment surpassing naturally occurring background levels due to anthropogenic activities such as nuclear power generation, medical procedures, and industrial processes (Hatra, 2018; Musa, 2019; Zakariya & Kahn, 2014). The distribution of active nuclear power plants as of 2020 can be seen in Fig. 1.7. These power plants are potential sources of radiation pollution, as they involve the operation of nuclear reactors that generate ionizing radiation. Ionizing radiation, encompassing electromagnetic waves such as gamma rays and X-rays, possesses sufficient energy to dislodge electrons from atomic structures, thereby instigating chemical alterations within biological tissues. Consequently, this phenomenon amplifies the likelihood of cancer, genetic mutations, and other detrimental health outcomes (Chaturvedi & Jain, 2019; National Research Council, 2006). Nonionizing radiation, such as radio waves and microwaves, can cause thermal effects on living tissue and may lead to biological effects at high intensities (Belpomme et al., 2018; Ng, 2003). The phenomenon of radiation pollution exhibits an enduring presence within the environment, spanning extended durations, thereby yielding substantial repercussions on both human health and the ecosystem, requiring careful monitoring, regulation, and management (Harrison, 2001; Nwachukwu et al., 2013).

Radiation pollution can have significant negative impacts on both humans and species. Exposure to ionizing radiation, even at low doses, has been associated with an amplified risk of cancer, genetic mutations, and other health effects (Prasad et al., 2004; National Research Council, 2006). The International Atomic Energy Agency (IAEA) reports that globally, an estimated 1 out of 20 cancer cases is attributable to radiation exposure. Additionally, radiation pollution can have direct impacts on

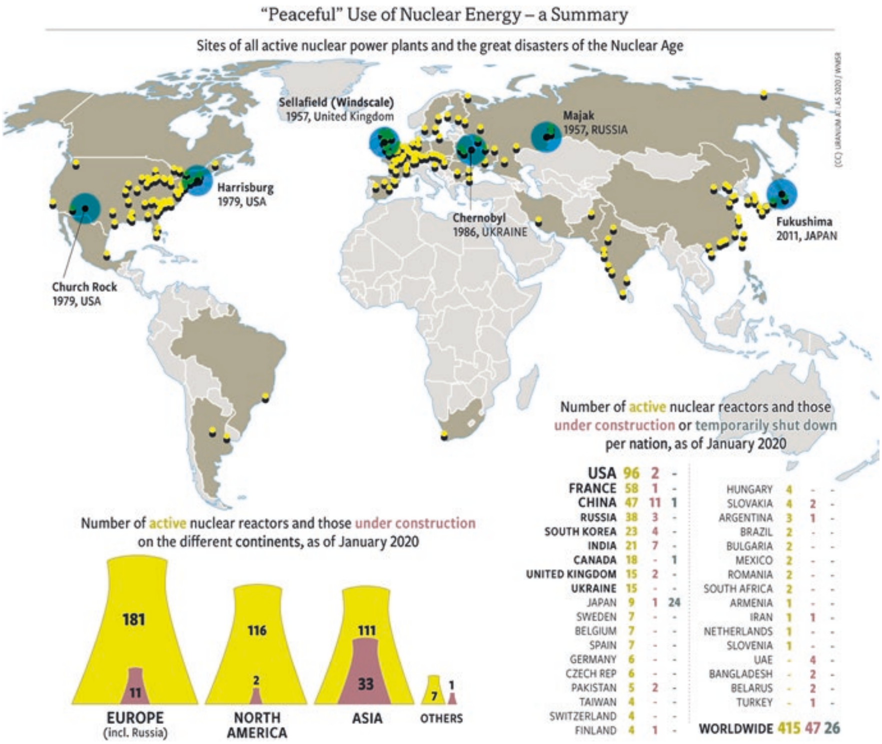

Fig. 1.7 Active nuclear power plants as of 2020. (https://www.nuclear-free.com/uranium-article/articles/nuclear-disasters-from-mayak-to-church-rock-to-fukushima-2.html)

wildlife and ecosystems, including genetic mutations, reproductive failure, and increased mortality rates (Bickham et al., 2000; Geras'kin, 2016; Møller & Mousseau, 2006). The United Nations Scientific Committee on the Effects of atomic radiation reports that marine organisms in the vicinity of the Fukushima Daiichi nuclear power plant in Japan have shown signs of physiological stress and genetic damage due to exposure to ionizing radiation. Furthermore, radiation pollution can have indirect impacts on ecosystems by altering food webs, causing population declines and affecting ecosystem services (Clements & Rohr, 2009; Reid et al., 2019). For example, many studies have shown that the release of radioactive material from the Chernobyl nuclear disaster in 1986 led to a decline in pollinator populations, which can have cascading effects on plant reproduction and ecosystem stability. Table 1.7 summarizes the major causes of radiation pollution, their origin, and their detrimental effects.

Given the serious health and ecological risks associated with radiation pollution, it is critical to develop effective regulatory frameworks and mitigation strategies to prevent or minimize exposure. Some important steps that can be taken are as follows:

Table 1.7 Major causes of radiation pollution, their source of origination and associated health impacts

Pollutant	Contamination sources	Health effects
Alpha particles	Inhalation or ingestion of radioactive materials	Damage to lung tissue, increased risk of lung cancer, and bone marrow damage
Beta particles	Inhalation or ingestion of radioactive materials	Skin burns, eye damage, and increased risk of cancer
Gamma rays	Nuclear power plants, medical procedures, and nuclear accidents	Increased risk of cancer, genetic mutations, cell damage, and immune system suppression
Neutrons	Nuclear reactors and nuclear weapons	Damage to DNA, increased risk of cancer, cataracts, and sterility
X-rays	Medical and dental procedures, industrial processes	Increased risk of cancer, genetic mutations, and cell damage

Sources: Christensen et al. (2014), Manisalidis et al. (2020), Narendran et al. (2019), Scott (2007), Tang et al. (2017) and Wall et al. (2006)

(i) Implementing regulatory measures: Governments can create and enforce regulations on radiation protection and safety, such as limits on radioactive emissions and exposure levels. This can include licensing and inspection of nuclear facilities, as well as waste management and disposal guidelines.
(ii) Developing radiation monitoring and detection systems: Continuous monitoring and early detection of radiation levels can help prevent or minimize exposure. This can include the use of radiation detectors, air and water monitoring systems, and remote sensing technologies.
(iii) Implementing emergency response plans: In the event of a radiation incident or accident, emergency response plans and procedures can help minimize exposure and prevent further contamination. This can include evacuation plans, decontamination procedures, and medical treatment protocols.
(iv) Encouraging the use of radiation-safe practices: Education and training on radiation safety practices can help prevent exposure and contamination. This can include proper handling, storage, and transportation of radioactive materials, as well as personal protective equipment and hygiene measures.
(v) Developing and promoting alternative technologies: Developing and promoting alternative technologies that do not rely on radioactive materials can help reduce the risk of radiation pollution. This can include renewable energy sources, non-destructive testing methods, and medical imaging technologies that use lower levels of radiation.

1.9 Conclusion

Pollution, as a broad concept, constitutes a significant ecological apprehension stemming from anthropogenic actions, including transportation, industrial processes, energy generation, and inadequate management of waste materials. The adverse effects of pollution include respiratory illnesses, cardiovascular diseases, genetic mutations, cancer, and other health issues. Pollution also affects natural ecosystems, including aquatic life and soil quality, leading to the destruction of biodiversity. Environmental pollution is a significant issue that negatively impacts the natural and human-made environment, affecting human health, animal life, and plant life. A comprehensive understanding of the various origins of pollution and its ramifications on the ecosystem and human society is imperative in formulating efficacious approaches to attenuate their repercussions.

Environmental pollution is a global issue that requires collective efforts from all stakeholders to mitigate its effects. By taking proactive measures and implementing effective solutions, we can build the capability to implement measures aimed at preserving the ecological system and ensuring the preservation of human health and overall welfare. We must recognize the importance of a clean environment and promote sustainable practices to ensure a healthier and brighter future for generations to come. To achieve a pollution-free environment, it is crucial to address the root causes of pollution and adopt a holistic approach. Governments, corporations, and individuals each bear responsibility for mitigating pollution levels. It is necessary to invest in research and development to create innovative solutions that can tackle pollution effectively. To combat pollution, we need to adopt sustainable practices, promote cleaner energy sources, and technologies, implement effective policies, and regulate waste disposal practices. We need to regulate the use of harmful substances and promote awareness of the issue to reduce pollution levels. It is crucial to monitor pollution levels and take corrective actions to prevent further damage to the environment. Moreover, individuals can also contribute to the cause by adopting eco-friendly practices such as reducing energy consumption, practicing proper waste disposal techniques, and advocating for the adoption and utilization of public transit systems. Educating people about the impacts of pollution and the benefits of sustainable practices is also essential in creating a culture of responsibility toward the environment.

In conclusion, environmental pollution is a complex issue that requires collective efforts from all stakeholders to mitigate its effects. By taking proactive measures, implementing effective solutions, and promoting awareness, we can work towards achieving a pollution-free environment. We must act now to protect the environment for future generations and ensure a sustainable future.

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Chapter 2
Geostatistical Methods and Framework for Pollution Modelling

Zaiema Rouf Khan and Arshid Jehangir

Abstract In recent years, pollution has become an important global issue due to its impact on people's lives and the environment and has caused severe problems for humans. Geospatial methods are techniques and tools used to collect, analyse, and visualize spatial data in various fields, such as geography, geology, ecology, urban planning, and public health. These methods allow researchers and practitioners to understand the spatial relationships and patterns of natural and human-made phenomena, which can aid in decision-making, policy development, and resource allocation. Geospatial methods involve the use of remote sensing, geographic information systems (GIS), and spatial statistics to collect, analyse, and visualize spatial data. These methods provide valuable information on the location, distribution, and intensity of pollution sources and their potential impact on human health and the environment. GIS can possibly be used to map the spatial distribution of pollution sources, such as factories, traffic, and agriculture, while remote sensing can be used to detect changes in land use and vegetation cover that may affect the quality of the environment. Remote sensing can be used to collect data on air quality and pollution sources. Satellite and aerial imagery can be used to map the spatial distribution of pollutants and provide information on the location and extent of pollution sources. This information can be used to identify areas of high pollution concentrations and develop mitigation strategies. Spatial statistics can be used to analyse the spatial distribution of pollutants and assess the spatial relationship between pollution sources and environmental variables. This can help to identify the factors that contribute to high pollution concentrations and assess the effectiveness of pollution control measures. In addition to geospatial methods, a variety of frameworks have been developed to facilitate pollution modelling. These frameworks provide a structured approach to model development and can help ensure consistency and accuracy in the modelling process. Overall, geospatial methods and frameworks provide a powerful tool for pollution modelling and can be used to inform policy and management decisions related to air and water quality. However, the accuracy and effectiveness of these methods depend on the quality and

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availability of spatial data and the selection of appropriate modelling techniques. Thus, the application of geospatial methods in the framework of pollution modelling has proven to be an effective tool in assessing the impact of pollution on human health and the environment. The integration of spatial data using geospatial methods provides valuable information on the spatial distribution of pollutants, pollution sources, and environmental variables, which can be used to develop effective mitigation strategies.

Keywords Environment · Geospatial models · GIS · Geo-visualization · Pollution · Remote sensing

2.1 Introduction

The term "geospatial technology" is used to designate a variety of contemporary techniques that contribute to the geographic mapping and analysis of the Earth and human society (McCoy, 2021). Since the earliest maps were created in ancient times, these technologies have seen some evolution (Chase et al., 2011). Numerous kinds of geospatial technology are currently available and may be used, which include the following (Fig. 2.1):

Remote Sensing Remote sensing involves the acquisition of information about the Earth's surface without physical contact (Pei et al., 2021; Rott, 2000). Satellite imagery and aerial photographs are primary sources of remote sensing data (Harvey

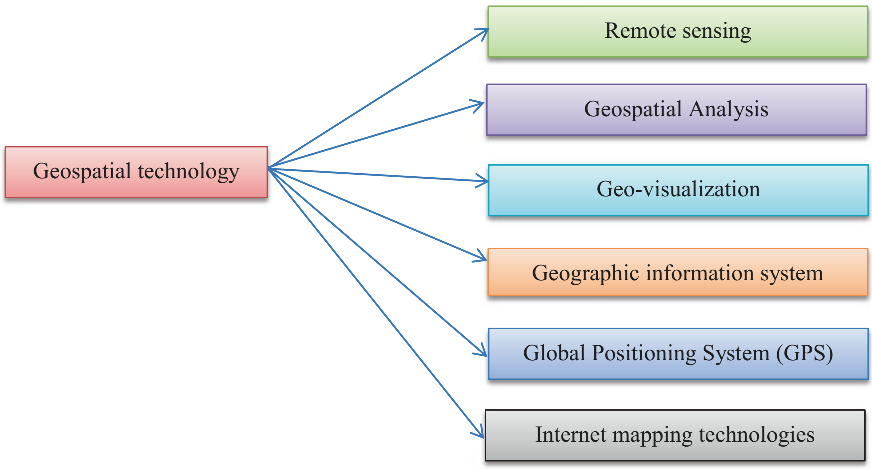

Fig. 2.1 Geospatial methods

& Hill, 2001; Ullah et al., 2020). This technology provides detailed and up-to-date information about land cover, vegetation, urban development, and environmental changes (Fonte et al., 2017). Remote sensing techniques are widely used to protect and preserve the environment by providing information that may be used in decision-making to save the environment (Gandhi et al., 2015).

Geospatial Analysis Geospatial technology facilitates the analysis of spatial patterns, relationships, and trends (Guo et al., 2012; Jing et al., 2018). It enables professionals in various fields, such as urban planning, natural resource management, emergency response, and logistics, to make informed decisions based on spatial data analysis (Greenough & Nelson, 2019). Geospatial analysis helps identify spatial clusters, perform proximity analysis, and assess the impact of factors on specific locations (Kang et al., 2019).

Geo-visualization Geospatial technology provides advanced visualization techniques to represent and communicate spatial information effectively (Tao, 2013). Interactive maps, 3D visualizations, and virtual reality (VR) applications enhance the understanding of complex geospatial data (Moran et al., 2015). Geo-visualization enables users to explore data from different perspectives, uncover patterns, and convey information to a wide range of audiences (Orland et al., 2001).

Geographic Information Systems (GIS) GIS is a fundamental component of geospatial technology. It allows for the creation, analysis, management, and visualization of spatial data (Al-Ansari et al., 2014; Velasco et al., 2013). GIS software enables users to overlay different layers of information, perform spatial analysis, and generate maps and reports (Chang, 2006). It serves as a framework for accumulating, organizing, charting, and analysing physical environment data at a particular spot on Earth's surface (Ali et al., 2020; Sherrouse et al., 2011). GIS creates geographical analyses, derived maps, and three-dimensional scenarios using layers of geographic data. This special power thus provides deeper insights into the data (Harris & Hodza, 2011).

Global Positioning System (GPS) GPS is a navigation system that synchronizes location, velocity, and time data for land, sea, and air travel by utilizing satellites, a receiver, and algorithms (Kaewket & Sukvichai, 2022; Noureldin et al., 2012). GPS uses a network of satellites to determine precise locations on Earth. It is widely used in navigation, surveying, and mapping applications (Shi et al., 2012). GPS receivers enable users to collect accurate positional data, which can be integrated with other geospatial data for analysis and visualization (Kanjo et al., 2008).

Internet Mapping Technologies The process of viewing, analysing, or sharing a visual representation of geospatial data in map form via the Internet is known as web mapping (Haklay et al., 2008).

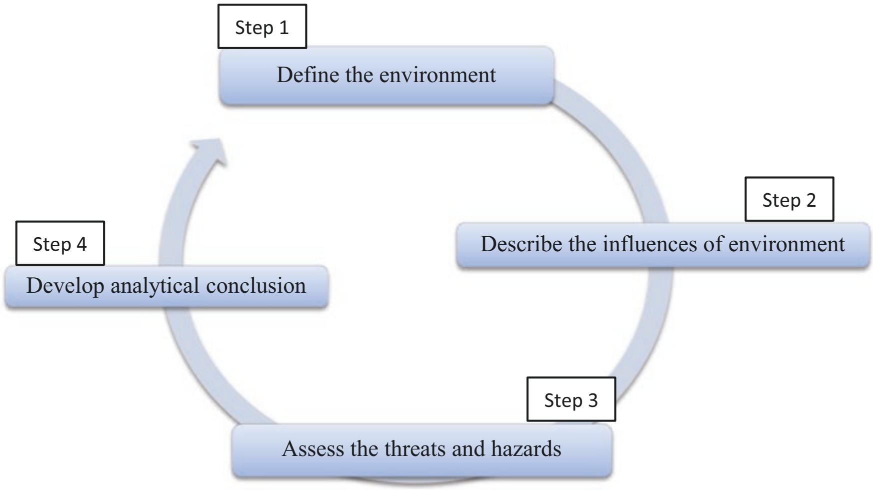

Fig. 2.2 Geospatial preparation process according to the NGA

Geospatial Preparation of the Environment (GPE)
The intelligence cycle and process are the foundation of the geospatial intelligence preparation of the environment (GPE) analytical method. According to the National Geospatial-Intelligence Agency (NGA), the steps are as follows (Fig. 2.2):

2.2 Geospatial Modelling of Air Pollution

Air quality is a significant factor in determining health, and numerous studies have shown the vast variety of harmful impacts of ambient air pollution on human health around the world. In particular, emissions that contribute to outdoor air pollution come from both artificial and natural sources. In many places, monitoring stations or systems have been put in place by policymakers (Jerrett et al., 2005; Kanaroglou et al., 2005) for legislative purposes. Researchers have also installed pollution sensors to measure individual exposure to air pollution in areas of interest (Steinle et al., 2015), such as busy highways, commercial and residential areas, and important thoroughfares (Steinle et al., 2013). The air pollution level in that area or neighbouring small areas can only be determined by the recorded measurements at these stations or sites (Gupta et al., 2006). Researchers have proposed a number of techniques, such as spatial averaging, nearest neighbour, inverse distance weighting (IDW), kriging, land-use regression (LUR) modelling, dispersion modelling, and neural networks, to estimate the concentrations of air pollutants in unmonitored areas using the measurements that are currently available (Karroum et al., 2020; Xingzhe et al., 2017). Air pollution modelling involves the use of remote sensing (Alvarez-Mendoza, 2023) and geospatial methods (Jumaah et al., 2019) and

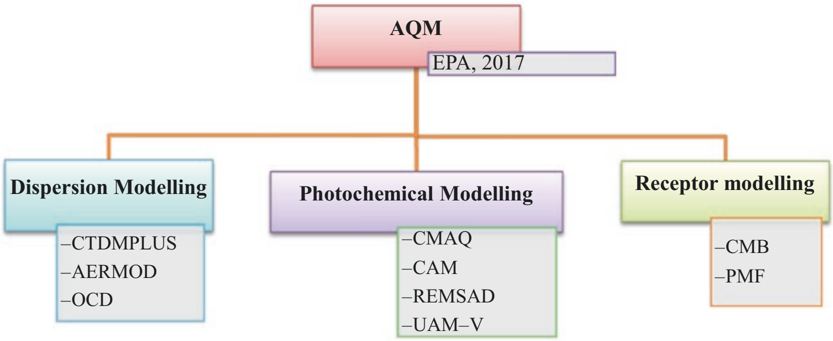

Fig. 2.3 Air quality models (AQM) recommended by Environmental Protection Agency (US-EPA, 2017)

Table 2.1 Models used in air pollution monitoring

S.No	Models	Full name	Used for	References
1.	AERMOD	AMS/EPA Regulatory Model	Steady-state plume air dispersion model	Hallaji et al. (2023), Josimović et al. (2023)
2.	CALINE-4	California Line Source Model	Line source air quality dispersion model	Goyal et al. (2010), Wang et al. (2016)
3.	OSPM	Operational Street Pollution Model	Street pollution dispersion model	Hertel et al. (1991), Rzeszutek et al. (2019)
4.	CALPUFF	California Puff Model	Non-steady-state meteorological and air quality modelling system	Xue et al. (2023), Li et al. (2023b)
5.	CALGRID	California Grid Model	Photochemical pollution	Yamartino et al. (1992), Xie et al. (2014)
7.	ADMS	Atmospheric Dispersion Modelling System	Atmospheric dispersion (pollutant emitted both continuously from point, line, volume and area source, or discretely from point sources)	Kalhor and Bajoghli (2017), Murana (2023)
8.	CTDMPLUS	Complex Terrain Dispersion Model	Complex terrain dispersion	Rzeszutek (2019), Khan and Hassan (2020)
9.	OCD	Offshore and Coastal Dispersion	Offshore emissions from point, area, or line sources on the air quality of coastal regions	Hanna and Drivas (1993), Huang (2015)

(continued)

Table 2.1 (continued)

S.No	Models	Full name	Used for	References
10.	CMAQ	Community Multiscale Air Quality	Estimation of ozone, particulates, toxics, and acid deposition	Onwukwe and Jackson (2020), Kukkonen et al. (2023)
11..	CAM	Comprehensive Air Quality Model	Multiple air quality issues, including tropospheric ozone, fine particles, toxics, acid deposition, and visibility degradation	Fernandez et al. (2019), Soni et al. (2022)
12.	REMSAD	Regional Modelling System for Aerosols and Deposition	Calculate the concentrations of both inert and chemically reactive pollutants	Kuhns et al. (2005), Nguyen et al. (2020)
13.	UAM-V	Urban Air-shed Model	To study air quality, especially ozone	Qin et al. (2019), Nguyen et al. (2020)
14.	CMB	Chemical Mass Balance	Localized nonattainment problems; also where steady-state Gaussian plume models are inappropriate	Feng et al. (2019), Zhang et al. (2021)
15.	PMF	Positive Matrix Factorization	Multivariate factor analysis	Feng et al. (2019), Song et al. (2019)

frameworks to simulate (Marquez & Smith, 1999) and analyse the distribution, transport, and dispersion of air pollutants in the atmosphere. According to the US-EPA, the most commonly used air quality models include the following (Fig. 2.3) and (Table 2.1):

Dispersion Modelling These models are employed in the permitting procedure to calculate the pollutant concentration at designated ground-level receptors close to an emissions source (Teggi et al., 2018). To describe the atmospheric mechanisms that disperse a pollutant emitted by a source, dispersion modelling uses mathematical formulations (Kakosimos et al., 2011). A dispersion model can be used to forecast concentrations at specific downwind receptor locations based on emissions and meteorological inputs (Awasthi et al., 2006). These air quality models are used to determine compliance with National Ambient Air Quality Standards (NAAQS) (Macpherson et al., 2017) and other regulatory requirements, such as Prevention of Significant Deterioration (PSD) and New Source Review (NSR) regulations.

Photochemical Modelling These photochemical models, which represent the large-scale chemical and physical processes in the atmosphere through a series of mathematical equations, simulate variations in pollutant concentrations in the atmosphere (Ibrahim, 2019). These models are applied at multiple spatial scales, including local, regional, national, and global scales (Daly & Zannetti, 2007).

Three-dimensional Eulerian grid modelling is currently used in the majority of operational photochemical air quality models (Fountoukis et al., 2022), mostly due to its capacity to characterize physical processes more accurately in the atmosphere and forecast species concentrations across the whole model domain (Ramacher et al., 2021).

Receptor Modelling Receptor models are statistical or mathematical methods for locating and calculating the sources of air contaminants at a receptor site (Salim et al., 2019). Contrary to photochemical and dispersion air quality models, receptor models do not calculate the contribution of sources to receptor concentrations using pollutant emissions, meteorological information, or chemical transformation mechanisms (Li et al., 2021). These models are based on observational techniques (Kim et al., 2021) that use the physical and chemical characteristics of particles and gases measured at receptors and sources (O'Reilly et al., 2023) to both detect and measure source contributions to receptor concentrations (Jain et al., 2021).

Vehicular Pollution Modelling Geospatial models are commonly used to predict and assess air pollution in urban areas (Matějíček et al., 2006). By using GIS, spatial data are analysed to identify where pollution hotspots are most likely to occur and to estimate the concentration of pollutants in areas affected by traffic (Wang et al., 2008). These models take into account several factors, such as traffic density, emission factors, meteorological conditions, and topography, to predict air pollution levels (Zhang et al., 2013). One comprehensive example of a GIS-based model for air pollution is the one presented by Gualtieri and Tartaglia (1997). This model evaluates air pollution due to road traffic in urban areas, depending on the geometric and environmental characteristics of the area studied (Gualtieri & Tartaglia, 1998). More recent examples in spatial modelling of air pollution in urban areas with GIS include analyses of environmental and social factors affecting exposure to pollution, as well as, mapping of air pollution sources (Moreno-Jimenez et al., 2016). Another approach is utilizing geospatial artificial intelligence (AI) to develop models for

Table 2.2 Key studies on vehicle emission modelling

S.No	Models	Visualization	References
1.	MOVES emission model	Display grid emission; using Python-based ArcGIS technology	Wohlstadter et al. (2016)
2.	Line source dispersion model	Display link-based concentrations; using Python-based ArcGIS technology	Barzyk et al. (2015)
3.	PARAMICS; CMEM; AERMOD	Model software view output	Misra et al. (2013)
4.	CMEM; MOVES	Display link-based emissions using Google map	Morris et al. (2012)
5.	VSP-based	Display the bus emissions by certain trips; Using Google map API system	Li et al. (2009)
6.	ADMS	Display the bus emissions by certain trips; Using Google map API system	Namdeo et al. (2002)

mapping and prioritizing the concentration of air pollutants (Liang et al., 2023). Overall, geospatial models and GIS technology offer an effective and efficient way to analyse air pollution data in urban areas, pinpointing pollution hotspots and providing valuable insights for environmental policymakers and urban planners. The research carried out on vehicle emission modelling is presented in Table 2.2.

Vehicle characteristics, road traffic circumstances, geography, weather, and other environmental factors all have an impact on vehicle emissions and how they affect air quality; this complexity makes it more difficult to regulate (Pinto et al., 2020). The best method to fulfil the aforementioned demands is via a real-time system (Reddy et al., 2018). A sufficient amount of real-time traffic information, including precise vehicle data, is required (Vigos et al., 2008) (e.g. fuel, type, and emission standard), traffic detection information (e.g. vehicle fleet composition, traffic volume, and traffic speed), road information (e.g. location, length, type, and direction), weather information (e.g. humidity, wind, temperature, clouds, and pressure) and additional details in urban settings (Ding et al., 2021) (Fig. 2.4).

Even though geospatial modelling has many benefits, it is not without drawbacks in regard to monitoring automobile pollution. There are a number of obstacles, such as the requirement for expertise in model construction and calibration, the necessity for accurate and readily available input data, and the uncertainty surrounding emission factors and model parameterization. Additionally, it might be difficult to adequately capture spatiotemporal fluctuations in pollution because of how complex metropolitan landscapes are and how dynamic traffic patterns are.

***$PM_{2.5}$* Pollution Modelling** The discipline of environmental research has recently undergone a revolution because GIS (Rahman et al., 2010), including $PM_{2.5}$ pollution modelling by integrating geospatial data with pollution measurements (Hvidtfeldt et al., 2018), makes it possible to locate pollution hotspots, make pollution maps, and see pollution patterns (Zhang et al., 2008) (Fig. 2.5). On the other

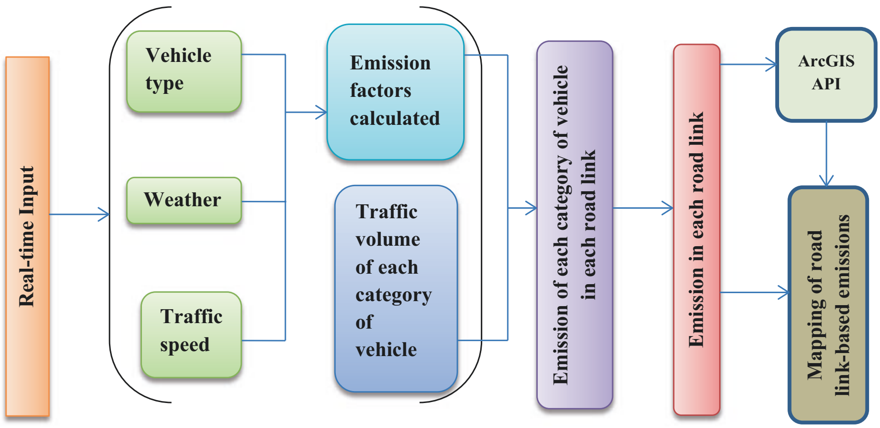

Fig. 2.4 Real-time vehicle emission calculation and mapping (Ding et al., 2021)

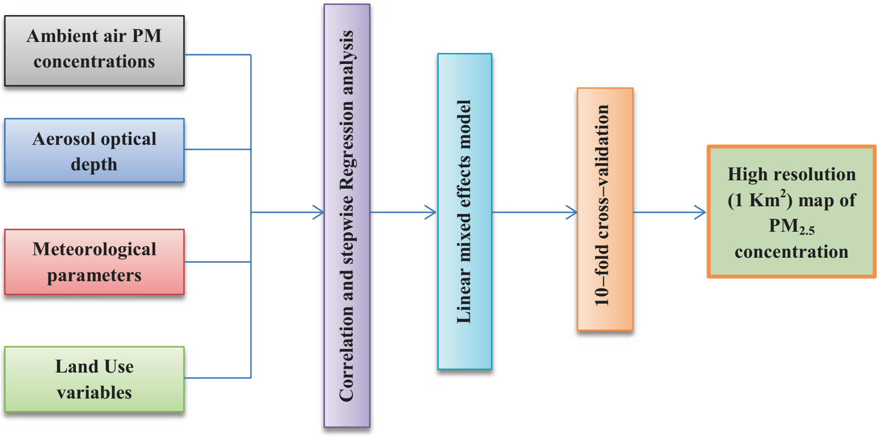

Fig. 2.5 Geospatial modelling for estimation of $PM_{2.5}$ (Lavanyaa et al., 2022)

hand, by gathering information about the Earth's surface, remote sensing methods that make use of satellite or airborne sensors have significantly improved PM2.5 models (Sorek-Hamer et al., 2020) and thus can estimate $PM_{2.5}$ concentrations over large areas (Chen et al., 2021). These data, combined with ground-based measurements, enable the development of accurate spatiotemporal models (Von Holdt et al., 2019). However, challenges persist, such as sensor limitations and the need for validation with ground truth data (Shirmard et al., 2022). Researchers have demonstrated land-use regression (LUR), a statistical modelling strategy that links $PM_{2.5}$ concentrations to land use and other pertinent variables (Chen et al., 2021). By considering factors such as traffic density, land cover, and proximity to pollution sources, LUR models can predict $PM_{2.5}$ concentrations at unsampled locations (Song et al., 2021). LUR is particularly useful in urban areas where fine-scale spatial variability exists. However, the reliance on monitoring data for model calibration can limit its applicability in data-scarce regions (Li et al., 2023a, b).

Furthermore, chemical transport models (CTMs) help to simulate the transport and transformation of pollutants in the atmosphere, providing insights into the sources and distribution of $PM_{2.5}$ pollution (Li et al., 2019). By considering emission inventories, meteorological conditions, and chemical reactions, CTMs offer a comprehensive understanding of pollutant behaviour (Chen et al., 2020). They also allow for scenario testing and evaluation of mitigation strategies (Fallmann et al., 2016). However, CTMs require extensive computational resources and detailed input data, making them more suitable for regional-scale studies (Kukkonen et al., 2012). Machine learning algorithms have gained popularity in $PM_{2.5}$ pollution modelling due to their ability to handle complex relationships between pollution and environmental factors (Ma et al., 2022).

2.3 Geospatial Modelling of Groundwater Pollution

The problem of groundwater contamination has increased alarmingly in recent years (Dutta Gupta et al., 2018) because of extensive and rapid population growth (Zhang et al., 2020), irregular planning, random expansion of cities (Singha et al., 2019), different land use-land class patterns, and erroneous sewage systems, including wastewater disposal from agricultural industries and urban areas (Berhe Zenebe et al., 2020). Remedial measures and treatment techniques for groundwater contamination are very expensive and often complex (Brusseau, 2019). Monitoring this precious resource is crucial for its protection but determining the extent of contamination on a regional scale and drawing boundaries around it is a difficult process (Singha et al., 2019).

Aquifer hazard assessments are now being conducted around the world using a variety of models that use different processes and procedures. More than 30 approaches have been developed by researchers to determine the vulnerability of groundwater. Three main approaches are available for aquifer vulnerability

Table 2.3 Geospatial models used for monitoring groundwater contamination

S.No.	Model	Full name	Used for	References
1.	DRASTIC	Depth to groundwater, recharge rate, aquifer, soil, topography Vadose zones' impact hydraulic conductivity	To evaluate the groundwater vulnerability mapping	Rajput et al. (2020), Alamne et al. (2022)
2.	AVI	Aquifer vulnerability index	Groundwater pollution vulnerability	Ghanbarian and Ahmadi Nadoushan (2019), George (2021)
3.	SINTACS	Water table depth (S), effective infiltration (I), unsaturated zone (N), soil media (T), aquifer media (A), hydraulic conductivity zone (C), and topographic slope (S)	Identifying the area where groundwater supplies are most vulnerable to contamination	Kumar et al. (2013), Noori et al. (2019)
4.	EPIK	Epikarst parameter, protective cover, infiltration, and karstic network	Vulnerability mapping of karst aquifers	Ghadimi et al. (2022), Kazakis et al. (2015)
5.	GOD	Groundwater index, overall lithology, and depth to groundwater	To determine groundwater vulnerability	Ghazavi and Ebrahimi (2015), Fannakh and Farsang (2022)
6.	GALDIT	Groundwater occurrence, aquifer hydraulic conductivity, height of groundwater, distance inland perpendicular from shoreline, impact of seawater, and thickness of aquifer	To assess groundwater vulnerability to seawater intrusion	Hu et al. (2018), Sujitha et al. (2020)

assessment: index-overlay, statistical, and process-based (National Research Council, 1993; Shrestha et al., 2017). Overlay-index models are the most popular models found in the literature (Table 2.3), namely, AVI (Stempvoort et al., 1993), DRASTIC (Aller & Thornhill, 1987), EPIK (Doerfliger & Zwahlen, 1997), SINTACS (Vrba & Zaporozec, 1994), GOD (Foster et al., 2002), IRISH (Daly & Drew, 1999), and GALDIT (Mitra, 2011).

Despite its many benefits, geospatial modelling for groundwater pollution monitoring has some limitations. These include the need for high-quality spatial data, the inherent uncertainty of predictions, and the challenge of integrating temporal variations (Rajitha et al., 2007). In addition, the complex nature of groundwater systems and the diversity of pollutants require careful consideration during model development and calibration (Brunner et al., 2017).

2.4 Monitoring of Soil Pollution

Soil pollution, which is the contamination of soil by various contaminants, including heavy metals, pesticides, industrial pollutants, and radioactive materials, poses serious threats to ecosystems, agricultural productivity, and human health (Gautam et al., 2023). Because plants absorb every nutrient from the soil, soil contamination has recently gained importance (Artiola et al., 2019). A significant amount of waste is produced as a result of rapid urbanization, industrialization, and population growth (Hossain et al., 2014), and the waste from industry and sewage is released into the soil (Murtaza et al., 2010) when used as a source of irrigation without sufficient treatment, hazardous heavy metals, persistent organic pollutants, microplastics, and high salt levels build up, which lowers the soil's quality. Similarly, the effluents discharged by sectors including tanning, textiles, and distilleries contain various sources of heavy metals, salts, and organic compounds (Bahuguna et al., 2022).

To effectively address soil pollution, accurate assessment and modelling of pollution patterns and processes are crucial. Geospatial methods and frameworks have emerged as powerful tools in soil pollution modelling, enabling the integration of spatial data, environmental factors, and advanced analytical techniques, thus enabling the quantification and visualization of soil pollution at various scales (Table 2.4).

2.5 Monitoring of River Pollution

Urban rivers become choked with municipal and industrial sewage due to unprecedented growth and human activity, among other factors (Sekharan et al., 2022). Micro, small, medium, and large industrial catchments and their surrounding residential areas are densely clustered in urban ecosystems around the world,

Table 2.4 Some geospatial models for monitoring soil contamination

S.No.	Model	Used for	References
1.	Kriging	To estimate pollution values at unsampled locations	Lin et al. (2011), Sun et al. (2019)
2.	MCDA	To assess soil pollution risks, prioritize, contaminated sites, and guide the decision-making process	Cartwright et al. (2022), Kazemi and Akinci (2018)
3.	SWAT	To simulate the transport of pollutants in soil systems	Lam et al. (2010), Zhang et al. (2013)
4.	EDSS	To aid in soil pollution management and mitigation	Van Der Perk et al. (2001), Oprea (2018)
5.	SoilGrids	To provide high-resolution global soil property maps, including soil pollution indicators	Liang et al. (2019), Chen et al. (2019)
6.	CART	To assess soil pollution risks, analyse pollution sources, and support decision-making in soil pollution management and remediation	Cheng et al. (2009), Wang et al. (2020)
7.	Soil landscape	To map soil properties and identify areas susceptible to soil pollution	Kang and Lin (2009), Xiong et al. (2014)

particularly in low- and middle-income nations (LMICs), as a result of mostly unrestrained development expansion and urbanization (Elmqvist et al., 2013; Sun et al., 2022). Urban rivers continue to be contaminated and choked by municipal and industrial waste as an apparently inevitable result, which opens the door to their extinction (Chandrashekhar, 2018; Strokal et al., 2021). Due to the existence of industrial clusters, the pollution situation along river sections in urban India is significantly worse than that in rural India (Panda et al., 2018). Changes in anthropogenic land use and cover (LULC) within a watershed have a detrimental effect on river water quantity (Samal & Gedam, 2021), and quality is a well-researched and widely accepted phenomenon in the literature (Santy et al., 2020). Geospatial models used for river pollution monitoring are given in Table 2.5.

If properly implemented, GIS-based monitoring will allow the extraction of information on the status of the river's water quality in close to real-time at any location along the river stretch (Glasgow et al., 2004), which shall help track the impaired river stretch (Mondal & Patel, 2018). This can help with analyses of transparent source apportionment. Examining LULC patterns and spatiotemporal fluctuations in river water quality helps to identify the origins of pollution in urban rivers (Yang et al., 2021), and GIS will help achieve this goal. Additionally, it will assist in tracking how frequently river segments have impairment (Sekharan et al., 2022).

Table 2.5 Geospatial models used for river pollution monitoring

S.No.	Model	Used for	References
1.	SPARROW	To estimate and map the source and transport of contaminants in rivers and streams	Xu et al. (2021), Wetherbee et al. (2022)
2.	SWAT	To assess river water quality and pollution impacts	Bui et al. (2019), Chen et al. (2022)
3.	AQUATOX	To assess the effect of contaminants in rivers and their associated impacts on aquatic organisms	Yeom et al. (2020), Çevirgen et al. (2020)
4.	MIKE	To assess river pollution and predict impacts	Nguyen et al. (2021), Lai et al. (2022)
5.	RiverWARE	To manage water resources, assess river pollution, and optimize pollutant load	Zagona et al. (2001), Yang et al. (2020)
6.	MATLAB	To simulate river water quality	Ning (2012), Ostad-Ali-Askari et al. (2017)
7.	COMSOL	To monitor river water quality	Al-Mansori et al. (2020), Mahmood and Mohammad (2021)
8.	QUASAR	To study water quality parameters in the river system	Whitehead et al. (1997), Mullai et al. (2012)
9.	QUAL2K	To assess changes in pollutant load and other pollution problems	Cho and Ha (2010), Bui et al. (2019)
10.	WASP 6	To interpret and predict water quality responses to natural phenomena and manmade pollution	Palmeri et al. (2005), Mbuh et al. (2019)
11.	HEC-RAS	To study contaminant transport and river water quality	Fan et al. (2009), Kim et al. (2023)
12.	QUAL2EU	To determine the pollution load and river water quality	Ranjith et al. (2019), Nada et al. (2021)
13.	SIMCAT	To study the fate and transport of pollutants in rivers	Ejigu (2021), Abed et al. (2021)

2.6 Conclusion

Geospatial approaches and frameworks have proven to be valuable tools in the field of pollution modelling. The combination of spatial data, environmental parameters, and pollution indicators enables comprehensive knowledge of the patterns, causes, and impacts of pollution. Geospatial models enable the visualization of geographical trends, the identification of hotspots, and the prediction of pollution dynamics, enabling the making of well-informed decisions about how to manage and analyse pollution. Geospatial modelling is very useful for evaluating pollution. These models offer high-resolution spatial analyses that enable the identification of pollution sources and vulnerable areas. The integration of numerous data sources helps to provide detailed risk assessments and accurate pollution estimations. Geospatial models aid in the simulation and forecasting of pollutant transit and fate, which is necessary to develop effective pollution management strategies. However, the limitations of geospatial approaches in pollution modelling must be understood. There are issues that need to be resolved regarding data accessibility and quality, model parameter uncertainties, and the complexity of environmental systems. Future technological and data availability developments will have a significant impact on how geospatial approaches for pollution modelling are developed. The effectiveness and precision of pollution assessments can be improved by the integration of cutting-edge remote sensing technologies, real-time monitoring systems, and machine learning algorithms.

In conclusion, by exposing the patterns, causes, and effects of pollution, geospatial approaches and frameworks have transformed pollution modelling. Due to ongoing advancements and interdisciplinary collaboration, geospatial modelling will continue to be crucial in addressing pollution concerns and guiding effective pollution control approaches. Geospatial approaches and cutting-edge technologies will surely be combined to produce assessments that are more precise and timely, promoting environmentally responsible behaviour and preserving ecosystems and human health.

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Chapter 3
GIS-Based Modelling for Estimation of Water Quality Parameters: A Review

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Abstract This chapter offers a comprehensive review of geographic information system (GIS)-based approaches for estimating water quality parameters. It highlights the advantages of using GIS such as integrating satellite imagery and spatial data and conducting spatial analysis. The chapter emphasizes the significance of water quality monitoring and the limitations of traditional analysis methods. It explores various types of GIS-based models, including empirical, process-based, and hybrid models. Additionally, it suggests the use of remote sensing and machine learning techniques, such as deep learning, for more accurate and timely water quality forecasting. The chapter covers the estimation of both optically active and inactive parameters through remote sensing. It summarizes previous studies utilizing GIS-based approaches, including machine learning, for water quality estimation. The limitations and challenges, such as uncertainty and validation, are discussed, along with recommendations for future research. The chapter highlights the potential of GIS-based modelling in improving water quality management and stresses the importance of interdisciplinary collaboration.

Keywords Case studies · GIS · Modelling · Water quality · Remote sensing

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3.1 Introduction

Water is an essential natural resource that sustains life and provides numerous benefits to society. However, the quality of water has been deteriorating at local and global scales due to natural and human factors, which have significant implications for human health and the environment. Hence, there is a growing need for effective water quality management strategies that can address the complex and dynamic nature of water quality. The changes in the water can typically be monitored using biophysico-chemical parameters such as chlorophyll-a (Chl-a), coloured dissolved organic matter (CDOM), pH, conductivity, turbidity, etc. Water quality monitoring has traditionally relied on field monitoring, involving the collection of water samples from various water bodies at regular intervals. This method has been the primary source of information for assessing water quality. However, conducting large-scale spatiotemporal studies on freshwater systems using this approach raises concerns due to the significant time and costs involved in the process. Despite its effectiveness, the conventional practice of field monitoring, which includes frequent sampling from different locations, proves to be both time-consuming and expensive. When undertaking extensive studies to monitor water quality over broader geographical and temporal scales in freshwater systems, these factors become significant issues. One approach to improve water quality management is by using geographic information system (GIS)-based modelling. GIS-based modelling allows for the integration of spatial and nonspatial data to identify patterns and relationships that can be used to estimate water quality parameters. GIS-based modelling has gained popularity in recent years due to its ability to provide accurate and timely information for decision-making.

Motivation for GIS-Based Modelling for Water Quality

The significance of water quality evaluation and management has significantly grown over time, primarily due to increased awareness of environmental impacts and health implications. Despite efforts to mitigate water pollution, global water bodies continue to suffer from untreated pollutants discharged into them. Existing measures may lack coordination and effectiveness. The consumption of poor-quality water poses risks to human health, soil quality, and crop growth (Shammaa & Zhu, 2001). However, conventional methods of measuring water quality only provide general information about the water body and may not be directly applicable to models that assume complete mixing with other sources. Moreover, assessing water quality through physical sampling programs has been both costly and time-consuming for many decades. In this context, GIS-based modelling has emerged as a valuable tool for parameterizing input data in hydrologic and water quality models. By incorporating geographical and temporal characteristics of influencing factors, GIS allows for a better representation of hydrologic components and pollutant generation. The integration of remotely sensed data and GIS visualization capabilities, along with various models, enhances decision-making for water resource management (Abayazid & El-Adawy, 2019). Pollution mapping techniques using GIS aid in identifying the extent of pollution, while overlaying thematic layers helps pinpoint pollution sources (Bahrami & Zarei, 2023). Furthermore, GIS facilitates evaluating and managing nonpoint sources to enhance water resources. As a result, GIS-based modelling of water quality parameters has become indispensable in environmental management (Ruhela et al., 2022). The use of GIS offers the advantage of incorporating diverse data sources and creating spatially explicit models, providing valuable insights into water resource conditions. Making informed decisions becomes more accessible as data are visualised and analysed within a spatial context, aiding in identifying areas that require intervention to improve water quality. The motivation behind using GIS-based modelling lies in the necessity for more efficient water resource management, ensuring their sustainability for future generations.

Geospatial Data Sources

There are several geospatial data sources available for water quality. Here are some examples:

USGS National Water Information System (NWIS) This is a comprehensive data source for water resources data in the United States, including water quality data. It provides access to data from over 1.5 million sites across the country. Over the last few years, scientists have been trying to determine how humans affect the water cycle. To do this, they need a better way to access the huge amount of hydrological data. We now have sizable mission-oriented data repositories such as the EPA STORET and the National Water Information System (NWIS) of the USGS, which have helped to cover a sizable portion of the nation. However, their coverage (parameters) and geospatial data density vary from region to region. Their web interfaces can be used to obtain the data. The NWIS systems have approximately 1.7 million stations spread over the whole country.

National Centers for Environmental Information (NCEI) NCEI is in charge of one of the most comprehensive data collections in the world with regard to the atmosphere, coasts, geophysics, and oceans. This archive has information about many different things, from the sun's surface to the centre of the earth. In addition, it contains records obtained from very old tree rings and ice cores, as well as, images captured by satellites either in real-time or very close to it. Not only does NCEI store data, but it also makes products and provides services that make it simple for scientists, government officials, academics, nongovernmental organizations, and members of the general public to make use of the data. NCEI provides access to a variety of environmental data, including water quality data. It includes data from a variety of sources, including federal agencies, state agencies, and academic institutions.

Environmental Protection Agency (EPA) Water Quality Data Portal The US Geological Survey, The US Environmental Protection Agency, and the National Water Quality Monitoring Council all worked together to make the water quality portal. To date, this site includes more than 297,000,000 records about the quality of water for 50 states. Data on water quality gathered by the EPA and its partners are accessible through this portal. It includes data from rivers, lakes, streams, and other water bodies across the United States.

Global Lake Ecological Observatory Network (GLEON) GLEON is mostly a group of lake ecosystems linked together. GLEON has collected data from 50 different countries with more than 100 sites. GLEON is a network of scientists and researchers who work together to collect and share information about lakes all over the world. The GLEON database contains information that includes the quality of the water, temperature, and other environmental factors.

European Environment Agency (EEA) Waterbase Following the recommendations of the UN, the European Environment Agency has begun implementing the program for land use and ecosystem accounts. Its primary objective is to evaluate Europe's sustainable water use. The European Environment Agency (EEA) Waterbase includes data on rivers, lakes, and coastal waters across the continent.

World Water Quality Portal (WWQP) This is a global database of water quality data maintained by the United Nations Environment Program (UNEP). It includes data from over 12,000 monitoring stations across the world.

3.2 Models of Water Quality

Around the world, models of water quality are becoming more prevalent to report on water quality, assess risks, find, and assess the origin of water quality elements, and evaluate the results of various climate, hydrological, and management factors. Water quality modelling is the practice of utilizing mathematical models to simulate water quality conditions in a body of water. These models are used to forecast the concentration and movement of contaminants in bodies of water, as well as, to assess the efficacy of various management measures for improving water quality. Here are some examples of common water quality models:

Mass Balance Models These models replicate the origins, movement, and fate of contaminants in a water body using mass balance equations (Fig. 3.1). They are frequently employed to assess the consequences of pollution from small-scale sources, such as wastewater treatment facilities.

Empirical Models These models rely on statistical correlations between the parameters governing water quality and variables affecting the environment, including

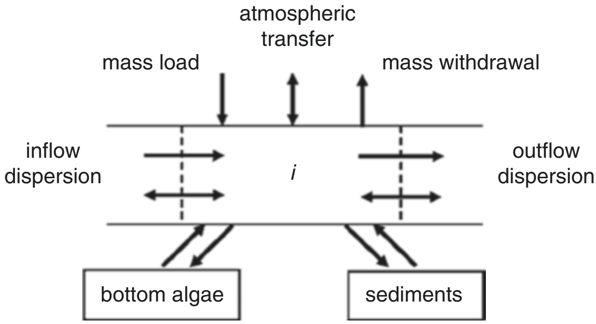

Fig. 3.1 Flow diagram showing the mass balance for components of the river system in reach i. (Source: Zhang et al., 2012)

temperature, pH and dissolved oxygen (Zhang et al., 2012). When there is a lack of comprehensive knowledge on the sources and distribution of pollutants, they can be useful for predicting water quality situations.

Process-Based Models These simulations represent the physical, chemical, and biological processes that have an impact on a body of water's quality. They can offer more specific information on pollution sources, transit, and destiny despite often being more sophisticated than empirical models.

Hydrodynamic Models These models represent how water flows and contaminants are transported in response to hydrodynamic factors such as currents and tides. They are utilized to evaluate the spatial and temporal distribution of contaminants in a body of water (Fig. 3.2).

Integrated Models These models blend different types of models to simulate how water quality parameters, hydrodynamics, and other environmental factors interact in a complicated way. They are beneficial for evaluating the efficacy of various water quality improvement management strategies.

Numerous water quality parameters, including nutrients, dissolved oxygen, pH, temperature, and pollutants, can be simulated using water quality models. They are helpful tools for comprehending how human activity affects water quality and for creating effective management plans to safeguard and replenish water resources.

Water Quality Data

Water quality data refer to information gathered about the biological, physical, and chemical properties of water at a specific location. These data are used to assess the health of aquatic ecosystems, as well as to identify and manage pollution sources

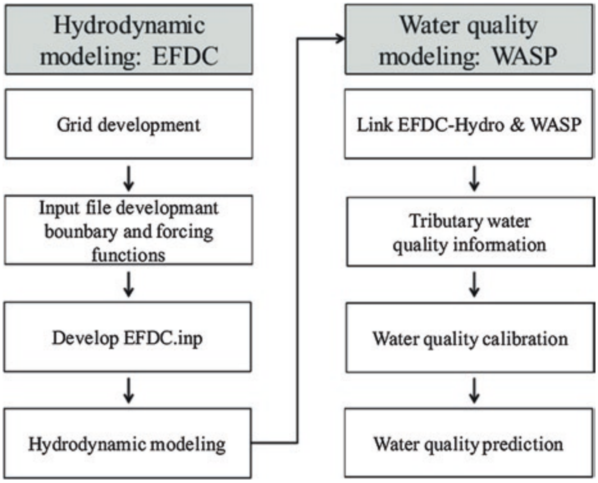

Fig. 3.2 Example of the hydrodynamics water quality modelling process used for the prediction of chlorophyll-a. EFDC: environmental fluid dynamics code, WASP: water quality analysis simulation program. (Source: Seo et al., 2012)

that may affect water quality. Water quality data can be gathered from numerous sources, including the following:

Monitoring Stations These are actual places where regular measurements of water quality metrics are taken. Rivers, lakes, streams, and other bodies of water are all potential locations for monitoring stations.

Laboratory Testing Water samples from a specific site can be collected and sent to a laboratory for analysis. Laboratory testing can provide us with more particular information on water quality characteristics such as nutrient content, pH, and dissolved oxygen.

Remote Sensing Water quality parameters, including water temperature, turbidity, and chlorophyll concentrations, can be gathered using remote sensing technologies such as satellites and airborne sensors (Ritchie et al., 2003).

Citizen Science Citizen science initiatives include the general public in gathering information on water quality (Capdevila et al.,2015). Participants may take water samples, gauge the temperature of the water, or note aquatic life observations.

Water quality data can be used to assess aquatic ecosystem health, identify pollution sources, and design management strategies to conserve and restore water resources. Water quality data must be collected and analyzed regularly to ensure that changes in water quality over time are appropriately recognized and managed.

3.3 GIS-Based Water Quality Modelling Approaches

GIS-based water quality modelling approaches leverage geographic information systems (GIS) to seamlessly integrate spatial data with water quality parameters, facilitating the simulation and assessment of pollutant movement in water bodies. These models play a vital role in predicting water quality conditions, identifying pollution sources, and supporting decision-making for effective water resource management. The integration of mathematical simulations or techniques into GIS enhances its inherent ability to analyze geographical trends and water quality properties (Vogiatzakis, 2003). Moreover, when combined with ecological modelling, GIS offers a compelling opportunity to comprehensively monitor and study environmental resources, demonstrating promising potential for widespread application in nature conservation (Lu et al., 2020). The adaptability, efficiency, and user-friendliness of GIS-based modelling approaches make them well-suited for simulating water quality parameters and conducting essential calculations, as mentioned by Rawat and Singh in 2018. The growing utilization of water quality models in tackling real-world challenges, as demonstrated by Gaafar et al. in 2020, further underscores the significance of integrating GIS in this field. By fusing spatial data, mathematical simulations, and ecological insights, GIS-based water quality modelling emerges as a valuable tool to understand, manage, and protect water resources in an increasingly complex and interconnected world. The Streeter–Phelps model (S–P model), developed by Streeter and Phelps in 1925, was the world's first GIS-based water quality model. Since this model's fundamental principle became acceptable, the concept and its altered form continue to be utilized in the present day (Wang et al., 2004). In contrast to approaches based on mathematical programming, the S–P model uses graphs to establish relationships between variables (Zhang et al., 2011). Several GIS-based water quality modelling approaches exist, and here are some commonly used ones:

Hydrological Models These models simulate the movement of water through catchments and river systems, considering factors such as flow rates, runoff, and erosion (Fig. 3.3). By incorporating water quality parameters into the model, it becomes possible to track pollutant transport and estimate their concentrations downstream.

Water Quality Index (WQI) Models WQI models use multiple water quality parameters to generate an index that represents the overall quality of a water body. GIS is used to spatially map the WQI, highlighting areas with different water quality levels and identifying potential pollution hotspots.

Pollutant Load Models These models estimate the amounts of pollutants entering a water body from different sources, such as point sources (e.g. wastewater treatment plants) and nonpoint sources (e.g. agricultural runoff) (Fig. 3.3). GIS helps in identifying the locations of these sources and quantifying their contributions to water pollution.

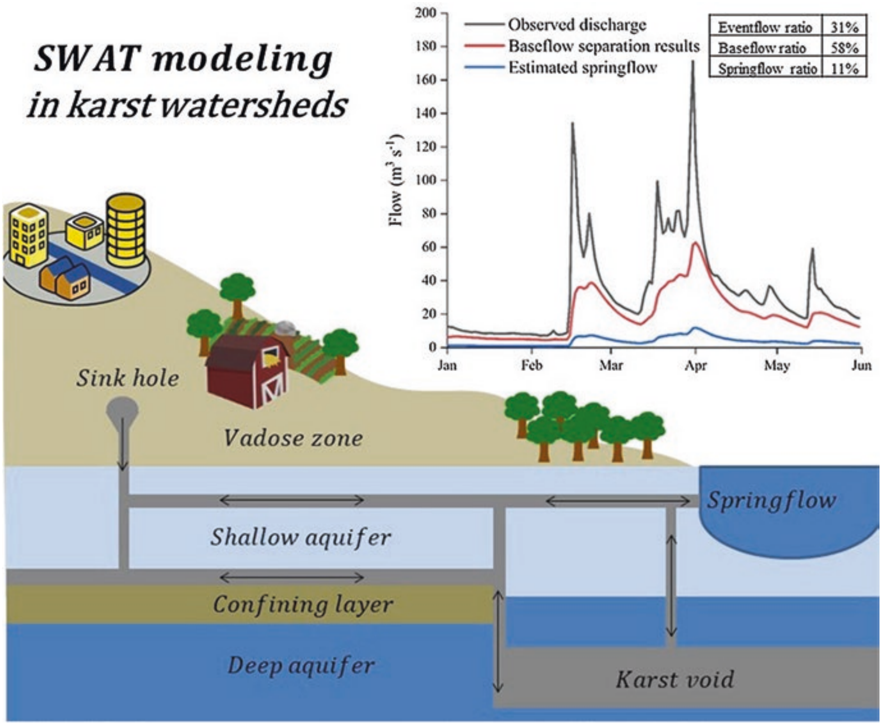

Fig. 3.3 Simulating nonpoint source pollutant loading in a karst basin: A SWAT modelling application. (Source: Zeiger et al., 2021)

Distributed Hydrological Models These models take into account the spatial distribution of hydrological and water quality parameters within a watershed. They consider variations in land use, soil types, and topography to better understand pollutant behaviour across the landscape.

3D Water Quality Models These models use GIS data to create three-dimensional representations of water bodies, allowing for a more accurate simulation of water quality dynamics. This is particularly useful in reservoirs or estuaries, where stratification and mixing of water layers play a crucial role in water quality.

Eutrophication Models Eutrophication is a process where excessive nutrients, particularly nitrogen and phosphorus, lead to algal blooms and water quality degradation. GIS-based eutrophication models help identify areas at risk and support nutrient management strategies.

Sediment Transport Models GIS is used to analyze erosion and sedimentation processes, which can transport pollutants and degrade water quality. Sediment transport models help predict sediment deposition patterns and their impact on water bodies.

Scenario-Based Models GIS-based scenario modelling allows for the evaluation of various management strategies and their potential effects on water quality. Decision-makers can use this approach to identify the most effective measures for pollution control and restoration.

Some examples of GIS-based water quality modelling approaches, along with brief descriptions, are presented in Table 3.1:

Geospatial and Artificial Intelligence–Based Approach

With the rapid advancement of computing and artificial intelligence (AI), water quality analysis has witnessed significant improvements in both descriptive and predictive capabilities (Tiwari et al., 2018). Utilizing IoT devices equipped with AI models, real-time detection of harmful bacteria and classification of contaminants has become achievable. This marks a departure from the traditional laborious and time-consuming process of manually collecting and analyzing water samples, which has historically hindered prompt decision-making during critical events. To address this issue, combining deep learning techniques with remote sensing data, particularly utilizing regression models such as RNN (recurrent neural networks) and LSTM (long short-term memory) models, enables proactive water quality estimation (Ahmed, 2022). By employing these powerful models, it becomes feasible to make multivariate and multioutput predictions displayed in a time-series format. Wang et al., (2019) identified the characteristics of water pollutants and trace industrial point sources of pollutants in Shandong Province, China, using an artificial intelligence system called the integrated long short-term memory network (LSTM), cross-correlation, and association rules (apriori). Zhang et al., 2022 applied a novel deep learning architecture (ConvLSTM) to retrieve 6-year changes in water quality variables, at Dongping Lake, an impounded lake located in the Yellow River in China and observed good estimation accuracy across optically active and inactive parameters with R2 greater than 0.77 for all water constituents (Fig. 3.4).

Over the past decades, numerous academic researchers have sought high-accuracy predictions of water quality using various models. These models can be broadly classified into two main types: conventional models, including multiple linear regression (MLR) and autoregressive integrated moving averages (ARIMA), which predict future values linearly, and artificial intelligence-based models. In real-world water quality scenarios, nonlinearity is often present, especially in river water quality modelling. Recognizing the limitations of linear models, researchers have turned to nonlinear models such as Gaussian processes (GP), support vector machines (SVM), artificial neural networks (ANN), and fuzzy models. These nonlinear models have been proposed in the last two decades to address the demand for accurate predictions in the presence of nonlinearity (Rajaee et al., 2020). In a study conducted by Aldhyani et al. (2020), the accuracy and utility of AI models in forecasting the water quality index (WQI) were evaluated. They employed “Nonlinear

Table 3.1 Examples of GIS-based water quality models

GIS-based models	Description
SWAT (soil and water assessment tool)	SWAT is a widely used hydrological model that integrates GIS data to simulate water quality processes at the watershed scale (Grunwald & Qi, 2006). It considers land use, soil properties, climate, and topography to predict nutrient and sediment transport in rivers and streams. SWAT has been applied in various studies to assess the impacts of land use changes on water quality and to develop management strategies for reducing pollution.
CE-QUAL-W2	This three-dimensional water quality model is often applied to large water bodies, such as lakes and reservoirs. It uses GIS-based spatial data to simulate hydrodynamics and water quality parameters, including temperature, dissolved oxygen, and nutrient concentrations. CE-QUAL-W2 helps understand stratification patterns and predict the effects of nutrient loading on eutrophication.
HSPF (hydrological simulation program-fortran)	HSPF is a comprehensive hydrological and water quality model that uses GIS data to represent catchment characteristics, land use, and hydrologic processes. It simulates the fate and transport of various pollutants, such as nutrients and sediments, in streams and rivers. HSPF has been applied in watershed studies for pollutant source identification and assessment of best management practices (BMPs).
QUAL2K	This water quality model is widely used for rivers and streams, simulating various water quality parameters, including dissolved oxygen, nutrients, and organic matter. GIS data is employed to represent stream segments, flow rates, and pollutant sources. QUAL2K has been utilized in studies related to point and nonpoint source pollution management and to support total maximum daily load (TMDL) calculations.
SPARROW (spatially referenced regression on watershed attributes)	SPARROW is a statistical modelling approach that incorporates GIS data to estimate nutrient (e.g. nitrogen and phosphorus) loads in rivers and their spatial distribution. It considers land use, hydrology, and other watershed attributes to identify areas with high nutrient contributions and assess their impacts on downstream water quality.
SWMM (storm water management model)	SWMM is commonly used for urban water quality modelling, particularly in stormwater management. It utilizes GIS data to represent urban infrastructure, such as drainage networks, impervious surfaces, and green spaces. SWMM helps assess the effects of urbanization on water quality and to design stormwater management systems to mitigate pollution.
DRASTIC model	The DRASTIC model is a widely used method for assessing the vulnerability of groundwater to contamination from various pollutants. The model provides a qualitative assessment of the intrinsic groundwater vulnerability based on a combination of seven hydrogeological parameters viz. depth to water (D), recharge (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (I), and conductivity of the aquifer (C).

(continued)

Table 3.1 (continued)

GIS-based models	Description
Generalized watershed loading function (GWLF)	GWLF is a widely used model for predicting nonpoint source pollution in watersheds (Lehning et al., 2002). Nonpoint source pollution refers to the pollution that originates from diffuse sources, such as agricultural runoff, urban stormwater, and atmospheric deposition, rather than specific point sources like industrial discharges. The GWLF model was developed to estimate the loading of pollutants, such as sediments, nutrients (e.g. nitrogen and phosphorus), and other contaminants, into water bodies from various land uses within a watershed. It is a GIS-based model that takes advantage of spatial data, including land use, soil types, slope, weather, and other relevant parameters, to simulate the generation and transport of pollutants from different parts of the landscape.
WRASTIC model	WRASTIC model stands for 'Water-Resources Appraisal for Sinkholes and Springs in a Terrane of Inefficient Conduit. ' It was developed by the US Geological Survey (USGS) and is designed to assess the vulnerability of karst aquifers to contamination (Jenifer & Jha, 2022; Niculae et al., 2021). Karst aquifers are unique geological formations characterized by soluble bedrock (e.g. limestone) that can create sinkholes, caves, and conduits, making them highly susceptible to rapid groundwater flow and potential contamination. The WRASTIC model incorporates a series of parameters to evaluate the vulnerability of a karst aquifer viz. water-table depth, recharge characteristics, aquifer media and material, soil/overburden characteristics, terrane or karst landscape features, inetic features (flow path characteristics), and conduit flow characteristics.

Autoregressive Neural Network Models (NARNET) and Long Short-Term Memory (LSTM) Deep Learning Algorithm" for WQI forecasting using datasets comprising water quality samples and their corresponding indices from various locations in India. The dataset consisted of seven distinct parameters, namely, dissolved oxygen, pH, conductivity, biological oxygen demand, nitrate, fecal coliform, and total coliform. The NARNET and LSTM models were trained and validated to predict the WQI using Pearson's correlation coefficient (R) to assess the relationship between important data characteristics for forecasting WQI values. The results indicated that the NARNET model outperformed the LSTM model in predicting the WQI based on the estimated R-value. Furthermore, for the "Water Quality Classification" (WQC) prediction, three models – support vector machines (SVM), Naive Bayes, and K-nearest neighbor (KNN) – were used. Among these, the SVM approach demonstrated a high degree of accuracy in WQC predictions. The study highlighted the efficacy of the NARNET model for WQI forecasting and emphasized the SVM model's superior performance in WQC predictions when compared to the Naive Bayes and KNN algorithms.

Tiwari et al. (2018) estimated the water quality index using two different clustering techniques: fuzzy C-means and subtractive clustering-based ANFIS for the Satluj River in northern India. The integration of nonlinear models in water quality prediction has expanded the scope and accuracy of these analyses. By leveraging

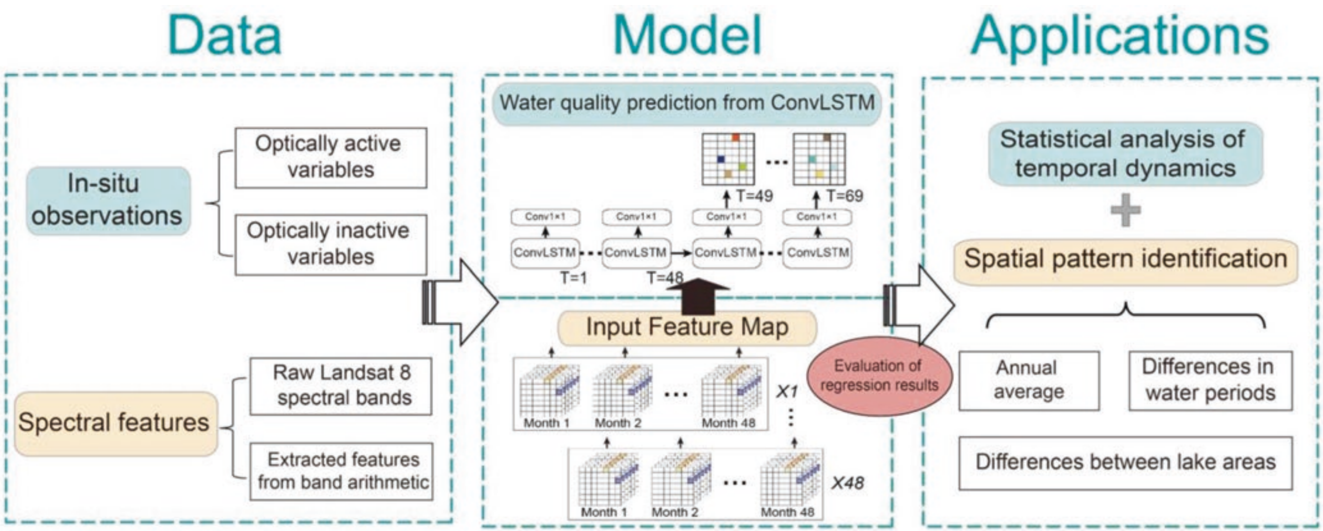

Fig. 3.4 Framework for water quality variable retrieval and spatiotemporal analysis based on remote sensing and deep learning techniques by Zhang et al., 2022 (Source: Zhang et al., 2022)

the power of AI and embracing nonlinearity, researchers and decision-makers are better equipped to understand and manage water quality, contributing to more effective environmental conservation and water resource management.

3.4 Groundwater Quality Monitoring Using GWQI

The groundwater quality index (GWQI) model is widely used to assess groundwater purity and consider management techniques. It utilizes various water quality indicators, condensing multidimensional groundwater data into a single numerical value (Mohammed et al., 2022). GWQI creation involves phases such as sample collection, weight selection, parameter standardization, and aggregation (Stigter et al., 2006). Significantly influential parameters such as NO3– and F– receive higher weights than Na + and K+ due to their vital role in determining groundwater quality (Adimalla & Taloor, 2020). Computation of relative weight (*Wi*): For the computation of *Wi*, the equation mentioned below is used:

$$Wi = \frac{wi}{\sum_{i}^{n} wi} \tag{3.1}$$

Here,

Wi = relative weight, *wi* = individual parameter weight, *n* = total number of parameters.

***Quality Rating** (Qi)* *Qi* is a scale that depicts the quality rating of a parameter. It is obtained by considering the parameter's concentration in every sample of water (*Ci*), dividing it by the applicable WHO standardized constant (*Si*) and then multiplying by 100. The *Qi* calculation is as follows:

$$Qi = \frac{Ci}{Si} \times 100 \tag{3.2}$$

The subindex (SI*i)* calculation is as follows:

$$SIi = Wi \times Qi \tag{3.3}$$

Finally,

GWQI is calculated by factoring in SI*i*:

$$\text{GWQi} = \sum_{i=0}^{n} SIi \tag{3.4}$$

Here, SIi = ith parameter's subindex, Qi = concentration-based rating, n = the total number of parameters.

3.5 Estimation of Surface Water Quality (SWQ)

In the past few decades, the combination of remote sensing and GIS has proven to be highly effective in monitoring surface water quality. Limnologists studying inland and coastal water bodies have extensively utilized satellite images from ERTS-1/Landsat 1, which was launched in 1972 (Bukata, 2013). To conduct such studies, an integrated research framework that encompasses spatial features, collected data, and a computational database has become a crucial component, as emphasized by Ritchie et al. in 2003. This integrated approach allows researchers to leverage the power of remote sensing and GIS technologies, enabling comprehensive and informed assessments of surface water quality in various environments. Satellites and airplanes are equipped with sensors that measure the radiation reflected from the surface of water bodies at different wavelengths. These measurements are then translated into various water quality indicators. Over time, the field of remote sensing has seen significant advancements, allowing for the effective monitoring of optical and nonoptical parameters (KC et al., 2019), such as total suspended solids (TSS), chlorophyll-a (chl-a), turbidity, Secchi disk depth (SDD), pH, and dissolved oxygen (DO). These advancements have greatly improved the accuracy and reliability of water quality assessments through remote sensing techniques.

Optically Active Water Quality Parameters

Optically active environmental parameters alter the interaction of visible light with water. The productivity and pollution of the aquatic body may be measured by retrieving these indicators from satellite imagery, which becomes a realistic approach for identifying disturbance in aquatic ecosystems. It sheds light on ecologic conditions, plant growth, and the effects of pollution from both natural and artificial causes, and it enhances the chance of determining water quality (Arora et al., 2022). Pollutants, as well as, the trophic conditions and health of aquatic ecosystems, might all be determined by these parameters.

Chlorophyll-a Chlorophyll-a (chl-a) is a common parameter used to assess the ecological condition of both freshwater and marine water. It serves as an indicator of productivity and is present in various algae throughout the algal community. Hence, developing models with maximum chl-a sensitivity is crucial for estimating chl-a concentrations through GIS-based modelling (Gurlin et al., 2011). Algae contain different plant pigments, such as chlorophyll-s (green) and carotenoids (yellow), contributing to their colour variations. Chlorophyll-a is the most prevalent chlorophyll pigment found but other types of algae, such as yellow-brown algae and blue-green algae, may have additional chlorophyll pigments (Gorde & Jadhav, 2013). While this diversity of pigments could lead to underestimating the output of algae with multiple colorus, chlorophyll-a is still commonly used for direct eutrophication measurement, impacting water quality assessment. Chlorophyll-a is a crucial parameter in evaluating water quality and ecological conditions, despite potential limitations related to pigment diversity in different algae. GIS-based modelling techniques help estimate chl-a concentrations and contribute to effective water quality monitoring and management efforts.

Colored Dissolved Organic Matter (CDOM) CDOM plays a significant role in biogeochemistry due to its impact on light transmission and the generation of reactive oxygen species. It also offers protection to organisms against the damaging effects of light (Guéguen et al., 2005). As a crucial parameter indicating trophic status, CDOM significantly influences drinking water quality. However, it hampers algal biomass growth by reducing accessible light intensity and impeding biological processes such as photosynthesis (Slonecker et al., 2016). In nearshore areas, where runoff interacts with saltwater, CDOM from river runoff becomes the primary natural source of CDOM in the seas. This presence of CDOM can lead to an overestimation of chlorophyll-a (Chl-a) by satellite sensors. The strong UV-ray absorption by both CDOM and Chl-a makes it challenging to accurately predict Chl-a through satellite imagery (Chen et al., 2007). To enhance the monitoring of water quality, it becomes crucial to consider the origins and distribution of the optical characteristics of water, especially when CDOM is present. Understanding the dynamics of CDOM and its interaction with Chl-a can contribute to more accurate assessments of water quality and the ecological condition of aquatic environments.

Turbidity Turbidity is a key parameter frequently used to describe the purity of water and is influenced by factors such as temperature, biological compounds, suspended particles, and nutrients (Ghanbari et al., 2012). In turbid water, light disperses and is absorbed instead of travelling in straight lines due to various elements, such as silt, clay, plankton, fine substances, and small organisms (Lloyd, 1987). Turbidity is primarily impacted by algae and suspended particles. Both runoff and sediments from the bottom can introduce particles, such as dirt or dead leaves, into the water. Factors such as erosion from construction sites, agricultural areas, and riverbanks contribute to increased sediment flow. Additionally, in shallow lakes, turbidity can be raised by motorboats, strong winds, or bottom-feeding species such as carp disturbing bottom sediments. Increased turbidity can lead to decreased primary and secondary production and reduced overall productivity. It also impairs light penetration, affecting aquatic ecosystems.

Total Suspended Solids (TSS) Total suspended solids (TSS) refers to the quantity of solid particles present in a liquid, typically water, and includes organic matter, minerals, and other contaminants. Monitoring TSS is crucial for assessing the condition of aquatic ecosystems and managing drinking water quality. High levels of TSS can have adverse effects on both human health and aquatic environments, serving as indicators of pollution and environmental degradation. The presence of TSS in runoff can cause water to become turbid, reducing its overall quality (Shammaa & Zhu, 2001). Various factors influence the TSS value of water, including sewage, household waste, and effluents from industrial and agricultural activities. Excessive TSS levels can lead to the clogging of water channels, ultimately shortening the lifespan of reservoirs and dams (Tamene et al., 2006). Monitoring and controlling TSS levels are essential to safeguard water quality and maintain the health of aquatic ecosystems.

Optically Inactive Water Quality Parameters (pH, DO)

Optically inactive water quality indicators refer to parameters that do not alter the path of light through water and, as a result, do not affect the colour or transparency of the liquid. Despite their lack of direct impact on light, these factors remain crucial in determining the condition of water bodies due to their significant effects on aquatic life and human health. To indirectly estimate nonoptically active parameters, a significant correlation between nonoptically and optically active parameters has been commonly used (Mathew et al., 2017; Wu et al., 2010). In a recent study by Guo et al. (2021), the recovery of nonoptically active characteristics of small watersheds was investigated using Sentinel-2 images. The researchers presented and compared different machine-learning models to find suitable approaches for recovering water quality parameters. By exploring indirect relationships and leveraging machine learning, this research contributes to advancing the assessment of water quality and understanding the impact of optically inactive indicators on aquatic ecosystems.

pH The pH scale is a measure of how acidic or basic a water solution is (Gorde & Jadhav, 2013). Monitoring water pH is crucial for assessing water quality and ensuring the reliability and purity of water for consumption, as it can impact human health. Water with a pH below 7.0 is considered acidic, while water with a pH above 7.0 is considered basic or alkaline. Most biological life can thrive in environments with a pH ranging from six to nine. During summer months, high temperatures can cause a rise in pH levels in water reservoirs (Patil et al., 2012). This can lead to slower photosynthesis and reduced absorption of $CO2$, affecting the dissolved oxygen level in water bodies. Anthropogenic activities can also influence pH levels in water, and areas with naturally low pH levels may be more susceptible to pollution inputs and subsequent deterioration (Ringwood & Keppler, 2002). Monitoring water pH is essential for understanding its impact on both human health and aquatic ecosystems. Proper regulation and management of pH levels are vital for ensuring safe and sustainable water resources.

Dissolved Oxygen (DO) Dissolved oxygen (DO) is a critical indicator of the water system's condition and its capacity for recovery. It reflects the rate at which oxygen is demanded and released in water, making it essential in assessing water quality (Abayazid & El-Adawy, 2019). A typical reading of 6.5 mg/l is considered indicative of moderate water quality (APHA, 1995). However, low DO levels can lead to an imbalanced system and aesthetically undesirable signs in the water body (Alam et al., 2007). DO levels can be affected by various parameters, such as temperature, salinity, and air pressure. Additionally, inputs of organic matter, fertilizers, and human activities such as wastewater discharges and agricultural runoff can impact DO concentrations. Low DO levels in water can create favourable conditions for the growth of hazardous bacteria, including those causing botulism, which can be fatal if ingested. Moreover, water with low DO concentrations may have unpleasant tastes and odours, discouraging people from consuming sufficient water for good health. Monitoring and maintaining adequate DO levels in water bodies is crucial for supporting aquatic life and ensuring safe and pleasant drinking water for human consumption.

Eutrophication and Algal Blooms

Prediction of Eutrophication

Eutrophication is characterized by the excessive presence of organic compounds, primarily nutrients, in water bodies, leading to uncontrolled growth and decomposition of organic matter, bacteria, and algal populations (Fig. 3.5) (Xu et al., 2001). As these species die, oxygen depletion (hypoxia) occurs, hindering the growth of fish and other organisms. Eutrophication events can reduce the values of reservoirs and compromise drinking water treatment (Landsberg, 2002). The process of eutrophication involves an overabundance of nutrients nourishing aquatic ecosystems, resulting in degraded water quality (Donia & Hussein, 2004). This excessive nutrient input negatively impacts the biological stability of aquatic ecosystems, leading to ecological, social, and economic consequences for human usage of limited water resources. The yearly cost of repairing the damage from eutrophication in the United States alone is projected to be approximately $2.2 billion (Dodds et al., 2009).

The eutrophication process in aquatic ecosystems is complex and multidimensional, making it challenging to rely on a single variable to accurately describe the eutrophic level (Presented et al., 2015). To assess eutrophication, consideration of numerous variables is necessary, but each variable's function and dynamics may lead to different eutrophication tendencies, complicating the spatial measurement of eutrophication levels. To address this complexity, suitable approaches and instruments are needed to spatially synthesize the eutrophication trends provided by multiple metrics. Here, a geographic information system (GIS) offers a simple solution, enabling the creation of thematic maps that display the location of eutrophication. Over the past three decades, coastal water eutrophication has been recognized as a

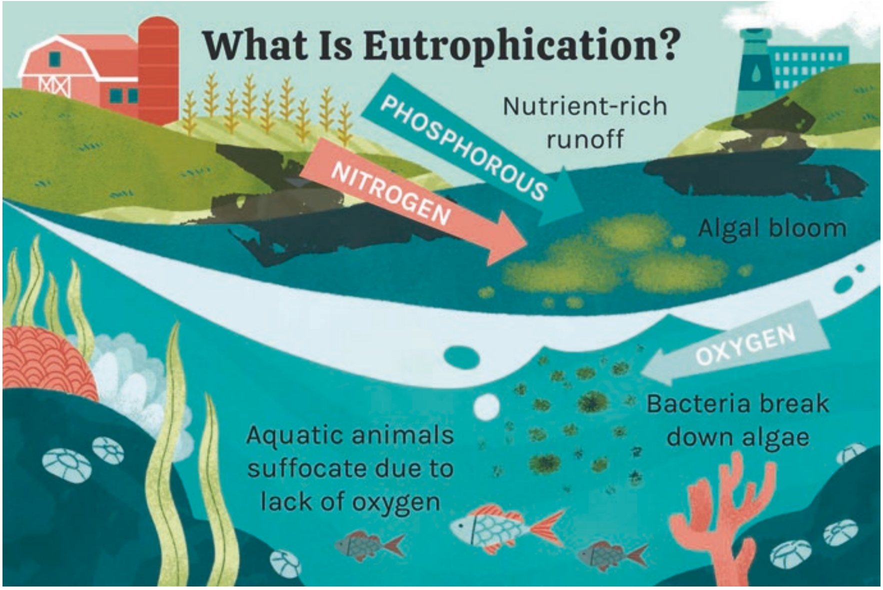

Fig. 3.5 Eutrophication process

significant risk to aquatic environments, leading to the development of various techniques for classifying waters into distinct categories and quantitatively assessing coastal water trophic conditions.

The Maryland Automated Geographic Information System, the first commercial GIS system, was developed by ESRI in 1973. Over the years, ESRI continued to advance their technology, eventually leading to the creation of ArcGIS in 1999 (Hiscock et al., 2003). GIS software has become a powerful tool for analyzing and visualizing spatial data, making it invaluable in various fields, including environmental research. A study conducted by Hiscock et al. (2003) used GIS-based modelling to investigate how phosphorus loading varied in Florida basins based on soil type, land use, and rainfall. Their research revealed a significant association between developmental activities and eutrophication.

Several studies have utilized GIS analysis to study water quality and trophic conditions in various water bodies. Hameed (2010) classified fifty reservoirs based on data from monitoring water pH and/or alkalinity using GIS analysis. Gupta et al. (2012) assessed nutrient levels in the Rönne River in 2011 and predicted potential runoff in watersheds using GIS. In Turkey's shallow Uluabat Lake, Akdeniz created trophic state index (TSI) maps using the IDW (inverse distance weighted) approach of ArcGIS. Similarly, Anoh et al. (2012) investigated the trophic condition of the Taabo River in the Ivory Coast, highlighting areas with the highest contamination through multicriteria analysis of water quality metrics. Recently, Mushtaq et al. (2022), derived the trophic state index (TSI) for the freshwater Himalayan Lake using Landsat 8 satellite data and a regression analysis approach in Kashmir, India.

GIS-based modelling has proven valuable in monitoring eutrophication in water bodies, allowing for a comprehensive understanding of this complex process.

Prediction of Harmful Algal Bloom (HABs)

The influx of nutrients from agricultural activities can have far-reaching consequences on water quality and ecosystem health, particularly when it leads to the proliferation of harmful algal blooms (Fig. 3.6). Increased nutrient input, especially from nitrogen-based fertilizers, fuels the rapid growth of harmful algae, leading to the production of excessive toxic compounds in the water body that can detrimentally impact the overall ecosystem (Glibert et al., 2006; Howartw et al., 1996; Landsberg, 2002; Fleming et al., 2011). The Gulf of Mexico serves as an example where nitrogenous compounds from fertilizers have been identified as the main sources of total nitrogen in the water (Howartw et al., 1996). However, one of the major challenges for academics studying algal bloom models is the lack of sufficient geographical and temporal datasets in many vulnerable regions worldwide (Anderson, 2009). In these areas, comprehensive field-based measurements needed to monitor algal blooms are often absent.

Recent advancements in remote sensing and GIS-based modelling approaches offer promising solutions to address these limitations. The complexity of aquatic ecosystems, characterized by the diversity and interconnectedness of their constituent parts, poses a significant challenge to accurately modelling algal blooms (Recknagel et al., 1997). Despite substantial research efforts, including observation-based studies (Izadi et al., 2021) and incorporation into physical-based models (Skogen et al., 1995), the underlying mechanisms and causality of algal blooms remain incompletely understood (Lee et al., 2003; Donaghay & Osborn, 1997). Data-driven approaches, such as those increasingly utilized in combination with or as alternatives to physical-based models (Karul et al., 2000; Lee et al., 2003), offer an avenue to overcome these complexities.

Earlier attempts to simulate harmful algal blooms (HABs) through GIS-based modelling examined numerous causal factors, including temperature (Cha et al., 2014), hydrologic fluxes (Raine et al., 2010), ocean currents (McGillicuddy et al., 2005), and hydrodynamic variables (current, flow, upwelling, and downwelling) (Cusack et al., 2016). These parameters were then utilized for mapping, modelling, and predicting seasonal bloom formations (Aleynik et al., 2016), providing early signs of disturbance. While GIS has been used to identify and map HABs based on a few ecological factors in earlier studies, such as chlorophyll-a concentration (Balch et al., 1989; Gower et al., 2004; Hu et al., 2005; Stumpf et al., 2003), or a combination of two (Ahn et al., 2006; Ecol et al., 1999; Raine et al., 2001; Stumpf and Tomlinson, 2005) or three parameters (Tang et al., 2004), most GIS-based HAB detection strategies have limitations due to various factors (Shen et al., 2012). Despite efforts to incorporate more variables in ecosystem models, few regions have effective monitoring and warning approaches that encompass all relevant factors (Cusack et al., 2016), leaving gaps in HAB detection and response in various areas.

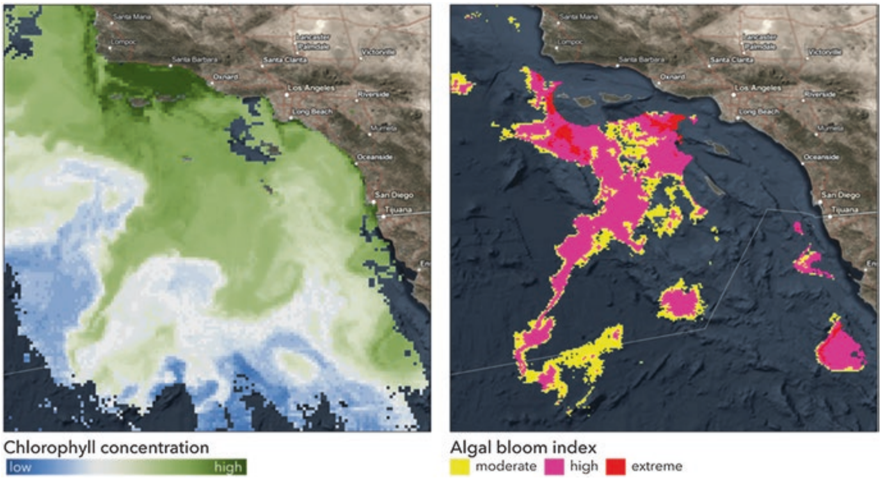

Fig. 3.6 Chlorophyll concentrations and the algal bloom index near the coast in California, United States, and Mexico. (Source: https://www.esri.com/en-us/industries/blog/articles/sdg-14-and-life-below-water-what-space-can-tell-us-about-the-slimy-stuff-at-the-beach/)

Enhancing GIS-based modelling by considering a broader range of ecological parameters may offer more comprehensive insights into HAB dynamics and contribute to better management and mitigation strategies.

Case Studies

The use of GIS-based simulations is crucial for investigating variations in water quality over space and time, leading to the creation of reliable water quality prediction models. These models can forecast important parameters such as pH, water surface temperature, dissolved oxygen (DO) concentration, nitrogen, and phosphorus levels (Mushtaq & Nee Lala, 2017; Mushtaq et al., 2022; Rudd et al., 2018; Van Soesbergen & Mulligan, 2014). Furthermore, GIS assists climatic modellers in utilizing extensive climatic data to develop effective mitigation policies (Farjad et al., 2016). It enables researchers to study the impacts of climate fluctuations on groundwater-dependent areas and visualize climate change using remote sensing data (Jakeman et al., 2016). The visualization and mapping capabilities of GIS platforms such as ArcGIS, QGIS, and Redlands-California are invaluable for communicating spatial information to policy and decision-makers. Through GIS, 2D, 3D, and 4D water quality status maps based on chemical concentrations can be stored and generated.

Numerous researchers have made significant progress in connecting GIS-based analysis to water quality parameters. For instance, Demlie (2015) and Troudi et al. (2020) studied surface salinity in wetlands, highlighting the influence of climate on the hydrological cycle. Van Soesbergen and Mulligan (2014) investigated groundwater distribution considering climatic inconsistencies using general circulation models (GCMs). Farjad et al. (2016) demonstrated the challenges in understanding the effects of meteorological changes on water resource management through globally dispersed modelling techniques. Moreover, researchers such as Sheng (2013) utilized integrated GIS and hydrological modelling software to examine the impacts of climate variability on groundwater contamination and treatment in the Rio Grande Basin. GIS has proven valuable in groundwater quality mapping as well (Singh et al., 2013). Demlie (2015) and Jakeman et al. (2016) suggested that an approach to groundwater preservation and sustainable utilization requires improved knowledge, and GIS plays a key role in achieving this. Currently, various GIS plugins and modules are utilized to test and simulate water quality parameters, providing researchers with powerful tools for studying and managing water resources effectively. Some of them are summarized in Table 3.2.

3.6 Challenges, Future Directions, and Recommendations

GIS-based modelling for water quality faces various challenges and has several future directions for improvement. One of the main challenges is the uncertainty associated with the modelling process due to limitations in data quality and modelling assumptions. Advancements in remote sensing and GIS techniques have provided significant benefits to water quality modelling, although the limitations of the study still need to be addressed. Moreover, the current models still have limitations, including the lack of consideration for the spatial and temporal variability of water quality parameters. Future research in this field should focus on incorporating optically active water quality parameters and developing more accurate modelling techniques. The potential for GIS-based modelling to improve water quality management and monitoring is significant, and its proper implementation could have a significant impact on the environment.

Uncertainty Assessment and Validation Uncertainty assessment and validation are critical components of GIS-based modelling for water quality parameters. Uncertainty in modelling results can arise due to data quality, model assumptions, parameter estimation, and the choice of modelling techniques. It is important to assess and validate the uncertainty associated with GIS-based water quality modelling to ensure the reliability and accuracy of model predictions. Sensitivity analysis, Monte Carlo simulation, and error propagation analysis are some of the methods used for uncertainty assessment in GIS-based water quality modelling. Sensitivity analysis involves examining the model's response to changes in input parameters, while Monte Carlo simulation involves generating random input parameters to simulate model outputs. Error propagation analysis quantifies the impact of errors in input data on model outputs.

Validation is another critical step in GIS-based water quality modelling. It involves comparing the model's predictions with observed data to assess its accuracy. Validation methods include statistical measures such as the correlation coefficient, root mean square error, and coefficient of determination. The validation

Table 3.2 GIS plugins and modules currently used to test and simulate water quality parameters

Model	Author	Study region	Research objective	Significant findings
WASP (water quality analysis simulation program)	Shabani et al. (2021)	The Woodbridge watershed is in Perth Amboy, New Jersey	The external coupler handled flow data aggregation and mass preservation issues throughout the flood incident by coupling HEC-RAS and WASP.	The external coupler case study showed that strain, initial concentrations of contaminants in a surface substrate (and their geographic distribution), and suspended particles affect sediment-coupled pollutants during and after flooding.
	Żelazny et al. (2023)	Dunajec River, Poland	The WASP can analyze water quality changes and create ways to prevent surface water effects.	In the study, more sources of microbial contamination will raise the likelihood of infection due to more pollution sources, and failure risk increases.
	Mbuh et al. 2019)	Shenandoah River basin, Virginia	To show how temperature, stream flow, and velocity affect water quality across seasons and levels on distinct watershed sections.	Complexity and sensitivity reduce model error, according to sensitivity tests. The model overemphasized total nitrogen and phosphorus but predicted DO levels similar to observed data.
	Moses et al. (2015)	Akkulam–Veli Lake, Thiruvananthapuram, India	In this investigation, WASP predicts DO, PO_4^{3-}, NO_3^-, chlorophyll-a, and BOD.	Precipitation impacts tropical lake water standards. After a long drought, heavy summer precipitation brings a lot of organic matter into the lake through drains, raising PO_4^{3-} and chlorophyll-a levels.
	Bouchard et al. (2017)	Brier Creek, Georgia United States	This work enhanced the water quality analysis simulation program (WASP) to model the multiwalled carbon nanotube (MWCNT) nature and transit in surface waters.	The first Brier Creek water categorization showed that MWCNTs were mostly in the water column, while below-surface and subsurface sediment items increased in frequency and proximity to the source, indicating that MWCNT discharges could have long-term ecological consequences in the benthic region.

SWAT (soil and water assessment tool)	Ullrich and Volk (2009)	Elbe River system, Germany	Performed a SWAT sensitivity assessment for preservation administration parameters like tillage length, automated soil integrating efficiency, physiological soil mixing productivity, curve size, Manning's hardness coefficient for land flow, USLE-affirm behaviour aspect, and filter strip dimension.	The model lacks precision in crop rotations and even minor management changes. However, settings vary in sensitivity.
	Pisinaras et al. (2010)	Kosynthos River watershed, Northeastern Greece	The basin was segmented using various hydrologic response units (HRUs).	SWAT may test Mediterranean watershed management scenarios with higher effectiveness. The GIS-approach SWAT model application was a versatile and consistent water decision-making tool, notably for harmonizing with the water background command.
	Noori et al. (2020)	Watersheds in the Atlanta metropolitan area, USA	Used a process-oriented watershed model with an artificial neural network (ANN) to enhance water quality forecasts in unmonitored watersheds.	Nitrate models even outperformed site-calibrated SWAT models. This research shows the benefits of integrated simulation for water quality indicator prediction in unsupervised watersheds.
CE-QUAL-W2 (two-dimensional, laterally averaged hydrodynamic and water quality model)	Kurup et al. (2000)	Swan River estuary, Australia	CE-QUAL-W2 and TISAT salinity distribution predictions are compared to 1994 Swan River estuary field measurements.	When there is severe seasonal density stratified in the Swan River estuary, CE-QUAL-W2 outperforms TISAT.
	Zhu et al. (2017)	Xiaxi River, China	This model was updated to simulate mercury (hg) movement and cycling in aquatic bodies.	W2 predicted Xiaxi River hg and methylmercury concentrations. The W2 model predicted complicated hg transport and cycling in water bodies in this application.

(continued)

Table 3.2 (continued)

Model	Author	Study region	Research objective	Significant findings
Environmental fluid dynamics code (EFDC)	Li et al. (2007)	Water reservoir in China	The report reviewed reservoir water temperature studies in China and elsewhere and examined the EFDC model.	The calibrated result reveals that the three vertical traces in front of the dam average −0.15° absolute mean error and 2.0% relative error. February 2003–January 2004 verified the model. The average inaccuracy is −0.36°. EFDC simulations match observations.
	Jeong et al. (2010)	Geum River, South Korea	EFDC, an interactive numerical model, examined saltwater intrusion downstream of the Geum River.	Saltwater intrusion resulting from the barrage was 50.72 km (drought), 48.87 km (low), 46.56 km (normal), and 42.10 km (flood) validating the appropriate computation of the EFDC model.
AQUATOX (aquatic toxicology model)	LEI et al. (2008)	Songhua River, China	The AQUATOX model was developed to replicate this multimodal aquatic system's time-dependent nitrobenzene dispersion and ecological effects.	The sensitivity study showed that input water dilution, temperature, and beginning concentration affected water nitrobenzene concentrations the most.
	Park et al. (2008)		Streams, minor waterways, ponds, loughs, reservoirs, and inlets use the model. It links to watershed models HSPF and SWAT as part of BASINS.	The US Environmental Protection Agency has provided backing for its implementation in experimental tanks and borders, waterways, lakes, stream reservoirs, and estuaries for a period of two decades.

process often includes dividing data into training and validation sets, where the training set is used for model calibration and the validation set for model accuracy testing. It is important to note that uncertainty and validation are not one-time activities but ongoing processes that should be repeated periodically to ensure the model's reliability. Additionally, it is crucial to validate the model using independent datasets to avoid overfitting. By using proper uncertainty assessment and validation techniques, GIS-based water quality modelling can improve water quality management and monitoring.

Limitations Existing GIS-based water quality modelling approaches have several limitations that need to be considered to improve the accuracy and reliability of model predictions. One major limitation is the availability and quality of input data. Inaccurate or incomplete data can lead to incorrect model predictions, and the use of data from different sources can introduce inconsistencies and errors. Another limitation is the simplification of complex physical and chemical processes in water systems in model parameterization. The use of empirical relationships or assumptions to represent these processes can introduce errors in the model predictions. Furthermore, the use of constant parameters for dynamic systems can also lead to errors. Additionally, the spatial and temporal scales of the model can impact its accuracy. Smaller-scale models may not capture the variability in water quality parameters over larger areas, and vice versa. Moreover, temporal variability in water quality parameters, such as seasonal changes or short-term fluctuations, may not be adequately captured by models that use static inputs.

Furthermore, model calibration and validation can also be a limitation, as it is often difficult to obtain accurate and representative validation data, particularly for less commonly measured parameters. Inadequate validation data can lead to overfitting of the model, which may result in unreliable predictions. Overall, addressing these limitations is crucial for improving the accuracy and reliability of GIS-based water quality modelling approaches. This can be achieved through the use of high-quality input data, more advanced parameterization techniques, and the development of models that are appropriately scaled and validated.

Recommendations and Future Directions: GIS-based modelling for water quality parameters has shown promise but requires further development and improvement. Future research should focus on understanding the factors influencing water quality parameters, standardizing data collection methods, enhancing spatial resolution, promoting collaboration and data sharing, and integrating citizen science. The potential benefits of GIS-based modelling for water quality management are significant. It can offer valuable insights into the complex interactions affecting water quality and facilitate effective monitoring and mitigation strategies. By addressing the above-mentioned recommendations, GIS-based modelling can become an even more powerful tool for advancing water quality management and environmental conservation.

(i) *Early Detection of Water Quality Issues:* GIS-based modelling can provide early detection of emerging water quality issues, enabling proactive management and prevention of negative impacts.

(ii) *Identification of Hotspots:* GIS-based modelling can identify water quality hotspots and sources of pollution, enabling targeted management strategies and resource allocation.
(iii) *Real-Time Water Quality Monitoring:* GIS-based modelling can facilitate real-time water quality monitoring, enabling a rapid response to changes in water quality.
(iv) *Integration of Multiple Data Sources:* GIS-based modelling enables the integration of multiple data sources, providing a more comprehensive understanding of water quality parameters and their spatial distribution.

Generally, GIS-based modelling has great potential to improve water quality management and monitoring by providing timely and accurate information for decision-making. However, there are opportunities for further research and development, including the inclusion of machine learning, the development of standardized data collection methods, and the improvement of spatial resolution. By addressing these areas, GIS-based modelling can become an even more powerful tool for water quality management and monitoring.

3.7 Conclusions

Geographic information systems (GIS) have become indispensable tools for water quality assessment and management. Through the integration of GIS with various modelling approaches, they offer a comprehensive understanding of spatial patterns and the impacts of human activities on water quality. Utilizing geospatial data sources, remote sensing imagery, and water quality data, GIS-based modelling provides critical insights for environmental management and decision-making. To further improve the accuracy and effectiveness of these models, researchers are exploring advancements in artificial intelligence algorithms and data analysis methods, particularly for estimating optically inactive parameters. This progress promises a more comprehensive understanding of water quality, benefiting management and decision-making processes. One specific environmental issue where GIS-based modelling excels is addressing eutrophication caused by excess nutrients. Researchers are using these techniques to monitor eutrophication and predict harmful algal blooms spatially. By employing remote sensing and GIS technologies, data scarcity and ecosystem complexity challenges are addressed, enabling large-scale eutrophication management worldwide.

Moreover, GIS-based modelling has demonstrated its versatility in analyzing various water quality parameters and investigating links between climate change and water resources. Forecasting pH, water surface temperature, dissolved oxygen concentration, and nitrogen and phosphorus columns simplifies climate data for climate change mitigation. GIS has played a vital role in connecting water quality analysis to climate effects on groundwater-dependent areas, facilitating visual representation of climate change. Various GIS plugins and modules, including WASP, SWAT, CE-QUAL-W2, EFDC, and AQUATOX, are used to test and simulate water quality parameters, contributing to sustainable water resource management. In conclusion, GIS integration in water quality management and monitoring significantly enhances the sustainability and health of global water resources. By continually advancing GIS-based modelling techniques, researchers can continue to address environmental challenges and support informed decision-making for water quality and resource conservation.

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Chapter 4
Air Quality Monitoring Using Geospatial Technology and Field Sensors

Konika Sharma and Shweta Yadav

Abstract Air quality management is a public health priority at the global scale. Accurate air quality monitoring along with understanding the sources of air pollution is the first step to adequate air quality management. Apart from sampler-assisted ground-based monitoring of air pollutants, the use of geospatial technologies and the deployment of field sensors have surfaced as a new hope for strengthening the air quality monitoring network. This review provides information on the types, characteristics, and robustness of field sensors and geospatial technologies that are used for air quality monitoring and management. The technology used in sensors and the methodology for geospatial technologies have been discussed. We conclude that the evolving network of field sensors and cutting-edge geospatial technologies will certainly lead to better air quality management in India. The efforts in this direction will not only provide a sustainable solution to the current crisis of air pollution but also lead to the collection of highly time-resolved data from even remote and least studied hard areas where ground-based sampling is a limitation. The airshed approach in this context offers a sustainable solution by targeting and synergising air pollution management across administrative boundaries. The synergy between ground-based stations, geospatial technologies, and field sensors will lead to a hub of data resources that will help policymakers frame policies for air quality management. Additionally, this will be an asset to researchers working in the field of atmospheric chemistry and pollutant dynamics.

Keywords Air quality monitoring · Geospatial technologies · Integrated systems · Ground-based stations · Field sensors · Airshed approach

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4.1 Introduction

Clean and healthy air is an essential requirement for every living thing, especially for humans (Juginović et al., 2021; Singh et al., 2021; World Health, 2006). Air pollution is a global problem that has adverse effects on human well-being (in both urban and remote environments), crop productivity, a variety of animals and insects, and ecosystems in terms of the quality, applications, and services that they provide. This problem intensified with global industrialisation, which led to increased stress on natural assets, as well as greater irregularities in the allocation of economic resources. Air pollution gives rise to a substantial risk to human health and well-being, but preventing it has historically been viewed as less of a priority because of the rapid recovery of the losses before industrialisation. Consequently, there is a growing need for sophisticated statistical and machine learning (ML) resources, as well as the emergence of environmental organisations, the enactment of laws and policies, the development of widespread sensor systems, and the advent of digital technologies to evaluate, oversee, and communicate with both the general public and those responsible for environmental management concerning the state of air quality (AQ). Organisations such as the Environment Protection Agency (EPA, founded in 1970), the Intergovernmental Panel on Climate Change (IPCC, founded in 1988), the World Meteorological Organisation (WMO, founded in 1950), and the Global Environment Facility (GEF, founded in 1991) are some of the landmark developments in Air Quality Assessment and Management (AQA&M). Scientists came up with air quality sensors (AQS) in 1940 but it was not until the 1980s that world organisations gave directions on how to set up AQS networks and monitoring systems all over the world to control the effects of air pollution on the well-being of the general public. Nevertheless, these AQA&M networks are not very commercial in developing nations, such as India, where approximately 703 station networks were set up; Pakistan, where no such network is known yet; Sri Lanka, where a VAAYU network equipped with 78 stations was set up; and Bangladesh, with an ensemble of 11 stations. With the passing of the Air (Prevention and Control of Pollution) Act of 1981, air pollution monitoring and management have gained some momentum in India. The National Air Quality Monitoring Programme (NAMP), initiated by the Government of India, is believed to have been one of the earliest programmes to employ wide networks of sensors, including 883 AQ stations in 379 cities and towns, for the purpose of AQ monitoring. The programme was designed to monitor four major pollutants, namely, sulphur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter (PM) with aerodynamic diameters $\leq$10 μm (PM_{10}) and $\leq$2.5 μm ($PM_{2.5}$).

To measure and monitor ambient air quality, two main categories of sensor systems—(a) the ensemble of human-operated sensors and (b) a computerised system of sensors—are deployed on the ground. The vital elements of such sensor networks include temperature, humidity, precipitation, and gas sensors. A gas sensor is a transducer that measures the concentration of a gas by converting the intensity of an electrical signal into a proportional value (Kumar et al., 2011, 2013; Yi et al., 2015).

Gas sensors can be electrochemical, catalytic, solid-state, nondispersive infrared, or photoionisation devices. Because of these sensor and geosensor technologies (sensor networks that have been specifically developed to collect and analyse data pertaining to geospatial information) (Jung et al., 2008), the collection, analysis, and integration of geospatial and pollutant data have undergone a large-scale transformation. In addition, although still constrained to stationary locations, the advent of cutting-edge sensor systems such as the Internet of Things (IoT) and wireless sensor networks (WSNs) has improved the feasibility of ongoing air pollution assessment over wider regions. Extensive sensor systems for worldwide AQ surveillance and predictions include the Environment Observation and Forecasting System (EOFS), Global Environmental Monitoring System (GEMS) Air, and World Air Quality Index (WAQI), among others (Nandakumar et al., 2011).

The purpose of this work is to review the availability and application of available sensors and geospatial technologies for managing air quality. This assessment has been conducted to shed light on currently used pollutant monitoring and control strategies, including those for PM, SO_2, NO_2, carbon monoxide (CO), and ozone (O_3). For AQ parameters, the accessibility of satellite or sensor data sources, digital methods, and real-time dashboards is stated, which may aid scientists, researchers, policymakers, and others involved in formulating new policies and taking necessary steps.

4.2 Geospatial Technologies for Air Quality Monitoring

The scientific community has advanced quite far in terms of assessing Earth's geographic information, from the time of hand-drawn maps to the present day of GPS mapping. There is now a whole new genre of cartography to explore. Credit goes to geospatial technology, precise measurements may be taken on an extremely small scale and with as little error as possible. Today, more than ever, we recognise the importance of geospatial technology due to its widespread application in fields as diverse as farming, medicine, disaster recovery, forest management, administrative tasks, climate change investigation, military strategy, and resource management.

India's ecosystem for remote sensing and geospatial data is among the most developed in the world. The proliferation of geospatial applications has resulted in a deluge of data and information that must be optimally handled and used for the benefit of humanity and the solution of new and existing problems. Some of the most frequently utilised geospatial technologies include remote sensing (which uses space or aerial cameras and sensor systems to analyse distant objects or surfaces. The sensor platforms' data can help experts evaluate the target's features); Geographic Information Systems (GIS collects, manages, maps, and analyses physical environment data for a specific location on Earth. GIS creates maps and 3D scenes from geographic data layers and can highlight patterns, links, and situations in data, helping users make better decisions); Global Positioning System (Satellites, a reception device, and software coordinate position, speed, and time for atmospheric, marine, and terrestrial movement. GPS relies on trilateration. The technique shows that GPS devices need three satellites for precise positioning. One satellite's data locate a spot inside a vast circular area on Earth. Another satellite helps the GPS pinpoint that place. A third satellite pinpoints that spot on Earth).

Making use of high-resolution satellite imagery for remote sensing purposes is a valuable technique that enables improved interpretation and analysis of air pollutant concentrations. Satellite imagery is a valuable tool for quantifying and mapping air pollution due to its ability to offer a synoptic view of vast regions. Satellite sensors of varying spatiotemporal-radiometric details provide the means to assess the levels of detrimental air contaminants, including CO, NO_2, ammonia (NH_3), SO_2, volatile organic compounds, and PM. Spatial interpolation techniques are employed for the construction of a surface grid or contour chart. Such interpolation approaches are employed to estimate concentrations in the study area by utilising a limited number of known concentrations at specific points (Mishra & Parasar, 2021). GIS techniques have also been employed by several researchers to examine the spatiotemporal dispersion of pollutants in the air (JIA, 2019; Mohan & Kandya, 2015; Rohayu Haron Narashid & Wan Mohd Naim Wan Mohd, 2010; Singh et al., 2022).

Arabia (2019) conducted an analysis of diverse satellite remote sensing technologies to assess their potential for estimating air pollutants. Additionally, he evaluated the techniques employed for handling and retrieving satellite data to generate pollutant concentration maps. According to their findings, the diverse spectral resolutions of space instruments facilitate the identification of distinct types of atmospheric contaminants. The utilisation of air pollution measurements obtained from space is advantageous in the monitoring of air quality and the analysis of the extended-term trends of atmospheric pollutant concentrations. Rohayu Haron Narashid and Wan Mohd Naim Wan Mohd (2010) demonstrated the feasibility of leveraging a combination of remote sensing methodology and GIS strategies, specifically the kriging interpolation approach, for the purpose of monitoring air pollutant concentrations. Satellite imagery offers a cost-effective approach for generating air quality maps for a given region, particularly at a microscale level. The results of their assessment indicated that the implementation of satellite remote sensing and GIS methods hold promise for environmental managers and local authorities in the ongoing surveillance of AQ (at a microscale) in cities. Taloor et al. (2022) analysed the in situ and satellite-derived NO_2 emissions data pertaining to various urban centres in India, with the aim of evaluating the effects of the lockdown measures implemented due to the COVID-19 pandemic in the country. Furthermore, an analysis was conducted on the NO_2 database obtained using the Sentinel-5P TROPOMI sensor system across several areas within Punjab and the NCR. The study underscores the potential benefits of integrating in situ and satellite-based methodologies for evaluating alterations in air quality across urban areas in India. This approach holds promise for future investigations in other nations as well.

Numerous researchers have effectively employed geospatial artificial intelligence in disaster-related issues and agricultural investigations. Furthermore, it has been utilised in the cartographic representation and simulation of atmospheric contaminants within metropolitan areas. This approach comprises two methodologies,

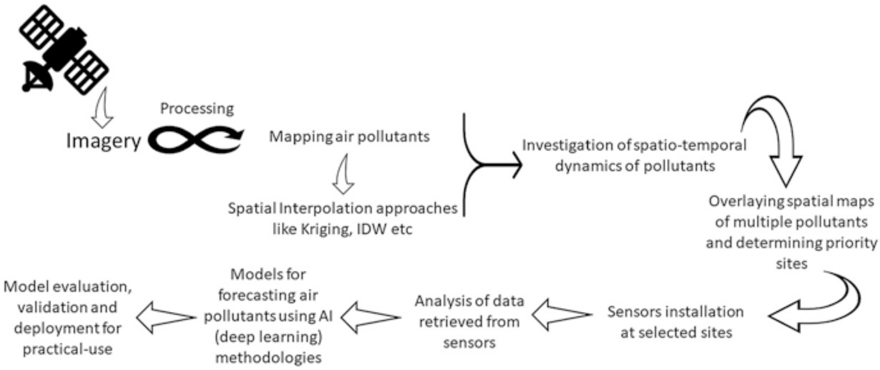

Fig. 4.1 Overview of the geospatial methodology used for air quality monitoring

namely, geospatial technology and artificial intelligence. Geospatial technology has the potential to facilitate spatiotemporal mapping of air pollutants and subsequent prioritisation of locations based on the results of this analysis. Artificial intelligence techniques, including deep learning, artificial neural networks (ANNs), and convolutional neural networks (CNNs), can be used to predict the concentration of pollutants (Mishra & Parasar, 2021). A general overview of the followed methodology is mentioned below and illustrated in Fig. 4.1.

Mapping of Atmospheric Pollutants The levels of atmospheric contaminants such as SO_2, NO_2, and suspended PM can be acquired through official governmental entities or by using image processing software to extract data from satellite imagery. The spatial distribution of air pollutants is analysed and represented through various GIS-based spatial interpolation techniques, such as kriging, splines, and inverse distance weighted (IDW) methods. The IDW method is employed in scenarios where the point density is significant, thereby enabling the derivation of a local surface variation for analytical purposes. The grid estimates of any arbitrary factor are calculated using a linearly weighted set of data. The feasibility of interpolation is contingent upon the spatial separation between the sampling sites and the target location for the interpolation. This technique is ideal for smoothly varying surfaces, as it employs a special kind of polynomial interpolation. It can predict valleys and ridges in the dataset, making it the ideal tool for portraying gradually altering terrain with tiny mistakes. Kriging is a method of spatial interpolation that models interpolated values using a Gaussian procedure with known covariance. This stochastic method has applications in many fields, such as pollution modelling, geochemistry, and catastrophe preparedness. It is predicated on the assumption that variation on a surface can be inferred from the distance between a set of sample points. This structure helps lessen the impact of random noise. All values within a specified range are computed. Value predictions are made using an improved weighted average algorithm in this method (Hadjimitsis et al., 2012; Mishra & Parasar, 2021).

Forecasting Atmospheric Pollutants Pollutants in the air can only be predicted with the help of photos taken across multiple dates. These pictures/images are then processed using numerous steps, including (1) *image acquisition,* which entails the procurement and retention of visual representations into a designated repository. Subsequently, the process involves converting it into a variable and generating load folders that contain images into arrays; (2) *image resisting,* which is a necessary step to address the discrepancy between the model's requirements and the actual image captured; and (3) *noise filtering in images* to reduce unwanted image noise. The process of image smoothing is a necessary prerequisite for the enhancement of various scales of image structures, and (4) *image splitting and morphological modifications* are necessary to effectively separate the foreground from the background, thereby facilitating the extraction of pertinent features. The implementation of morphological changes necessitates the application of edge smoothing. Upon completion of processing steps, the images may be utilised to simulate a model for the purpose of predicting air pollutant concentrations through the implementation of artificial intelligence and machine learning methodologies. Deep learning, a subfield of machine learning, has experienced significant momentum in its application across various domains. The process of constructing a deep learning model is based upon five crucial steps, which are enumerated as follows:

Defining Architecture To determine the architecture, it is necessary to conduct an analysis of the problem's characteristics. CNNs are a widely adopted approach for conducting image segmentation and classification tasks, particularly those that require intricate predictive analysis, owing to the inherent characteristics of the problem domain. The overall deep learning architecture employs either sequential models, functional APIs, or custom architectures that are capable of being defined for model building.

Model Structuring To prepare the model for the fitting or training process, it is necessary to perform model compilation. Some of the crucial elements of the training process are specified for the assessment process in the compilation phase. As a result of the inherent characteristics of the issue at hand, we will incur losses that must be determined at this stage. Additionally, we must make determinations regarding the optimisers and metrics to be employed, including precision and classification-related metrics.

Fitting of Model The process of fitting the model on the training dataset is a crucial step. The model is trained for a predetermined number of epochs, which refers to the number of iterations performed on the dataset. Throughout the entire training process, it is imperative to consistently assess the fitting step. Ensuring that the model under training exhibits enhanced accuracies and a decrease in the overall loss is of utmost importance. The prevention of overfitting of the model is also a crucial consideration.

Model Analysis and Forecasting The assessment of the deep learning model's efficacy in actual application instances is a crucial undertaking that will be executed. It is imperative to incorporate the predictions generated by our model on the test dataset, which was partitioned during the preprocessing phase, to validate the efficacy of the trained model. Additional randomised tests will provide further evidence of the efficacy of the method on untrained data.

Model Deployment The actual implementation of the model is the very last step yet crucial in the building of any model.

4.3 Application of Field Sensors for Air Quality Monitoring

Numerous techniques (as outlined in Fig. 4.2) can be used individually or in integration so as to get more comprehensive and cutting-edge observations for further AQ monitoring and assessment. The prevailing approach for monitoring air pollution involves the utilisation of advanced and established instruments. To ensure the precision and excellence of data, intricate measurement techniques are employed by these instruments, along with various auxiliary devices such as temperature regulators (heaters and coolers), humidity regulators, air filters (for PM), and integrated calibrators. As a result, these devices are typically associated with elevated costs, significant power consumption, substantial physical dimensions, and considerable weight. Recent technological advancements have made ambient sensors readily available, possessing attributes such as affordability, compact area, and rapid reciprocation times. Nevertheless, it is worth noting that low-cost and portable AQ sensors are unable to attain an equivalent level of data precision and quality as conventional assessment techniques and equipment. At present, air pollution information pertaining to areas lacking observation facilities is acquired through air quality modelling approaches, as per the literature. Nevertheless, the air quality model data exhibit a dearth of comparison and confirmation (Kaur and Kelly, 2022). Affordable, cost-efficient mobile, and compact environmental sensors offer a significant possibility to enhance the resolution (for both temporal and spatial scales) of atmospheric data. Furthermore, they have the potential to validate, refine, or enhance current ambient air quality models. The subsequent sections present an overview of the operational principles of low-cost and portable ambient sensors, which are extensively employed presently.

Gas Sensors

Gas detection systems have come a long way in recent years, and each has its own set of benefits and drawbacks. Electrochemical, catalytic, solid-state semiconductor, nondispersive infrared radiation absorption (NDIR), and photoionisation

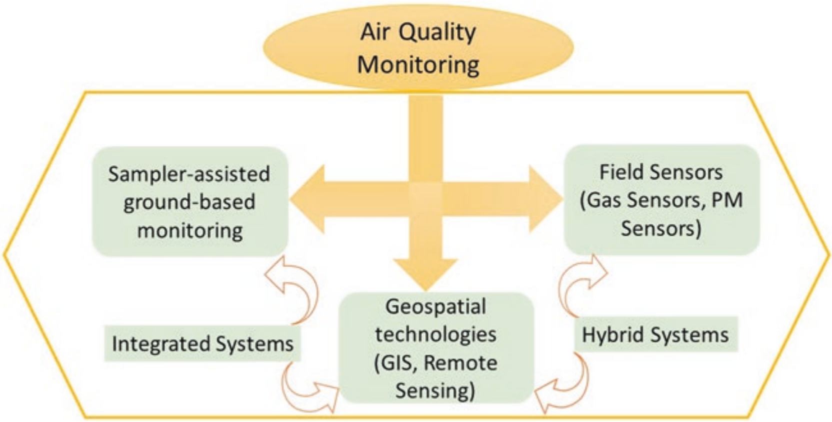

Fig. 4.2 Framework of categorisation of air quality monitoring approaches

detector (PID) sensors are the five types of inexpensive and conveniently movable gas sensors that have proven to be the most effective and popular to date. All of these sensors are cost-effective, lightweight (often under a hundred grams), and quick to respond (typically within tenths of a second to a few minutes). Although hundreds of potentially dangerous gases have been identified, there is currently no individual sensor technology that can accurately monitor them all. Various sensors can detect hazardous gases with varying degrees of sensitivity. However, no currently available portable gas sensor at a reasonable price has a similar level of data precision and reliability as stationary tracking equipment. In terms of accuracy and detection range, these low-cost gas sensors impart satisfactory performance (Aleixandre & Gerboles, 2012). In addition, it is necessary to calibrate every sensor prior to and following a certain period of operation. The calibration is done by exposing the sensor to a known concentration of a particular pollutant gas and then adjusting the sensor's parameters to reduce the discrepancy between the known level and the sensor reading. There are primarily four categories of hazardous gases that are tracked viz., CO, NO_2, O_3, and SO_2. It is established that for these four hazardous pollutants, there are two optimal sensor types, namely, solid-state and electrochemical sensor. To sum up, these are the most appropriate ones for sniffing out these four distinct classes of potentially dangerous gaseous pollutants in the context of air pollution monitoring. These two varieties of sensors form the backbone of the majority of the current efforts. The following is an explanation of how these two distinct kinds of sensors work.

Solid-State Gas Sensor The discovery of the operational mechanism of solid-state ambient gas sensors was made during the course of semiconductor p–n junction research, wherein the sensitivity of said junctions to numerous gaseous pollutants was observed. A solid-state sensor comprises a heating element and single or multiple metal oxides. The specific metal oxide utilised is dependent upon the intended ambient gas that the sensor is designed to detect. Metal oxides have the capability to undergo processing into a paste-like substance, commonly referred to as a bead-type sensor. Metal oxides may be deposited onto a silica chip through a process akin to semiconductor fabrication, resulting in a chip-type sensor. Upon exposure to ambient gases, metal oxides undergo dissociation to form charged particles or mixtures, which results in the amassing of electrons on the top layer of the metallic oxides. The conductivity of metal oxides is altered by this accumulation. Through the quantification of alterations in conductivity, scientists can infer the concentration of a particular type of surrounding gas. The solid-state gas sensor employs a heating source to enhance the reaction rate, leading to a robust electrical signal. The regulation of temperature is facilitated by the utilisation of the heating element, as the response of a particular type of ambient gas, characterised by a conductivity change, varies across distinct temperature intervals.

Electrochemical Gas Sensor Electrochemical gas sensors operate through electrochemical transformations, specifically redox reactions, occurring in the sensors. The electrical signal (current) initiated due to the interaction of the sensor with its surrounding gas molecules is directly proportional to the level of the gaseous pollutants. The electrochemical sensor comprises two essential components, namely, the working electrode (WE) and the counter electrode (CE). In cases where sensors necessitate third-party controlling power, the utilisation of a reference electrode (RE) is imperative. Usually, 2–3 electrodes are individually inserted into the sensor's electrolyte. Various sensors may employ distinct kinds of filter screens, electrolytes, and WEs to enhance the sensor's sensitivity towards a particular type of gaseous pollutant. To facilitate an optimal reaction between the ambient gas and the sensor while simultaneously mitigating the risk of electrolyte loss by leaking, the surrounding gas is initially directed via a capillary-style aperture and a hydrophobic barrier (Yi et al., 2015).

Upon the arrival of the gaseous pollutant at the WE, the redox reaction takes place. The electrode that has been specifically designed for a particular ambient gas serves as a catalyst for the aforementioned reactions. The concentration of the target ambient gas can be inferred by researchers through the measurement of the current between the WE and the CE. Sensors equipped with an RE utilise them to regulate the redox reactions, thereby mitigating prospective fluctuations in WEs resulting from degradation, albeit with the caveat that this approach may prove ineffective in the presence of fouled electrodes. It should be noted that a significant proportion of electrochemical ambient gas sensors necessitate a minimal quantity of oxygen and moisture for optimal operation. The chemical equilibrium on the surface of the sensor is impacted by wind velocity, which subsequently affects the readings of the sensor.

Particulate Matter Sensors

Quantification of PM is a complex process, with numerous methodologies for determining PM mass concentrations. The multifaceted characteristics of PM may lead to variations in outcomes across various measurement methodologies. Certain traditional monitoring devices employ a thermal component to mitigate the impact of fluctuating humidity and temperature. Nonetheless, the thermal component causes the semivolatile compounds to vaporise, and this poses a major limitation. Hence, certain instruments utilise a distinct drying mechanism in lieu of a heating component. The concentration of PM can be measured using techniques that fall into two distinct categories: (1) a direct reading instrument is capable of providing continuous measurements with a sampling interval of seconds or minutes, pertaining to the levels of PM in the surrounding atmosphere, and (2) another type of sampler is the filter paper-based gravimetric sampler, which utilises a filter to accumulate the particulate matter and necessitates periodic weighing in a laboratory setting. The process of assigning weights is a labour-intensive and time-consuming task that results in a significant time lag (measured in days) between data collection and dissemination. The gravimetric technique based on filters is commonly employed as the standard method in government organisations. It is important to acknowledge that while reference methods are utilised, they are not infallible and are susceptible to various artefacts, such as fluctuations in temperature and humidity, as well as the presence of semivolatile compounds. The four most frequent methods used for the continuous monitoring of PM levels in outdoor air are discussed below:

Tapered Element Oscillating Micro Balance Analysers (TEOM) Classical air pollution tracking techniques frequently employ tapered element oscillating microbalance analyser (TEOM) analysers. The frequency of the curved glass tube's vibrations in TEOM is directly related to its mass. The load and vibration frequency of the tube could be affected by the aerosol collected on it. Scientists can determine the PM mass concentration (μg/m^3) in the atmosphere by monitoring the frequency shift of the oscillating tube and the amount of air collected. The aerosols are collected via a size-selective inlet. A heating component is used to counteract the result of a change in humidity (Greene, 2005; Li et al., 2012).

β-Attenuation Analysers The β-attenuation analysers, also known as β-attenuation monitors (BAM), tend to serve as the primary PM estimation devices in classical air pollution assessment frameworks. Initially, the air is subjected to sampling via a size-selective inlet, which may be either PM_{10} or $PM_{2.5}$ and may or may not incorporate a heater/dryer mechanism to mitigate the presence of moisture in the air. Subsequently, the air flows via a filter medium, thereby effectively capturing the particulate matter. The filter paper containing aerosols is subjected to β-attenuation radiation. Following the designated estimation period, scientists can infer the weight of particulate matter present on the filter paper by gauging the amount of radiation passing through. The beta gauge system comprises two fundamental constituents, namely, a radiation source and a detector, which are positioned on either side of the sample under assessment. Furthermore, the data obtained from the detector are processed and transformed into a quantifiable outcome. When beta particles interact with matter, a portion of them undergoes absorption, while the remainder passes through. The absorption of beta particles is directly proportional to the thickness of the material. The determination of substance width is based on the comparison between the beta counts that traverse via the substance in question to the counts obtained in the absence of any material (Shukla & Aggarwal, 2022).

Black Smoke Technique Through a size-selective intake, the black smoke approach captures PM on a filter over the course of 24 h. The mass concentration of the PM is then calculated using a reflectometer's measurement of the filter paper's blackness. This type of monitoring apparatus is rather easy to use, reliable, and economical. The mass concentration is calculated by estimating the filter's load, and the level of PM changes depending on the region. This causes the darkness-to-mass coefficient to vary spatially as well as temporally.

Optical Analyses Optical analysers make use of the linkage of imaging, laser, or infrared light and ambient particulate matter. These analysers are battery-operated, portable, and compact. The three categories of optical analysers—direct imaging, light scattering, and light obscuration (nephelometer) analysers—can be divided based on the optical principle (Yi et al., 2015).

Light Scattering-Based Optical Sensors High-energy lasers are used as the light source in this class of optical analysers. The particle scatters the laser light as it moves across the detecting space, which only permits individual particle sampling (one at a time). The scattering is picked up using a photodetector. Scientists can thereby determine the dimensions of the particle by measuring the scattered light intensity. Additionally, it is possible to determine the number of particle counts by calculating the number of illuminating lights on the photo sensor. This method has the advantage of simultaneously detecting particles of distinct diameters (i.e. $PM_{2.5}$, PM_5, and PM_{10}) with a single analyser. However, the mass concentration must be calculated from the particle counts, which will lead to inaccuracies that impair the analysers' reliability and exactness.

Direct Imaging Particle Analysers Direct imaging particle analyser uses a halogen lamp to illuminate the molecules, casting their shadows onto a camera with a high resolution, high magnification, and high definition. Particles in the air are captured on film by the camera. After the video is captured, software analyses it to determine the PM's qualities. The numbers of PM and their sizes in the air can be measured. In addition, the particle colours and shapes may also be identified.

Nephelometer (Light Obscuration-Based Optical Analyser) A nephelometer is a light obscuration-based optical analyser used to determine the particle size and mass concentration in the air. It assesses particle concentration in a short amount of time, with a high degree of accuracy and a low detection limit. A silicon detector is employed in a nephelometer to estimate the overall light scattered by the PM, primarily liable for the overall reduction in light transmission. The light source is a near-infrared LED. Measurements of the scattered light magnitude and the scattering pattern can be used to immediately ascertain both the size variation and the loadings.

In regard to traditional air pollution monitoring systems, TEOMs and BAMs are often utilised due to their high data resolution and precision, huge size, significant mass, and high economic value. Despite the fact that the ratio of particle number to mass concentration varies spatially and temporally, light scattering and light obscuration optical analysers are widely used due to their compact size, lightweight, low cost, and continuous evaluation capability.

Airshed Concept

The airshed approach aims to address the problem of air pollution in a coherent manner across geographical and legislative borders. The delineation of an airshed holds paramount importance in the realm of managing air quality in urban areas. In academic discourse, an airshed is commonly understood as a geographical region where the dispersion of pollutants and emissions is predominantly impacted by local meteorological factors and topographical features (Abbots, 2014; Guttikunda et al., 2023). The demarcation of airsheds is typically delineated to encompass all significant sources of pollution within the immediate vicinity of a city's administrative limits. The determination of a city's size is a subjective evaluation, albeit contingent upon the incorporation of all significant contributing sources within its proximity. The objective is to encompass all the potential regions and point factors that are likely to add to the localised atmospheric pollution, regardless of the administrative jurisdiction, and to reduce the impact of long-distance regional transmission, which is referred to as boundary influence (Guttikunda et al., 2023). The utilisation of mesoscale atmospheric numerical models facilitates the recognition of airsheds via the application of back-trajectories, which enables the identification of the routes traversed by air while accumulating pollutants and may have potential implications in conducting extended epidemiological investigations pertaining to human exposure to air pollution (Gaines Wilson & Zawar-Reza, 2006; Zawar-Reza & Sturman, 2008).

Boosting the ambient air quality observation system is of utmost importance in obtaining a thorough comprehension of an area's pollution level and setting up a precise overview to facilitate source apportionment investigations (Beig et al., 2015; Ganguly et al., 2020; MOEF and CC, 2019). The expansion of said networks ought to take into account various factors, including but not limited to the size of the airshed, the necessary sampling size and frequency, as well as the process of site selection. In the context of ascertaining the optimal sample size and airshed locations, there exist numerous considerations that extend far from conventional heuristics and scientific structures. Urban regions characterised by significant levels of pollution and an elevated amount of human and commercial endeavours could necessitate a higher sample size and a wider airshed location compared to remote areas with less pollution and its originating sources. Periodic source apportionment investigations may need a larger than usual sample size to account for the effects of weather on air quality. Apart from the aforementioned factors, there exist distinct regulatory mandates that dictate the determination of an optimal monitoring network magnitude (Guttikunda et al., 2023). Airshed management is yet to be formally adopted for air quality management in India, despite the presence of preexisting systems and divisions that could potentially be leveraged for this purpose (Singh, 2016). The nation is further divided into distinct climate zones, ecological regions, hydrological basins, and land-use classifications, thereby emphasising heterogeneous regional attributes. Furthermore, the India Meteorological Department manages subdivisions that furnish regular updates on meteorological conditions. Despite the existence of such systems, the formal adoption of airshed management has not yet been realised.

Guttikunda et al. (2023) categorised the NCAP areas into 104 airsheds, which accounts for 5.3% of the national area. These airsheds inclusively encompass 164 cities and an overall population of 295 million, which represents 21% of the national population. Out of the total airsheds under consideration, 73 airsheds comprise a solitary city, 18 airsheds encompass two cities, and the remaining nine airsheds comprise three cities. There are four airsheds in India, namely, Delhi, Mumbai, Indore, and Chandigarh, which comprise 10, 8, 5, and 5 cities, respectively. A recommended approach for assessing and evaluating particulate matter pollution involves the utilisation of 2118 sampling sites across 104 airsheds. Urban areas may contemplate the implementation of hybrid monitoring systems, which entail the integration of a dense network of cheap, high-quality sensors with the already established regulatory monitoring network. The optimisation of clean air efforts under NCAP necessitates the implementation of an airshed level AQ monitoring plan, an augmented management network, and the amalgamation of data pertaining to the origin of emissions.

4.4 Ambient Air Quality Monitoring and Sensor Networks Currently in Use in India

In India, regulatory air quality monitoring is carried out beneath the purview of the Central Pollution Control Board (CPCB), which is a government agency that works in conjunction with the Ministry of Environment, Forest, and Climate Change (MoEFCC). This monitoring was made mandatory by the Air (Prevention and Control of Pollution) Act of 1981. The initial set of air quality standards in India was ratified in 1982, and subsequent changes took place in 1994 and 2009. Reference standards for TSP (total suspended particles), RSPM (respirable suspended particulate matter) or PM_{10} were originally set to be different for residential, commercial, and environmentally fragile areas. In 2009, the standards were updated, and one of the changes called for the establishment of a single norm for the $PM_{2.5}$ concentration at different kinds of locations (http://cpcb.nic.in/National_Ambient_Air_Quality_Standards.php).

The following subsection offers a discussion of the most prominent monitoring programmes carried out by several agencies and academic institutions in the country:

National Air Quality Monitoring Programme (NAMP) This is the most vital AQ monitoring initiative that the Indian government has ever undertaken. As of September 2022, there are a total of 379 cities and towns that have 883 air quality monitoring stations (https://cpcb.nic.in/uploads/Stations_NAMP.pdf). These operating stations monitor four primary pollutants: SO_2, NO_2, PM_{10}, and $PM_{2.5}$. The CPCB is responsible for managing the programme in collaboration with the State Pollution Control Boards (SPCBs) and the UT Pollution Control Committees (PCCs). Ground-based sample collection and analysis are also performed by regional and local educational institutions, in addition to national organisations such as the National Environmental Engineering Research Institute (NEERI) (https://cpcb.nic.in/monitoring-network-3/). The majority of said stations, pertaining to both residential and industrial sectors, are situated within urban regions, while their presence in rural areas is limited, as evidenced by studies conducted by Balakrishnan et al. (2014) and Gordon et al. (2018). It is noteworthy that residential combustion emissions, which are commonly linked to the use of solid fuels, constitute a significant contributor to air pollution nationwide (Balakrishnan et al., 2013; Venkataraman et al., 2018). To maintain consistency in sampling techniques among the various NAMP stations, standardised guidelines have been established at the national level for monitoring. These guidelines encompass a range of factors such as siting criteria, quality assurance and quality control procedures, measurement methodologies, and protocols for data reporting (CPCB, 2003, 2011). Apart from the monitoring sites established under the National Ambient Monitoring Programme (NAMP), various states, such as Maharashtra, Gujarat, Kerala, Odisha, Karnataka, Telangana, and Andhra Pradesh, have implemented the State Ambient Air Quality Monitoring Programme (SAMP) to conduct ambient air quality monitoring at supplementary locations (Pant et al., 2019).

The CPCB has established an ensemble of Continuous Automatic Air Quality Monitoring Stations (CAAQMS) in prominent urban areas. These stations are equipped to measure a range of contaminants, including PM ($PM_{2.5}$ and PM_{10}), gaseous pollutants such as SO_2, NO_2, NH_3, O_3, CO, and BTEX (benzene, toluene, ethylbenzene, and xylene), on a continuous basis throughout the year. CAAQMS are equipped with precise gas analysers and beta-attenuation monitors for air quality gauging and thereby offer exceptionally precise measurements (Malings et al., 2019; Sahu et al., 2021; Snyder et al., 2013). Nevertheless, the establishment of these networks incurs a significantly high setup cost, and their maintenance is challenging (Sahu et al., 2020), rendering robust CAAQMS networks impracticable. At present, urban areas with a populace exceeding one million are accorded precedence for the establishment of CAAQMS. It is anticipated that comparable stations will be established throughout all states and union territories. As of June 2023, there are 490 CAAQMS in approximately 260 cities all over India (https://app.cpcbccr.com/ccr/#/caaqm-dashboard-all/caaqm-landing). The majority of stations are managed through a collaborative effort between the CPCB and SPCB, wherein a financial agreement is established between the state and federal entities for cost sharing. The CAAQM station data is utilised for calculating the air quality index (AQI), which is accessible to the public through online platforms, smartphone applications, and the CPCB website archives historical data (CPCB, 2014).

System of Air Quality and Weather Forecasting and Research (SAFAR) The Indian Institute of Tropical Meteorology (IITM, Pune) collaborated with the Indian Meteorological Department (IMD) and the National Centre for Medium-Range Weather Forecasting (NCMWRF) to establish the SAFAR network in Delhi in 2010 under the Ministry of Earth Sciences (MoES) (http://safar.tropmet.res.in/) (Brauer et al., 2019). The SAFAR system of the network comprises air quality monitoring stations (AQMS) and automatic weather stations (AWS) that are set up amid the city boundaries. These stations have been strategically placed in various microenvironments of the region such as industrial, residential, background, urban, and agricultural regions, in accordance with global guidelines. This approach ensures that the urban environment is accurately represented.

Sophisticated online instruments are utilised to monitor air quality indicators at a height of approximately 3 metres from the ground. These equipments run continuously, and the database is systematically captured and preserved at 5-min intervals for the purposes of quality control and subsequent scrutiny. The programme is presently operational in Delhi (11 AQMS locations), Pune (11 AQMS locations), Mumbai (10 AQMS locations), and Ahmedabad (10 AQMS locations), having been launched in 2010, 2013, 2015, and 2017, respectively. There are intentions to extend the programme's reach to Bengaluru, Kolkata, and Chennai. The major pollutants monitored under the purview of this project include PM_1, $PM_{2.5}$, PM_{10}, O_3, CO, NO, NO_2, SO_2, black carbon, methane, nonmethane hydrocarbons, volatile organic compounds, benzene, and mercury, and some meteorological parameters, including ultraviolet radiation, precipitation, temperature, solar radiation, wind speed, and direction. SAFAR offers a mobile application that distributes computed Air Quality Index (AQI) measurements for the criteria pollutants, based on city-wide averages, as well as projected AQI values for the upcoming 2-day period. The aforementioned data are also conveyed through instantaneous exhibit panels situated in every urban centre. It is noteworthy that the AQI methodology employed in this programme differs from the CPCB-endorsed national approach (Beig et al., 2015). The air quality database obtained from the system is subject to a 3-year embargo period, after which it may be made accessible for general public usage upon appeal and submission of an apt rationale to the IITM Pune.

US Embassy Monitoring Stations Within the framework of the AirNow initiative, the United States Department of State administers $PM_{2.5}$ monitoring devices in five prominent urban centres in India, namely, Delhi, Mumbai, Kolkata, Hyderabad, and Chennai. These devices are situated on the premises of the respective Consulate/Embassy in each city. The data can be accessed by the public in near real time via the AirNow website (https://www.airnow.gov/international/us-embassies-and-consulates/#India). The website of the Consulate/Embassy also presents AQI values. Nevertheless, it is noteworthy that the AQI value reported is established on the air quality standards of the United States and employs a distinct formula. Consequently, it cannot be directly compared to the AQI values of India. The measuring devices are functional within the embassy/consulate premises, which are comparatively secluded from high traffic or industrial activities. In the majority of instances, the instruments yield $PM_{2.5}$ readings that are commensurate with those obtained from an urban site within the cities.

Chemical Transport Models India now has access to a number of operational forecast models. The Copernicus Atmosphere Monitoring Service (CAMS) delivers 10 × 10 km 4-day predictions from a network of seven chemical transmission models, and the rear modification with ground observational datasets is accessible for various particulate and gaseous pollutants (https://atmosphere.copernicus.eu/charts/packages/cams/). These projections are included in worldwide models that describe urban/regional baselines.

Using the 3D-WRF meteorological model and the GFS weather forecasts, along with pollutant levels generated by using the CAMx chemical modelling system and coupled to an active emissions tally, Urban Emissions supply 72-h (hourly and daily) average $PM_{2.5}$ and various other air pollutant levels. As a component of the Air Pollution Knowledge Assessment (ApnA) Programme (Brauer et al., 2019; Guttikunda et al., 2019), more precise (1 × 1 km) estimates are supplied for Delhi (http://urbanemissions.info/delhi-air-quality-forecasts/) and other regions in India, while the modelling domain spans the entire country at a spatial clarity of 25 × 25 km (http://urbanemissions.info/india-air-quality-forecasts/).

The Indian Institute of Technology Kanpur is involved in the Surface Particulate Matter Network (SPARTAN), a global initiative (having its origin in the United States) aimed at monitoring particulate matter. As a contributor to this network, IIT-Kanpur handles a site in which the $PM_{2.5}$ mass and several different chemical contents are analysed from samples collected by this network over the course of 9 days (Snider et al., 2015, 2016). These incorporated filter samples could be fragmented to measure daily or hourly PM concentrations when aggregated with continuous monitoring of particle light scattering using a nephelometer (Brauer et al., 2019).

Satellite-Based Measurements Estimates derived from satellites have also helped researchers to better comprehend India's air quality. India-specific $PM_{2.5}$ estimates (bias-corrected versus concomitant in situ data) were calculated using Multiangle Imaging Spectro Radiometer (MISR) aerosol products for the years 2001–2010 (Dey et al., 2012). According to the findings of this investigation, approximately half of India's population is located in regions where ambient $PM_{2.5}$ levels are above WHO's intermediate goal I. Seventy per cent of the Indian subcontinent had yearly $PM_{2.5}$ levels that were higher than the WHO's limit. Forty to fifty per cent of clear days had daily $PM_{2.5}$ levels in the Indo-Gangetic Plain and Mumbai that were higher than WHO intermediate target I. In approximately 70% of India's districts, PM_{10} exposure was found to be higher than WHO Interim Target I [analysed by using Modern-Era Retrospective analysis for Research and Applications (MERRA) reanalysis and Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation [CALIPSO] aerosol products] (Pande et al., 2018). The CPCB has begun implementing historical and future satellite-derived concentration estimations under the NCAP (MOEF & CC, 2019). This step will lead to the augmentation of the existing ground-based surveillance network with more efficiency.

A brief description of the abovementioned aerosol products is given below:

MISR Aerosol Products The Multiangle Imaging Spectro Radiometer (MISR) is a scientific instrument that is currently being utilised as one of the five instruments on board the National Aeronautics and Space Administration's (NASA) Terra satellite. Its primary objective is to gather crucial data on the underlying factors and consequences of worldwide climate change. The instrument employs a multiangle approach to observe the Earth from nine distinct angles, with the aim of enhancing the accuracy of atmospheric particle, cloud formation, and land surface cover analyses (https://www.jpl.nasa.gov/missions/multi-angle-imaging-spectroradiometer-misr). Throughout the duration of the Terra mission, MISR has played a crucial role in acquiring unique images of meteorological phenomena, including hurricanes and floods, and documenting the ramifications of atmospheric contamination on a global scale. The MISR stands out from other satellite instruments in the Earth Observation System (EOS) era due to its exceptional features, including a blend of high spatial resolution, a broad spectrum of along-track view angles, and precise radiometric validation and reliability (Diner et al., 1998). The MISR technique is capable of quantifying the shortwave radiance that emanates from the Earth's surface in four distinct spectral bands, with central wavelengths of 446, 558, 672, and 866 nm. This is achieved by capturing data at nine different view angles, which are distributed in both the forward and rear directions along the flight path. These angles are situated at 70.5°, 60.0°, 45.6°, 26.1°, and nadir. During a span of 7 min, the spacecraft traverses over the Earth, and MISR's nine cameras sequentially capture images of a 380 km wide area of the planet's surface. The instrument is capable of sampling an extensive range of scattering angles, spanning from approximately 60° to 160° at mid-latitudes. This enables the acquisition of valuable data pertaining to the microphysical properties of aerosols. The aforementioned perspectives encompass a range of air-mass factors, spanning from 1 to 3 (Kahn et al., 2010). This range provides a level of sensitivity that enables the identification of optically thin aerosol layers. Additionally, it facilitates the differentiation between surface and atmospheric contributions to the top-of-atmosphere (TOA) radiance, thereby aiding in the development of aerosol retrieval algorithms.

MERRA Reanalysis MERRA employs a 6-h update cycle for its variational data (3-DVAR) acquisition analysis algorithm, which is in accordance with the Gridpoint Statistical Interpolation scheme (GSI). The GSI has a number of improvements over the older 3D-VAR computations. In particular, the analysis solution's balancing qualities are enhanced by computing the observation-minus-background deviations with higher temporal precision and by employing a dynamic limit on noise (Rienecker et al., 2011). MERRA depends substantially on satellite radiance data, which encompass information from hyperspectral tools such as the Atmospheric Infrared Sounder (AIRS) installed on Aqua. To assimilate radiance data, it is necessary to employ a radiative transfer model (RTM) as the observation operator. GSI is integrated with the Community Radiative Transfer Model (CRTM) (Han et al., 2006). The principal objective of MERRA is to enhance the capacity of the reanalysis to replicate the hydrological and energy cycles by leveraging the extensive data obtained from the satellite observations comprising NASA's Earth Observing System (EOS). MERRA encompasses the entirety of the satellite era spanning from 1979 to 2016. It boasts a spatial resolution of 1/2 degree latitude by 2/3 degree longitude and comprises 72 vertical layers. The MERRA datasets are produced employing the Goddard Earth Observing System (GEOS) atmospheric model version 5.2.0 (Feng & Wang, 2019).

The MERRA-2 project was initiated with the purpose of offering a prompt substitute for MERRA and upholding the Global Modelling and Assimilation Office's (GMAO) dedication to maintaining a continuous near-real-time evaluation of the climate. The MERRA-2 reanalysis is designed to serve as an intermediary solution that relies on the latest advancements in modelling and data assimilation at GMAO (Gelaro et al., 2017). Its primary objective is to overcome the known constraints of MERRA while simultaneously paving the way for GMAO's ultimate objective of creating an integrated Earth system analysis (IESA) capability that integrates assimilation systems for the atmosphere, ocean, land, and chemistry.

CALIPSO The CALIPSO satellite was successfully deployed on April 28th, 2006, by NASA. It has contributed novel perspectives on the impact of clouds and atmospheric aerosols on the regulation of Earth's weather patterns, climate conditions, and air quality. The CALIPSO system integrates a dynamic lidar device with passive infrared and visible imaging tools to investigate the vertical arrangement and characteristics of slender clouds and aerosols across the entire globe (https://www.nasa.gov/mission_pages/calipso/main/index.html). The CALIPSO system furnishes a comprehensive analysis of attenuated backscatter at wavelengths of 532 nm and 1064 nm, along with the perpendicular polarisation segment specifically for 532 nm (Kar et al., 2010). The latest iteration (V.3.01) of CALIPSO data has been made available, featuring noteworthy enhancements to the cloud-aerosol screening module, as well as the inclusion of extended profiles beneath layers exhibiting pronounced attenuation. For the first time, the present iteration furnishes the integrated optical depth data for the column. The utilisation of the depolarisation ratio derived from the 532 nm channel is valuable in discerning the morphology of the aerosol particles. Additionally, the backscatter colour ratio is informative in determining the magnitude of the aerosol particles (Liu et al., 2008).

Low-Cost Sensors The exceptional ability of low-cost monitors has garnered much attention in recent years (Kumar et al., 2023). When connected, such networks could enable individual monitors to pool data from throughout the network, allowing for self-calibration, integrated network training, and the provision of high-quality, highly resolved spatiotemporal air quality information. Such sensors allow continuous assessments of air quality throughout an urban region at a relatively modest cost. Given challenges with sensor accuracy and precision, maintenance and calibration, and the fulfilment of human resources expenses for network data management and maintenance, this goal has only been partially achieved thus far. Community groups have also used low-cost sensors when official measurement data are either unavailable or deemed inaccurate (e.g. due to the paucity of faithful representation of certain hot spots). While there is no doubt that these types of initiatives have the potential to promote public knowledge and empowerment, some have voiced concerns that government air quality employees could be diverted away from their primary focus of air quality control to react to citizen enquiries based on erroneous or malfunctioning sensors. There are also concerns about a continuous and adequate supply of low-cost sensors because many of them have been developed by start-ups. As a result, several regional and national air quality control organisations have launched programmes to test and evaluate individual sensors and provide direction for how they should be used in networks (Agrawal et al., 2021; Nagendra et al., 2018; Prakash et al., 2022; Rai et al., 2017; Sahu et al., 2020, 2021; Tripathi et al., 2023; Zheng et al., 2018, 2019).

For instance, (Zheng et al., 2018) demonstrated that Plantower PM sensors reliably measured $PM_{2.5}$. They also showed how to validate PM sensors in the field using the Environmental Beta Attenuation Monitor (EBAM) as a standard for $PM_{2.5}$ readings in a wide range of environments. Employing high-resolution microsatellite imageries (PlanetScope, 3 m/pixel) and a low-cost sensor network, (Tripathi et al., 2023) proposed a strategy for estimating and generating $PM_{2.5}$ level visualisations at the subkkm level (500 m by 500 m). Chauhan et al. (2022) investigated the characteristics of PM and AQ by installing a Microtop Sun photometer and low-cost sensor at IIT Mandi and Dhampur (remote rural site) and further found that these inexpensive sensors provide reliable data and that a wide and dense sensor network is needed to gain insights into the variability in air pollutants (Sahu et al., 2021) presented findings from a study that involved the installation and validation of a network comprising six air quality monitoring systems that were constructed using Alphasense O_3 (OX-B431) and NO_2 (NO2-B43F) electrochemical gas sensors. In a study carried out by (Zheng et al., 2019), a novel approach was presented for the calibration of $PM_{2.5}$ readings obtained from multiple low-cost PM sensors in the field. The proposed method involves a pipeline that combines simultaneous Gaussian process regression (GPR) and simple linear regression techniques. This approach eliminates the need for predeployment collocation calibration and instead leverages all available reference monitors in the area to achieve accurate calibration on the fly.

In 2020, IIT Kanpur teamed up with Maharashtra PCB to validate PM sensors (financially assisted by Bloomberg Philanthropies). Overall, forty low-cost sensors were installed over 15 sites in the metropolitan region of Mumbai. These sensors included Plantower, Nova Fitness, and Telaire Dust Sensor (Kushwaha et al., 2022). Moreover, the precision and accuracy of Purple Air (PA) devices have been carried out by researchers from the University of California. They have tested two PA sensors at the US Embassy, New Delhi, and have also deployed approximately 40 sensors at different sites in Bengaluru. They have deduced that PA sensors are highly precise but their accuracy can change with time (Kushwaha et al., 2022). Furthermore, under the Aakash project running under the Research Institute for Humanity and Nature (RIHN) centre, a compact useful particulate instrument (CUPI) sensor has been given to the Aryabhatta Research Institute of Observational Sciences (ARIES), Nainital to explore how aerosols disperse based on variations in altitude across different observation sites on the foothills of the Himalayas (Report, 2020).

4.5 Challenges and Solutions

The preceding discussion lays out the current state of geospatial approaches and field sensors and the likely range of opportunities for the application of sensors, including ways in which sensors could be utilised to locate and reduce emissions from industrial pollution within and around their sources, as well as ways in which sensors could be applied at the community and individual levels to improve air monitoring networks. However, there are still several systemic technical and practical challenges associated with this burgeoning field of study. These include, but are not limited to, the creation of reliable sensors that generate high-quality data, the implementation of a thorough assessment of sensors, the incorporation of a database from more than one sensor of varying quality acquired from various origins (government and citizens), and the public's and government's ability to visualise and make use of sensor data. Some major challenges include limited proficiency in obtaining three-dimensional data and the impracticability of active monitoring. Numerous community initiatives are going on a global scale to obtain air pollution measurements through crowdfunding. Although such sensors can be advantageous in the creation of citizen science projects and the production of innovative data, there remain several uncertainties regarding the precision of measurements obtained through low-cost sensors. To date, there is no conclusive evidence to support the long-term reliability and precision of these monitors in the absence of regular calibration procedures. Current endeavours are being made to enhance the accuracy of these sensors, and recent analyses are reinforcing the argument for the implementation of meticulously crafted, low-cost sensors for the purpose of measuring air pollution on a municipal scale. With careful design, such networks have the potential to yield valuable information regarding the spatial distribution of pollutants and facilitate the identification of localised areas with high levels of pollution.

India has been in the international limelight because of the extremely high levels of air pollutants in many regions of the country; some cities in India have been ranked among the worst in the world for air quality, and there is growing public demand for action to be taken. It is challenging to use existing data for long-term trend analysis studies due to the lack of comprehensive databases on air quality, and even when the data are utilised, there exists high apprehension surrounding conclusive observations or findings. Attempts made recently, for instance, making long-term records from NAMP stations openly available, are encouraging and will likely encourage and facilitate further research on the problem. India's air quality monitoring has come a long way in the past 20 years, and there are currently ongoing attempts to develop a national air quality monitoring programme, with particular emphasis on establishing CAAQMS in India's major areas. Air quality management, higher-order scientific investigation, and epidemiological analytic activities would all benefit from increased support from more robust regulatory air quality monitoring networks in India, given the substantial health burden associated with exposure to degraded air quality in India.

Faster and higher-quality data in India might be possible with a hybrid monitoring strategy. Recent progress in satellite-based management of AQ, as well as the advent of crucially placed ground-based monitoring sites that assess aerosol optical depth using sun photometers in conjunction with $PM_{2.5}$ chemical content, suggest that this approach may help improve the accuracy of satellite-based estimates from both global and regional viewpoints. Additionally, the inputs required by receptor models for source allocation can be gleaned from the data collected at such strategically placed measurement sensors. Insights into source contributions such as this could improve air quality management predictions and programme evaluation.

4.6 Conclusion

The alarming increase in the concentration of air pollutants in urban areas is the primary motivation for conducting research on air pollution monitoring. The satellite remote sensing approach makes it possible to quantify the levels of air contaminants. Additionally, GIS-based spatial interpolation techniques can be used to rank the relative importance of different places. In addition, considering the disastrous consequences that air pollutants have on human health, it is essential to make projections regarding the concentrations of air pollutants through the use of model simulations. The purpose of this research is to provide a thorough review of the satellite remote sensing techniques that are used in mapping and prioritising the levels of air pollutants, as well as to predict the concentration of air pollutants. Because they provide comprehensive and synoptic views of wide areas in a single snapshot, sensor data gathered from suitable satellites are anticipated to be useful for monitoring and mapping air pollution. Using a combination of GIS and remote sensing, air quality can be assessed over a considerable area.

Researchers are pushing the boundaries of the concept of the Next Generation Air Pollution Monitoring System (TNGAPMS) by using cutting-edge sensing technologies such as microelectromechanical systems (MEMSs) and wireless sensor networks (WSNs). Many innovative techniques for monitoring air pollution have been established and validated at this point. All these systems show that it is possible to create a monitoring system for air pollution that provides a high level of spatiotemporal detail, is cost- and energy-efficient, can be easily deployed and maintained and is easily accessible by both the general public and trained professionals. Such systems have the potential to be a ready-to-use, potent, and helpful tool by alerting end users to potentially excessive levels of pollutants and allowing them to take easy measures to reduce their impact. Because of its several benefits, including reduced prices, less noise, and lower electricity usage, the use of low-cost sensing technology to monitor air quality, both indoors and outdoors, is being advocated. Furthermore, reference tools are still required for validation and calibration; therefore, their use is not yet completely decentralised.

4.7 Recommendations

The following suggestions/recommendations can be adapted to enhance the effectiveness of air quality monitoring networks related to geospatial technologies and field sensors in India:

(i) The potential for a hybrid approach is suggested by the improvements in satellite-based air quality monitoring and the strengthening comprehension of the significance of high-resolution spatial dynamics in urban regions. The option of an integrated framework, as presented in Fig. 4.3, can be perceived as a strategy for amalgamating existing, monitoring endeavours rather than a completely novel system. Therefore, we characterise this framework as a supplementary approach to current endeavours, which encompass the maintenance and improvement of the customary terrestrial surveillance system, with the aim of optimising the attainment of valuable data for the purpose of air quality governance.

(ii) Satellite-based methodologies do not serve as a substitute for ground-based surveillance. Instead, both techniques can be amalgamated to enhance the spatiotemporal range. Data feeds from geostationary satellites are used almost in real time with a focus on India and have the potential to offer additional information to improve communication among individuals, predictions, and source evaluation. This is in contrast to the current polar-orbiting satellites that only provide snapshots once or twice a day.

(iii) Large-scale deployment of monitors equipped with low-cost sensors can aid in the creation of emission inventories of pollutants, the identification of pollution hotspots, and the conduct of real-time exposure assessments, all of which are necessary for the development of effective mitigation measures. To better attain the Sustainable Development Goals (SDGs) related to public well-being, minimising the negative environmental effects of urban areas and adapting to climate change, India's smart cities initiative aspires to formulate recommendations for urban planning and land-use shifts.

(iv) To determine if a validation/calibration process can make low-cost sensors functional without the need for reference instruments, it is suggested to conduct more studies, specifically in different settings and with new sensors that are emerging regularly and for an extended measurement period.

(v) The potential of machine learning and data mining for analysing AQ data from sites in different areas and establishing airshed limits should be explored so that the geographical scope of air quality monitoring can be broadened, even with a limited number of monitoring stations.

(vi) Improvements in low-cost monitoring, prospective satellite missions, and focussed field initiatives are all promising developments for this network. This integrated network could be improved in the future to better estimate global exposure, which is crucial for large-scale studies such as the Global Burden of Disease and the United Nations' SDGs.

(vii) Data assessment can be carried out through the utilisation of third-party data evaluation, annual instrument intercomparisons, and calibration. Furthermore, it is crucial to gather and disseminate metadata, which refers to descriptive details about datasets, to facilitate improved cataloguing and contextually appropriate utilisation of data. Moreover, it is imperative to archive and disseminate information pertaining to the efficacy of monitoring networks, including crucial metrics such as the annual data capture rate, as well as instrument calibration and performance evaluation.

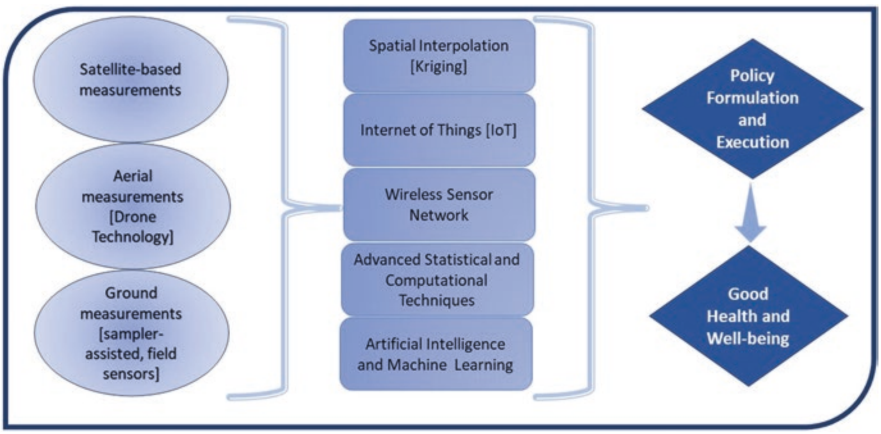

Fig. 4.3 Framework for an integrated system of air quality monitoring

(viii) The integrated airshed framework presents a cost-effective solution for enhancing air quality statistics at both national and regional levels. This approach facilitates the linkage of local data to global satellite-based measures and a worldwide network, thereby addressing current information gaps. Moreover, it establishes a basis for enhancing the efficiency of routine connections in the future.

(ix) Enhanced prospects for collaboration among the central and state pollution control boards, as well as regional academic and research institutions, have the potential to facilitate pollution mitigation endeavours. The integration of research and policymaking, along with the promotion of research and development at PCBs, can effectively address existing gaps in the system. The airshed approach offers a sustainable solution by targeting and synergising air pollution management across administrative boundaries. Although this concept is in the evolving stage in India, several states have already initiated airshed approache to tackle air pollution, and the emphasis on the focussed implementation of airshed approaches will certainly result in better air pollution management.

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Chapter 5
Geospatial Techniques and Methods for Monitoring and Assessment of Soil Contaminants

Amar Kumar Kathwas, Pranata Hazra, Rakesh Saur, Barnali Saha, Loveraj Singh, Leela Gariya, Shruti Kumari, and Harshita

Abstract Soil is the medium that is fundamental for thriving life on earth, as it provides support to flora and fauna. Soil contamination is a prime source of health hazards for humans as well as animals. The use of soil extravagantly as a sink for dumping toxic and solid waste coupled with the use of enormous quantities of chemical fertilizers significantly alters the biological, physical, and chemical state of soil. This alteration causes depletion of the organic and biotic elements from the soil, leading to land degradation and desertification. The contaminants entering soil leach and percolate soil layers and are transported to surface and underground water sources, while some are absorbed by plants, which further enter the food chain, seriously affecting biotic life on earth. Currently, human interventions with the soil in terms of mining, industrialization, agriculture, and management result in the deterioration of the existing soil state. In India, nearly two-thirds of the land is under degradation. Soil contamination is a serious worldwide problem that requires quick and stern measures to constrain and reverse the process of land degradation. This study aims to highlight some of the geospatial methods and techniques that are used worldwide for the assessment and monitoring of soil contaminant dynamics. Moreover, the study also highlights the various effects of different soil contaminants on humans and the earth's environment.

Keywords Effects · Geospatial techniques · Monitoring · Soil contamination

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5.1 Introduction

Soil, a mixture of finely divided mineral particles (sand, silt, and clay) along with organic matter, water, gas, and living organisms, covers the majority of Earth's land mass and is a fundamental component for thriving and sustaining flora and fauna in an ecosystem. In its original form, it is uncontaminated; however, any addendum caused by xenobiotics intentionally and unintentionally by human beings results in the alteration of the original physical, chemical, and biological state and levels of the soil, causing contamination (Abrahim & Robin, 2008; Martinez-Mera et al., 2019; Sutherland, 2000). The exponential growth of the human population in the last few decades has led to increased demands for energy, transportation, healthcare, housing, water, and food, causing transitions in land use/land cover (LULC), destruction of natural vegetation and wetlands and expansion of croplands. The unprecedented transitions of LULC in combination with industrialization and combustion of fossil fuels significantly increased the level of greenhouse gases, namely, carbon dioxide, lead, and nitrogen oxides along with other harmful gases, which in turn led to the increased temperature of Earth's atmosphere (Chabukdhara & Arvind, 2012; Han et al., 2006; Kayiranga et al., 2023; Li et al., 2004; Wuana & Felix, 2011; Zhang & Liu, 2002). This transition in the earth's atmospheric status negatively impacted crop health, causing decreased crop yields and making crops prone to diseases and infestation by pests and fungi. To overcome adversaries and meet food demands, the use of a large proportion of chemical fertilizers, pesticides, fungicides, nematicides, and herbicides for increased crop productivity has become the new norm. The use of such chemicals not only leads to decreased nutritional values of crops but also increases the exposure of humans and animals to numerous harmful compounds and health disorders. The effects of some of the fungicides, insecticides, and herbicides are presented in Table 5.1.

The introduction of such chemicals in an ecosystem not only contaminates soil but also affects its biochemical properties; moreover, these compounds/elements leach and are translocated, contaminating the local source of fresh waters such as ponds, rivers, and aquifers. Long-term use of such chemicals results in alteration of soil biomass and structure, resulting in land degradation and desertification. Furthermore, soil contamination caused by organic compounds such as polycyclic aromatic hydrocarbons (PAHs), a by-product produced due to incomplete combustion of organic compounds, fossil fuels, and spillage of petroleum products due to natural disasters or industrial and domestic activity, has dire and long-lasting impacts. Since PAHs are hydrophobic in nature, soil is one of the major sinks in nature. These PAHs are then transported from soil to crops and surface and groundwater sources through precipitation and surface runoff. A large number of PAHs are mutagenic and carcinogenic in nature, raising concerns about their intrusion and occurrence in the food chain and human ecosystem. Since petroleum is one of the major sources of PAHs and is easily released into the environment during the process of extraction, transportation, and storage, it entails a large amount of caution owing to its impact on the environment and human health.

Table 5.1 Effects of fungicides, insecticides, and herbicides on the human body

Types of chemicals	Effect on body
Fungicides	
Benomly	Cirrhosis
Metaram	Thyroid gland
Nabam	Nerve damage
Zineb	Diarrhea
Dichloran	Kidney
Insecticides	
DDT	Carcinogenic
Dieldrin	Dizziness
Endosulfan	Diarrhea
Dicofol	Headache
Methoxychlor	Nervous system
Herbicides	
Glyphosate	Nervous system
Metribuzin	Organ weight
Dacthal	Liver damage
Sethoxydim	Tremors
Trifluralin	Dermal irritation

Other forms of soil contaminants include Cd (cadmium), lead, Ni (nickel), As (arsenic), Tl (thallium), Cu (copper), Hg (mercury), Zn (zinc), and Cr (chromium), which are characterized as heavy metals with atomic weights and densities more than five times those of water. Some of these naturally occurring elements are generally found in areas close to industrial, mining, milling sites or metal, paint, and petrochemical plants. Moreover, chemical fertilizers used as supplements to increase the soil metal content in plant growth areas are also a major source of heavy metal contamination. Since these are complex compounds and do not degrade chemically or microbially easily, unlike organic compounds, they persist in soil for a much longer duration, posing health risks to humans and animals and ecological life under direct contact, ingestion, or through induction in the food chain.

With the advancement and development of human civilization, the risk of heavy metal contamination in soil poses a great threat to the earth and environment (Liu et al., 2016). In developing countries, rising anthropogenic activities and industrialization, coupled with a lack of waste management processes, have become a major source of carcinogenic soil pollution (Al-Farraj et al., 2013). This study presents a review of the various types of soil contamination and geospatial methods and techniques for their assessment and monitoring. Soil pollution or soil contamination is directly related to soil fertility and food security and is an important issue for decision-makers across the globe (Hammam et al., 2022).

5.2 Literature Review

Stalin et al. (2010) analyzed the level of chemical contamination of Tambaram Taluk in Pammal Panchayat near Chennai, where more than 145 tannery industries were functional over a long time period. To assess the level of contamination, they assigned ranking and weightage to the pollutants. Parameters such as pH, Ec, and TDS were selected, and soil samples were collected at three different depths. Interpolation techniques such as inverse distance weighting (IDW), spline, kriging, and trend were used to prepare the spatial distribution layers of various parameters in the geographical information system (GIS) environment. The weights against each parameter were computed using the analytical hierarchical process (AHP), and subsequently, using the overlay operation on the respective layers, the severity of the contaminated areas was assessed.

Manii (2014) performed an analysis of soil contamination based on data from 26 soil samples in Babylon, Iraq. The focus of the study was primarily on three elements, namely, chromium (Cr), nickel (Ni), and lead (Pb). The collected soil samples were chemically analyzed, and thereafter, using the spatial interpolation technique kriging, the spatial distribution map of the soil contaminants was prepared. Kwiatkowska-Malina et al. (2020) used geostatistical methods to assess the degree of soil contamination in the context of Ni, cadmium (Cd), As, and Pb in the province of Poland. The study also focused on assessing its relation with dry/wet deposition from atmospheric air (Kowalska et al., 2018). The objective of the study was to identify the degraded areas and the emitters of contamination. Web Map Services (WMS) was used for the generation of maps in the GIS domain. Using the interpolation technique, maps of contamination for Silecia were prepared.

In the context of soil pollution, in a mining district named Nakhlak of Central Iran, Moore et al. (2016) performed an investigation for potentially toxic metals such as As, Co, Mo, Ni, Pb, Cd, Sb, Ag, Cu, Cr, and Zn. They identified 26 sampling locations using GPS for data collection and spatial representation. An integrated method comprising geostatistical techniques, chemical analysis, and various pollution indices was used to evaluate the potential of different toxic metal contaminations in soil samples (Paustenbach et al., 1993; Oumenskou et al., 2018a, b). Hou et al. (2017) focused on the application of GIS techniques and multivariate statistical methods to understand the primary aspects of this domain. The study considers different aspects related to the dynamics of heavy metal soil contamination in the spatial domain. Soil sampling was accomplished using grid and composite sampling techniques. Several programs have been implemented to differentiate different land use/landcover and soil types (Bonelli & Manni, 2019). The commonly used spatial interpolators were IDW interpolation, ordinary kriging, multivariate statistical assessment methods, principal component analysis (PCA), and cluster analysis. The review also focused on various decisive and conforming parameters in the spatial domain of HM contamination in soils. The results of the examination revealed contamination related to heavy metals (HMs) and their potential sources. The study also provided insight into how HMs are highly heterogeneous and may exist in particular localities at elevated concentrations in soil (Kahangwa, 2022).

Balamurugan (2014) assessed soil contamination using GIS techniques in Pammal Panchayat at Tambaram taluk, Chennai. The analysis was carried out to assess the level of soil contamination and chemical properties such as pH, sulfate, chromium, chlorides, electrical conductivity, and total dissolved solids, and organic matter. To accomplish the task, approximately 33 samples were collected at different depths (0.3 m, 0.9 m, and 1.5 m). Based on geo-tagged points and sample properties, a continuous layer for each depth was prepared using interpolation techniques. Furthermore, different reclassification methods (manual, defined, equal, quantile and neural, and standard deviation) were used to generate continuous maps. By the cross-validation process of various interpolated continuous layer maps with the chemical characteristics of the field data, the best interpolation method was identified.

EL-Rawy et al. (2020) assessed the arable land of the Nile Valley (Minia Governorate) for heavy metal contamination, namely, essential trace constituents (B, Cu, Fe, Zn, and Mn) and toxic heavy elements (Se, As, Cr, Co, Pb, Ni, and Cd). A systematic sampling technique was used for the collection of soil samples at various depths: 0–30, 30–60, 60–90, and 90–120 cm. Using atomic absorption spectrophotometry, the contents of As, Se, Cr, Cd, Pb, Ni, Co, and Cu were determined. The metal pollution index (MPI) was incorporated to assess the various degrees of heavy metal content hazards.

Jiang et al. (2019) performed an investigation to determine mercury contamination and its spatial dynamics. The objective was achieved by collecting approximately 104 soil samples under three subclasses, that is, croplands comprising farms carrying out vegetable, paddy, and orchard cultivation in the southeast portion of China. A multiple linear regression technique was used in the context of the spatial domain to identify the factors responsible for mercury contamination. Subsequently, the extent of mercury concentration was assessed using geographic information system (GIS) and spatial analysis in the various croplands. GIS methods and techniques, comprising proximity assessment, buffer assessment, and morphology analysis, were used in geospatial data processing for extracting geographical influencing parameters of the soil Hg concentration variance in arable areas. Proximity assessment was used to determine the distances between the sample location and distance from roads, distance from rivers, and distance from chimneys. The buffer investigation was performed to compute the distribution of construction sites in all different types of land by generating a buffer distance around the sampling location to a particular distance (Gholizadeh et al., 2018; Gholizadeh & Kopačková, 2019). Statistical methods (mean, maximum, and standard deviation) of soil Hg content were also computed to assess the basic status of soil Hg contamination.

Li et al. (2004) showed an elaborate survey using systematic sampling methods and techniques for identifying metal contamination in urban soils. Geochemical maps of total metals in land surface soils produced on the basis of GIS technology. Different hot spot regions of metal contamination were recognized from the composite metal geochemical map, especially in the old industrial and residential regions. The kriging geostatistical technique was utilized for the interpolation of geospatial data types. The variogram was also adopted to deliver mathematical changes in the variation of contamination property over the surface area on the basis of the direction and distance of two sampling locations (D'Or et al., 2009).

Another study by Al-Khuzaie and Maulud (2022) focused on the precise determination of the concentration of trace elements in the soil. Twenty-eight representative soil sample profiles were collected from Al-Shamiyah city. Using the geoaccumulation index (I-geo) and pollutant load index (PLI), they analyzed the concentration of elements present in soil with reference to standard concentrations. Finally, the spatial or geographical distribution of the heavy metal pollutant elements was mapped using the inverse distance weighted technique in the GIS domain. Similarly, Oumenskou et al. (2018a, b) studied agricultural soils to identify heavy metal contamination since with increasing agricultural activities, soil pollution is becoming a major concern worldwide. This study examines heavy metal contamination in the Tadla Plain of Morocco with the utilization of different geoaccumulation indices and GIS. In their assessment, the geoaccumulation indices, enrichment factors, contamination factors, and load pollution index (LPI) clearly indicated the influence of anthropogenic activities as a major source of heavy metals.

Shaheen et al. (2019) used autocorrelation Moran's I and empirical Bayesian kriging techniques to analyze the concentration of heavy metals. Pollutants such as cadmium, chromium, lead, and physiochemical parameters were assessed at three different soil depths in the industrial area of Sheikhpura (Pakistan) (Fig. 5.1). The severity of contamination was evaluated using the geoaccumulation index and Nemerow integrated pollution index for the delineation of contaminated areas.

Yang et al. (2019) developed a diverse approach to estimate unknown soil pollution concentrations in soil in response to the spatial regression or interpolation

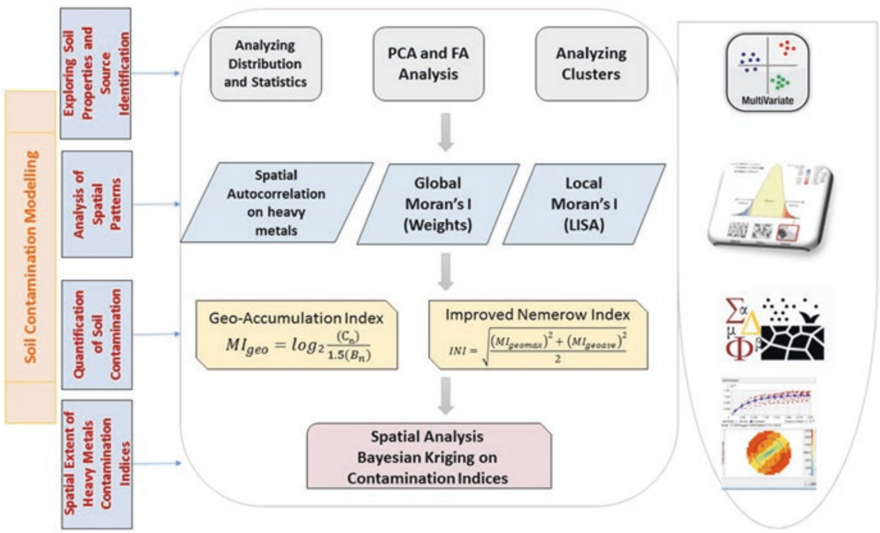

Fig. 5.1 The techniques used by Shaheen et al. (2019) for geospatial modeling of soil contamination by selected heavy metals in the industrial area of Sheikhupura, Pakistan. (Source: Shaheen et al., 2019)

method for heavy metal concentrations. They utilized the spatial outlier detection method for identifying anomalous soil collection points, and later, the investigation segregated between normal and outlier point areas. Spatial regression and interpolation techniques were considered for analyzing the normal and outlier datasets, respectively. Finally, prediction-based soil pollution mapping was generated from the hybrid combination of spatial regression and interpolation techniques. Jin et al. (2019) analyzed the risk of residents toward the exposure to contaminated soils directly or indirectly related to public open spaces. They incorporated principal component analysis to investigate the dominant variables that help in regulating the heavy metal variables and echo potential sources. Moreover, cluster analysis was also applied to categorize datasets with similar patterns in certain groups automatically by an algorithm to reduce intragroup variability and increase intergroup variability (Young & Hammer, 2000). The main parameters considered were then subjected to geostatistical analysis. Finally, the systematic combination of GIS with multivariate statistical assessment proved valuable for elucidating anthropogenic and natural sources.

Khalil et al. (2013) assessed waste materials from mines as various sources of soil contamination. Climate factors such as high rainfall give rise to metal dispersion in semiarid areas, as soils are scarcely vegetated. Therefore, in this review, the researchers assessed the nature and magnitude of soil contaminants from the Kettara mine in Morocco with the help of geochemical and geostatistical techniques. Wastes from mines were sampled, and assessments were carried out for the 41 chemical elements. The statistical methods, namely, minimum, maximum, mean, and median for the central tendency, standard deviation, and variation coefficient were considered for the assessment of the dispersion of the datasets.

Darwish et al. (2014) performed an investigation in the southern region of the El-Hussinia Plain of the El-Sharkaiya Governorate, Egypt. The study was primarily focused on salt-affected soils, as the concentration of salts is significantly related to crop growth. Soil parameters such as EC, pH, SAR, ESP, $CaCO_3$, OM, and soil texture along the longitudinal slope were measured. Landsat 7 ETM+ data along with ground control points from the toposheet were used for geo-registration. Linear interpolation was used to generate a 30 m spatial resolution digital elevation model. They used supervised classification to obtain the land-use map. Geostatistical techniques such as kriging and simple regressions were also used. The linear spectral technique was also applied to predict the soil salinity. Multiple linear regression was used to generate the salinity map based on the best-correlated indices. Miletić et al. (2022) determined soil contamination by analyzing ten different potential toxic contents and evaluated its associated ecological risk by using different indices. They collected agricultural surface soil samples from 200 sites. In terms of the field survey, cadastral parcels were identified, and the locations of the sampling points were collected using a GPS system to locate the exact geographical locations of the points. Another study by Hammam et al. (2022) focused on soil contamination analysis for the nearby area of El-Moheet drainage in Egypt. Six heavy metals were considered for analysis. They used LANDSAT-8 (OLI) images for the study area and performed supervised classification to derive the land-use map. Sixty random locations were selected for soil sample collection near the El-Moheet drainage, and their geographical locations were collected. Methods such as principal component analysis and contamination factors were used to measure the soil contamination levels. Ordinary kriging was used to generate the degree of contamination map. Furthermore, along with the land-use map and degree of contamination map, a spatial pattern map of soil contamination was prepared.

Alam et al. (2015) studied soils from various land-use regions in Lahore City, Pakistan, to assess the concentrations of heavy metals such as cadmium, chromium, nickel, and lead. More than 100 samples were collected randomly from the six land-use regions, which were classified into park, commercial, agricultural, residential, urban, and industrial. Every sample was assessed in the lab with the help of the tri-acid digestion technique. The statistical methods of analyzing variance, correlation, and cluster analysis were used to assess all data and information. However, in addition to kriging, a geostatistical technique was performed in the GIS domain to develop a model and to predict the spatial concentrations of the four heavy metals, namely, Ni, Cr, Cd, and Pb. Therefore, the results showed a significant correlation among the heavy metals in the urban region and industrial areas. Wu et al. (2014) also presented a study on various soil contaminations. In the analysis, they assessed the levels of several trace elements with the help of the enrichment factor, geoaccumulation index, pollution index, and principal component analysis. Three soil contamination indices in combination with the PCA technique were used to analyze the concentration and proportion of soil contamination in that area. PCA merged with GIS was successfully used to differentiate trace metals present in natural and anthropogenic forms.

5.3 Geospatial Techniques for Monitoring Soil Contaminants

Soil contamination refers to any soil substance that exceeds natural occurrence and negatively affects the ecosystem. When heavy metal and salt concentrations increase in the soil and cross the tolerance limit, they start appearing in crops, also affecting the food chain and human health. Accurate heavy metal spatial distribution maps are an important key to mitigating their impacts on ecosystems (Hammam et al., 2022; Yu et al., 2020). Some common chemicals contaminating the soil are hydrocarbons, solvents, pesticides, poly-nuclear aromatic hydrocarbons such as naphthalene, and HMs such as manganese, cadmium, nickel, chromium, zinc, lead, and copper (Mohammed et al., 2016). With the development of space technology for monitoring and assessing earth system processes and anomalies, the use of geospatial technologies, namely, remote sensing, GIS, and GPS globally expanded significantly. Since it is easy to use, environmentally friendly, and cost-efficient, it provides many essential advantages over traditional techniques, such as speed, portability, range of elemental quantification, sample preparation, and simplicity in identifying contaminants for prevention and remediation. Remote sensing techniques allow the collection of data over large areas and a comprehensive outlook on soil

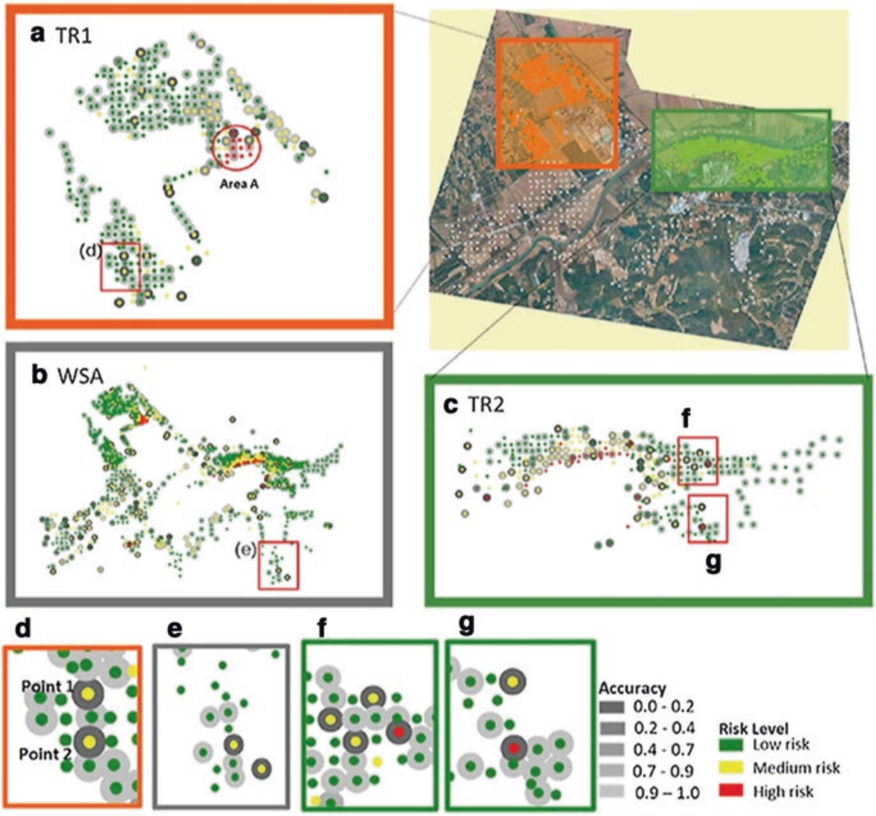

Fig. 5.2 Jia et al. (2021) studied soil pollution using drone image recognition and machine learning in arsenic-contaminated agricultural fields in China. (Source: Jia et al., 2021)

contamination (Caeiro et al., 2005; Wang et al., 2023; Wulf et al., 2015). Satellite imagery and aerial surveys can cover immense territories, allowing the identification and plotting of contaminated sites on a zonal or even intercontinental scale. This broad coverage acts as a helping hand in identifying the hotspots and interpreting the extent of contamination across different regions. Geospatial techniques help in the early detection of potential soil contamination before it spreads widely, and by monitoring the variations in land-use patterns, vegetation health, and soil moisture content, remote sensing can provide evidence of contamination risks or root causes (IAEA, 2004). This early detection helps with timely mediation and protective measures to alleviate the impacts of contamination. With more advancement of the technology soil contamination are studied by combining high-resolution aerial imaging (HRAI) with machine learning algorithms (Jia et al., 2021) (Fig. 5.2). In the literature, numerous methods and techniques are available for monitoring soil contaminants. Some of the methods for investigating the presence and extent of soil contaminants in an area are discussed below:

Inverse Distance Weighted Interpolation

It is a deterministic mathematical method that assumes that the values closer are highly correlated compared to the values that are distant from its function. Mathematically, it can be represented as:

$$Z_{x,y} = \frac{\sum_{i=1}^{n} Z_i d_{x,y,i}^{-\beta}}{\sum_{i=1}^{n} d_{x,y,i}^{-\beta}} \tag{5.1}$$

Where, z_i is the control value of the *i*th sample point, $d_{x,y,i}$ is the space between $Z_{x,y}$ and z_i, and b is user-defined. The algorithm provides weights to points based on the inverse distance of power, agreeing with logical intuition. The accuracy and precision of the algorithm can be significantly improved by considering a significant number of neighboring point samples (n) and the exponent (b) to yield an optimal agreement between the predicted and measured values.

$$Z(B) = \sum_{n}^{i=1} \lambda_i Z(xi) \tag{5.2}$$

Where, $z(B)$, area and λ_i, weights value, respectively.

Creating a Soil Contamination Map

$$Z^* = \sum_{n}^{i=1} \lambda_i Z(xi) \tag{5.3}$$

$\boldsymbol{Z^*}$ is the estimated Kriging method value, which is the unsampled point, $\boldsymbol{z_i}$ is the known value of dispersed data spatially in the sample point, $\boldsymbol{\lambda_i}$ is the weight of each data point, and $\boldsymbol{N}$ is the total number of data in the Kriging estimation.

$$bz^* = E(z) - E(z^x) = E(z) - E\sum_{N}^{i=1} \lambda_i Z_i = 0 \tag{5.4}$$

Where, $\boldsymbol{bz^*}$ bias indicator of $\boldsymbol{z^*}$, data used in Kriging sum weights must be **1**. The following equation is the kriging equation for unbiased estimation:

$$1 - \sum_{N}^{i=1} \lambda_i Z_i = 0 \tag{5.5}$$

Apart from the abovementioned techniques, some of the simple and complex indices were developed by several researchers that help in the accurate monitoring and assessment of the severity of soil contamination in the soil and are discussed below.

Simple Indices

The group comprises simple index contaminants with specific HMs (heavy metals).

Geoaccumulation Index (Igeo) The index is used for the assessment of soils for HM contamination. The assessment is based on the HM contents in the amount of HM in the O and A horizons of soil with respect to specified GB (Muller, 1969). The values of the index help in categorizing the soil into several categories based on the extent and severity of contamination.

$$I_{\text{geo}} = \log 2 \frac{C_n}{1.5\,\text{GB}} \tag{5.6}$$

Where, C_n represents each heavy metal concentration; the geochemical background is GB, and 1.5 is constant.

Single Pollution Index (PI) The present index is used for determining the heavy metals that pose the highest threat to soil in an area. The output of the index is used as input for certain complex indices, such as the PINemerow Index (Guan et al., 2014; Varol, 2011). The mathematical representation of the index is presented below:

$$\text{PI} = \frac{C_n}{\text{GB}} \tag{5.7}$$

Where, C_n signifies the amount of HM in soil, and GB represents the value corresponding to the geochemical background.

Enrichment Factor (EF) The index quantifies the influence of human-driven activity on soil in terms of HM concentration. To measure and assess the anthropogenic influence, the amount of HM content with high consistency is considered as a reference point in both the GB and analyzed sample. The elements used as references can be assessed using the equation below (Sutherland, 2000):

$$\text{EF} = \frac{\left[\frac{C_n}{Lv}\right]\text{sample}}{\left[\frac{C_n}{Lv}\right]\text{background}} \tag{5.8}$$

Where, $\left[\frac{Cn}{Lv}\right]$ represents the content of analyzed heavy metal (C_n) and metals, namely, Fe, Al, Ca, Ti, Sc, and Mn (L_V) in the soil sample and $\left[\frac{C_n}{Lv}\right]$ background are considered as references of the analyzed heavy metal (C_n). If the EF value ranges from 0.5 to 1.5, it can be quantified as a particular present soil heavy metal caused by natural occurrence, and if exceeds 1.5 EF, caused by anthropogenic activities (Elias & Gbadegesin, 2011).

Contamination Factor (C_f) The index assesses the soil contamination in consideration of the HM content from the upper part of the soil, and the amount of HM observed during the preindustrial period is used as a reference, which is given by Hakanson (1980). Mathematically, it can be computed using the formula given below:

$$C_f = \frac{C_m}{C_{p-i}} \tag{5.9}$$

Where, C_m – mean concentration of heavy metal, C_{p-i} – preindustrial substance value.

Biogeochemical Index (BGI) There exists no universal index for evaluating the intensity of HM concentration in soils under land use such as grassland and forest, and the Biogeochemical Index (*BGI*) bridges the gap (Mazurek et al., 2017). For the computation of the index, the amount of HM in the O horizon and the underlying A horizon of soil is absolutely essential. The computation of the BGI can be carried out using the following formula:

$$\text{BGI} = \frac{C_n O}{C_n A} \tag{5.10}$$

Where, C_nO is the amount of certain HMs in the *O* horizon and C_nA denotes the HM content in the *A* horizon. The index is helpful in determining the capability of the *O* horizon to absorb contaminants. An index value higher than 1 signifies a higher absorption capability of the *O* horizon. Moreover, the index does not consider the *O* and *A* horizon soil particle density; therefore, the output of the index is merely an assumption (Mazurek et al., 2017).

Complex Indices

This group of indices allows us to assess the data in a comprehensive way. For the computation of each index, the total concentrations of each HM and, in some cases, the calculated values of the individual indices are also used.

Sum of Contamination (PI_{sum}) PIsum is the most common index for measuring HM contamination in soil. The index can be defined as the totality of all HM contents and can be given mathematically as:

$$\text{PI}_{\text{sum}} = \sum_{n}^{i-1} \text{PI} \tag{5.11}$$

Where, PI is the single pollution index and n represents the number of total heavy metals analyzed.

Pollution Load Index (PLI) The PLI is used for the overall analysis of the degree of contamination in soil. The index provides a means for presenting soil deterioration due to heavy metal accumulation (Varol, 2011). The index signifies the geometric mean of PI considering the equation given below:

$$\mathrm{PLI} = \sqrt[n]{\mathrm{PI}_1 \times \mathrm{PI}_1 \times \mathrm{PI}_{1\ldots\ldots\ldots\ldots}\mathrm{PI}_n} \tag{5.12}$$

Where, n represents the considerate quantity of HM, whereas PI signifies the computed values for the Single Pollution Index.

Average Single Pollution Index (PI_{avg}) The index developed by Gong et al. (2008) and Inengite et al. (2015) is primarily used for the computation of soil quality. Mathematically, it can be represented as:

$$\mathrm{PI}_{\mathrm{avg}} = \frac{1}{n}\sum_{n}^{i-1}\mathrm{PI} \tag{5.13}$$

Where, n is the considered HM and PI is the single pollution index value. Index values higher than 1 signify low quality of the soil, signifying a higher degree of contamination (Inengite et al., 2015).

Multielement Contamination (MEC) This index is used for assessing the pollution of HMs considering their concentration in the various horizons of the soil (Adamu & Nganje, 2010; Kloke, 1979). Index values higher than 1 signify the existence of anthropogenic activity on the HM concentration in soil and can be computed using the following formula:

$$\mathrm{MEC} = \frac{\left(\frac{c_1}{T_1} + \frac{c_1}{T_1} + \frac{c_1}{T_1} + \ldots \frac{c_n}{T_n}\right)}{n} \tag{5.14}$$

Where, C is the HM concentration, T is the bearable level and n is the type of HM.

Contamination Security Index (CSI) Basically, CSI is an informative index that signifies the intensity of HM content in the soil (Pejman et al., 2015). For the computation of the CSI index, the low range effect and median range effect values are taken into consideration (Long et al., 1995). The index is also proven helpful in determining the toxicity edge exceeding which the adverse effects of contamination are observed on soil and the environment. The index can be computed using the equation given below:

$$\mathrm{CSI} = \sum_{n}^{j=1} w\left(\left(\frac{c}{\varepsilon}\right)^{\frac{1}{2}} + \left(\frac{c}{\varepsilon}\right)^{2}\right) \tag{5.15}$$

Where, w signifies the computed weight of each HM component (Pejman et al., 2015) and C denotes the concentration of HM.

Degree of Contamination (C_{deg}) The computation of the degree of contamination by HM can be assessed utilizing this index (Hakanson, 1980), and its mathematical representation is presented below:

$$C_{\deg = \sum_{n}^{i=1} C_f} \tag{5.16}$$

where C_f signifies the contamination factor and n is the number of analyzed HMs.

Furthermore, multivariate methods are also considered for assessing soil contamination using geospatial techniques. In this study, we will discuss two multivariate analysis methods, namely, multicriteria decision-making (MCDM) and principal component analysis (PCA).

Multicriteria Decision-Making

Multicriteria decision-making (MCDM) eases the decision-making process (Fig. 5.3). It is useful for solving numerous complex problems that can be accurately modeled using it. The MCDM technique can be divided into two parts: multi-attribute decision-making (MADM) and multi-objective decision-making (MODM). MCDM and MADM are commonly used for the assessment or selection of many alternatives in limited quantities. Decision-making systems play an important role in providing support for important analysis.

Fig. 5.3 Main steps of multicriteria decision-making. (Source: Taherdoost & Madanchian, 2023)

Analytic Hierarchy Process (AHP) The multicriteria method was developed by Saaty in the 1970s. Globally, the method is widely used and trusted for multicriteria studies making the best decisions (Cahyapratama & Sarno, 2018). The computational process of AHP is accomplished in various stages, in stage one, we determine the problem followed by the set of solutions, and the later stage involves the compilation of the problem hierarchy. Then, the weights corresponding to each influencing parameter are computed by comparing the parameter importance toward the problem in pairs.

$$\bar{a}_{jk} = \frac{ajk}{\Sigma_{l=2} a_{lk}} \tag{5.17}$$

$$\Sigma\,\text{column} = k1 + k2 + k3 + \ldots. + kn \tag{5.18}$$

Furthermore, the computation of the eigenvalues is carried out by multiplying each column of the paired matrix in the same row and then being lifted by an existing criterion number.

$$\lambda_1 = \left(k1 \times k2 \times k3 \times \ldots \times kn\right)^2 \tag{5.19}$$

Measures of consistency are very important to ensure that result accuracy.

$$\text{CI} = \frac{\left(\lambda\,\text{max} - n\right)}{n} \tag{5.20}$$

Where, CI stands for *consistency index,* $\lambda_{\max}$ stands for maximum eigenvalue, and n stands for number of elements.

To assess the hierarchy consistency, it is necessary that the consistency ratio (CI/IR) is <= 0.1.

$$\text{CR} = \frac{\text{CI}}{\text{IR}} \tag{5.21}$$

where CR stands for consistency ratio, CI stands for consistency index, and IR stands for index random consistency.

Principal Component Analysis (PCA) PCA is a statistical technique to reduce the dimension of the parent dataset by converting it into a new set of variables known as principal components (PCs) (Zhiyuan et al., 2011). Reducing the large number of parent datasets yields faster computation with a higher rate of accuracy. The various PCs generated are uncorrelated and ordered in such a way that the *k*th PC has the *k*th largest variance among all the newly generated PCs. Therefore, the maximum variance is found in the first principal component. In this way, the generated components extensively explain smaller portions of the variance that are uncorrelated with each other. The computation of the principal components involves certain steps, which are described below.

Standardization The range of variables is computed and standardized to analyze each variable's contribution equally. To transform the variables at the same scale, the following formula can be used:

$$Z = \frac{\text{VALUE} - \text{MEAN}}{\text{STANDARD DEVIATION}} \tag{5.22}$$

where

$$\text{Mean} = \frac{\text{Sum of the Terms}}{\text{Total number of terms}} \tag{5.23}$$

$$\text{Standard Deviation} = \sqrt{\in} \frac{(x - \text{mean})^2}{n} \tag{5.24}$$

$\boldsymbol{X}$ = dataset value and n = total number of values in the dataset.

Covariance Matrix Computation In this step, we understand the dynamics of the variables of the data in reference to the calculated mean value. To separate the high covariance matrix, interrelated variables are calculated using the given equation:

The covariance matrix is given as follows:

$$\text{Covariance Matrix} = \begin{bmatrix} \text{COV}(X,X) & \text{COV}(X,Y) \\ \text{COV}(Y,X) & \text{COV}(Y,Y) \end{bmatrix} \tag{5.25}$$

where

$$\text{Conariance} = \frac{\text{Sum}\,(X - (\text{Mean of } X)(Y - (\text{Mean of } Y))}{\text{Number of data points}} \tag{5.26}$$

Feature Vector To assess the variables' principal components, define the eigen value and eigen vectors. A is any square matrix. A stands for nonzero vector, v stands for eigenvector of an if:

$$Av = \lambda V \tag{5.27}$$

λ is the corresponding eigenvalue.

The above-described methods and techniques are some of the easiest yet efficient methods used by researchers worldwide to assess the spatial extent, location, and severity of soil contamination. Apart from the methods presented above, there also exist several other methods that are widely used; however, they require a large number of datasets and more time.

5.4 Conclusion

This study focuses on developing insights into the needs and methods for assessing soil contamination. Since the soil in its original state is pure, explicit human interventions, and developments are leading precious soil resources toward contamination by unmanageable elements and chemicals, which take many decades and centuries for decomposition and have detrimental impacts on living organisms when in contact or ingested. The prime sources of these elements and compounds are the sites where human activities such as industrialization, mining, and agriculture are prominent; however, there are much larger impacts in terms of space and time. With the realization of the soil contamination problem, the development of multiple measures came into light to monitor and assess the extent of contamination. With the advancement of geospatial technology, the assessment and monitoring of contaminants have become significantly easier in nature. The use of GIS techniques coupled with statistical methods not only provides the location and extent to which contamination is spread spatially but also provides the location of suitable sites where toxic materials and metals can be dumped. Human civilization is growing at an exponential rate, and we must realize that soil is a very precious resource for the sustenance of life on the surface of the earth. Therefore, it is of vital importance for humans to restrain the process of soil contamination. Here, we tried to present some of the most effective measures for monitoring and assessing soil contaminants using geospatial and statistical measures. We believe the methods will be useful for the identification of probable soil contamination locations and the development of measures to constrain the impact of various contaminants on living organisms.

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Chapter 6
Geospatial Modelling and Framework for the Detection and Mapping of Noise Pollution

Rakesh Saur, Amar Kumar Kathwas, Pranata Hazra, and Barnali Saha

Abstract With advancing human civilization, the migration of people to urban city centres and its expansion in terms of spatial extent has seen unprecedented growth in the last couple of decades. This resulted in the expansion of urban infrastructures and transportation networks. Owing to the huge crowd of humans in city centres, the issue of noise pollution has widely expanded, resulting in poor quality of life due to overexposure to high-intensity sound from transportation vehicles. Studies around the globe reveal numerous methods and attempt to monitor noise pollution and restrain its impact on human ecology and the environment by taking necessary steps. In this study, an attempt has been made to discuss the efficient and potent methodological framework for noise prediction modelling. Primarily, three methods have been discussed considering the pros and cons of each model and its efficiency in the various landscape structures. Based on the framework, datasets incorporated for computation and generation of noise maps, integration in GIS domain and the probable efficacy of the models were predicted.

Keywords Geospatial · GIS · Modelling · Noise pollution · Traffic · Urban

6.1 Introduction

With the advancement of human civilization, humans unknowingly created numerous problems for themselves. One of the major human-induced problems during the current time period is environmental pollution, namely, water, air and noise, which is intensifying exponentially and significantly affecting both the health of humans and the environment (Farooqi et al., 2020; Firdaus & Ahmad, 2010; Geravandi

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et al., 2015; Mohamed et al., 2021; Ukaogo et al., 2020; Vinay Kurakula & Kuffer, 2014). Among the various types of pollution, noise is a major concern for the quality of life (Flanagan et al., 2023; Jamrah et al., 2006; Martín et al., 2006; Mehdi et al., 2011; Pathak et al., 2008a; Singh et al., 2018; Yang et al., 2020). Derived from the Latin word 'nausea', noise signifies any excessive, undesirable sound induced by human activity that disrupts human and animal life. Humans perceive sound between 16 Hz and 20 kHz, above which sound is uncomfortable and disrupts normal life. With the unceasing development of infrastructure and the progression of transportation modes, the intensity of noise pollution is inclined to increase daily (Bluhm et al., 2004; Garg et al., 2013; Griffiths & Langdon, 1968; Lu et al., 2019; Öhrström et al., 2006; Parris & Schneider, 2009; Vijay et al., 2015).

Principally, noise generated from traffic, transport, industries, factories, domestic sources and neighbourhoods is a major source of environmental noise pollution (Baffoe et al., 2022; Bunn & Zannin, 2016; Cai et al., 2018, 2019; Chowdhury et al., 2012; Farooqi et al., 2020; Michali et al., 2021; Ming Cai et al., 2019; Montes González et al., 2020; Pathak et al., 2008b; Alam et al., 2020a). According to various studies, noise levels of higher levels tend to cause serious illness in humans both emotionally and psychologically, which includes impairment of health, hypertension, change of heart-beat, elevated blood pressure, poor performance, annoyance and hearing impairment causing effects on residential, social and working performance (Cabrera & Lee, 2000; Gupta et al., 2018; Hammer et al., 2014; Ma et al., 2018; Oguntunde et al., 2019; Stansfeld & Matheson, 2003). According to the guidelines listed by the Environment (Protection) Act, 1986, the permissible levels of noise in the various areas are presented in Table 6.1.

Currently, noise pollution in large urban centres is regarded as one of the major problems for communities (Horonjeff, 2022; King & Davis, 2003; Korfali & Massoud, 2003; Picaut et al., 2019; Weinstein, 1982; Yukawa & Matsubara, 2019). The noise level in some Indian cities is much higher than the prescribed standard by the CPCB, Central Pollution Control Board and MoEF, Ministry of Environment and Forest, Govt. of India (Kalawapudi et al., 2020; Sahlathasneem & Surinder, 2023; Alam et al., 2020b, c; Ranjan et al., 2023; Ranpise & Tandel, 2022; Yadav et al., 2023). According to the latest report from the United Nations Environment Programme (UNEP), globally, Dhaka (the capital of Bangladesh) is the noisiest city in the world, followed by Moradabad (Uttar Pradesh, India) and Islamabad (Pakistan). Moradabad recorded 114 dB of noise. Delhi, Kolkata and Asansol in West Bengal and Jaipur are a few other Indian cities where a high level of noise pollution has been recorded (Dubey et al., 2020a; Kamble, 2019; Lokhande et al., 2021; Mishra et al., 2019; Yadav et al., 2021). To reduce the impact of noise, steps

Table 6.1 Permitted noise levels in various areas

Type of area	Day time	Night Time
Industrial area	75	70
Commercial area	65	55
Residential area	55	45
Silence zone	50	40

need to be taken during the planning phase; otherwise, the measures can be less viable and overpriced.

Various studies have been performed regarding the measurement of noise levels in urban areas. The results of these studies reveal the overexposure of urban areas to noise pollution (Filipponi et al., 2008; Hachem et al., 2015; Laxmi et al., 2019; Martí et al., 2012; Masum et al., 2021; Morillas et al., 2018; Santini et al., 2008). Karthik and Raju (2015) emphasized in their investigation the importance of dataset quality and the model used for the generation of noise maps. The findings of the study revealed that the noise at the hotspots was significantly higher than the permissible limits issued by the pollution control board of Tamil Nadu. Moreover, it was also observed that the impact of noise from traffic is inversely proportional to the height of the building. Banerjee et al. (2008) evaluated the impact of various factors impacting the traffic noise level. Using statistical methods, they delineated factors responsible for elevated levels of noise. The findings reveal that the traffic variables, namely, traffic volume, types of vehicles, width of road, time along with land use and land cover variables, significantly influence the intensity and duration of noise in a location. Various researchers have argued that noise, which is primarily sound, propagates in all directions; therefore, conventional 2D mapping and monitoring of noise pollution might not present the overall severity of noise and requires 2.5 D or 3D assessment at the hot spots (Mandjoupa et al., 2022; Tang et al., 2022; Kurakula et al., 2007). Kurakula and Kuffer (2014) demonstrated the application of a 3D urban model developed using laser-scanned data to study the extent of noise pollution in a local scenario in Delft, the Netherlands (Fig. 6.1). The study focused on the incorporation of noise barriers in the model to mitigate the impact of noise from hotspots.

According to studies conducted by researchers around the globe, the detrimental impact of noise pollution is not limited to humans but also induces significant disruption in the behaviour, sleep cycle, communication ability and habitat of animals Bar, 2021; Berger-Tal et al., 2019; Ditchkoff et al., 2006; Domer et al., 2021; Rabat,

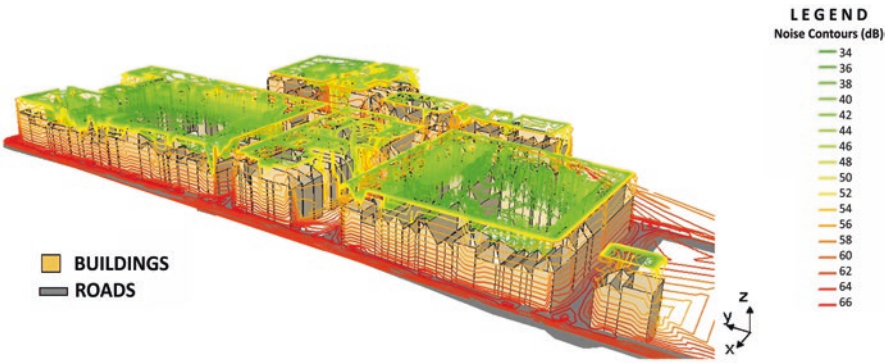

Fig. 6.1 Noise contour lines developed by Kurakula and Kuffer (2014) in combination with 3D city model of Delft, the Netherlands. (Source: Kurakula & Kuffer, 2014)

2007; Rutz et al., 2020; Senzaki et al., 2020). Moreover, a large number of studies conducted by marine environmentalists, especially during the COVID-19 pandemic, uncovered the negative impact of noise from boats and ships on marine life forms in terms of mating behaviour, habitat selection, migration, detection of prey and predators and orientation (Chahouri et al., 2022; Erbe et al., 2019; Mortensen et al., 2021; Popper & Hawkins, 2019; Tidau & Briffa, 2019). Kaplan and Mooney (2015) performed an investigation to track the vessel noise on the three reefs in the US Virgin Islands National Park over a period of four months. The findings of the study revealed that boat and vessel noise overlap with the sound produced by reef organisms, which largely influences the communication ability of aquatic animals.

Owing to the effects of noise pollution on humans, numerous noise propagation models have been developed to date. The earliest road traffic noise model was presented in the 1952 Handbook of Acoustic Noise control, which was later modified by some researchers and was offered for speeds of 35–45 mph. Comparatively, a newer model named the FHWA traffic noise prediction model was developed by Barry and Reagan of the United States of America's Department of Transportation Federal Highway Administration. The highlight of the model was the assumption that the point source is travelling at a constant speed. The average errors reported were −0.05, −0.95 and −1.3 dBA at 15, 30 and 60 m, respectively (Steele, 2001). Modelling noise using the empirically derived physical and empirical relationships between traffic, road networks and land use is an efficient method for areas with small spatial extents, such as the municipal level. The CNOSSOS-EU (Common Noise Assessment Methods) model was developed for all of Europe so that the results from different countries can be compared. The model framework was formulated to model road, rail, industrial and air noise levels (Bąkowski, 2019; Morley et al., 2015; Kephalopoulos et al., 2012, 2014).

Hamad et al. (2017) employed an artificial neural network (ANN) to model road traffic noise in Sharjah City in the United Arab Emirates. The results were compared with the two conventional models, namely, the Basic Statistical Traffic Noise model (BSTN) and the Ontario Ministry of Transport Road Traffic Noise model (ORNAMENT). The ANN model outperformed both the conventional models, and the findings reveal that the distance from the edge of the road was the most significant factor, whereas traffic volume was the least significant. Aguilera et al. (2015) explored the application of the land use regression (LUR) model for the assessment of the long-term spatial variability of road noise in three European cities. The results obtained were compared with the standard noise models developed for each city. The findings of the study revealed that the LUR does not show any systematic difference and can be used as a promising tool for noise monitoring.

The noise maps can be used not only for the identification and quantification of noise problems at local and regional scales but also for the development of proper measures for the planning and management of towns and sources of noise (De Carvalho & Szlafsztein, 2019; Hedblom et al., 2019; Klompmaker et al., 2019; Liu et al., 2019; Nieuwenhuijsen, 2020; Paiva et al., 2019; Rivkin et al., 2019). The monitoring and assessment of noise can be significantly upscaled with the integration of spatial datasets, improved mathematical models and advanced mapping

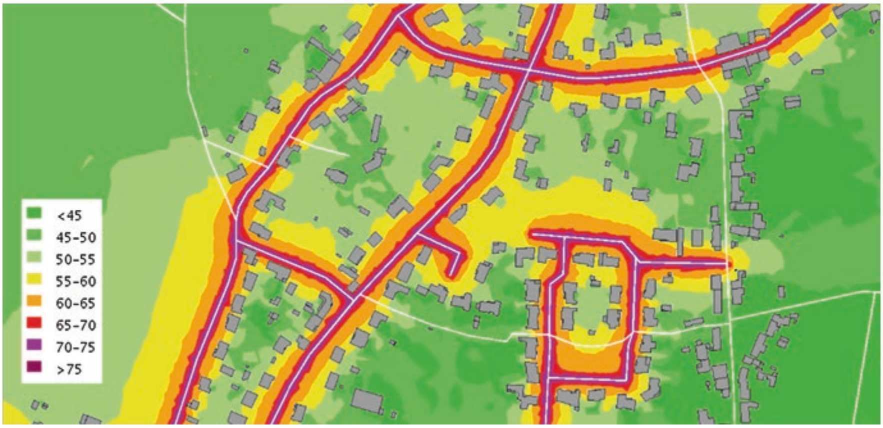

Fig. 6.2 Open-source noise contour map developed by Bocher et al. (2019). (Source: Bocher et al., 2019)

techniques in geographical information system (GIS) environments (Ameen et al., 2021; Cinderby et al., 2008; Gheibi et al., 2022; Khan et al., 2018; Wawa & Mulaku, 2015). Dubey et al. (2020b) performed a study to monitor and model noise levels in Lucknow, India, using smartphones and web GIS. The noise levels predicted were verified from readings obtained from a standard noise meter for similar locations. The findings of the study reveal that the predicted noise levels on the maps were significantly accurate with an error of ±4.5 dB.

Similarly, the study conducted by Bocher et al. (2019) describes an open-source noise mapping tool in a GIS environment (Fig. 6.2). The tool was implemented for a French city, and its integration with cartographic and population datasets was significantly easier. The model performed significantly well and produced noise maps in real time. The various set of tools offered by GIS helps in cataloguing, conversion, visualizing and handling spatial datasets of the real world to obtain requisite variations, interpretations and interpolation of data required for obtaining desired results and for the assessment of its impact on the flora and fauna of the region. Owing to all the facilities provided by GIS, GIS can be considered a vital tool that aids in the precise development of strategy and mitigation measures for curbing the impact of noise on humans, animals and their environment.

6.2 Methodology for Noise Modelling

The literature shows that there exist numerous noise prediction models varying from simplistic to complex, such as NMPB-08, Calixto, multiple regression and multipoint equivalence (Dutilleux et al., 2010; Kuldeep et al., 2021; Okumura & Kuno, 1992; Pal & Gauri, 2010; Soni et al., 2022; To et al., 2002). This chapter's primary focus is on models to monitor and predict noise in an urban environment.

Therefore, we discuss some of the efficient methodological frameworks (MFs) working in urban environments, namely, Nordic (Chang et al., 2012; Electronics, 2002), and the road noise prediction model (Bocher et al., 2019).

MF I – The Nordic Noise Model

The Nordic prediction model is designed based on two prime assumptions: first, beyond 300 meters from the road, the noise is not significantly annoying, and second, the model performs in neutral to moderate wind and temperature environments. The major dataset required for the model comprises the following:

(i) Traffic volume of light and heavy vehicles
(ii) Speed of the vehicles
(iii) Distance between the receiver sensor and the centreline of the road
(iv) Relative height of road from its surrounding
(v) Location of height and barriers
(vi) Location of the receiver in comparison with the surrounding ground, road surface
(vii) Type of ground (soft or hard)

According to the model, the energy equivalent continuous sound pressure level ($L_{\mathrm{Aeq},24}$) over a period of 24 hours is used and is calculated using the equation given below:

$$L_{\mathrm{Aeq}} = L_1 + \Delta L_2 + \Delta L_3 + \Delta L_4 + \Delta L_5 \tag{6.1}$$

The computation is carried out by dividing the length of the road into multiple exons, and the ($L_{\mathrm{Aeq},24}$) for each section is computed separately. Furthermore, the computed ($L_{\mathrm{Aeq},24}$) of each road section is integrated for the cumulative ($L_{\mathrm{Aeq},24}$) computation. The integration is carried out using the equation given below:

$$L_{\mathrm{Aeq}} = 101\,g\left(\sum_{i=1}^{n} 10^{L_{\mathrm{Aeqi}}/10}\right) \tag{6.2}$$

The computation of the L delta coefficients used in Eq. 6.1 is carried out in multiple stages and is described in the following sections.

Stage I – Basic noise level (L1)

It is a function of the number of light and heavy vehicles and their speed v. The amount of noise is computed at a distance of 10 meters from the centreline of the road for a specified period of 24 hours. The noise levels from the light vehicle are categorized into two parts:

(a) $L_{\mathrm{AE,10\,m}}$(light) = 71 db(A) for vehicle $30 \leq v < 40$ km/h(6.3)
(b) $L_{\mathrm{AE,10\,m}}$(light) = 73.5 + 25lg(v/50) $v \geq 40$ km/h(6.4)

The cumulative $L_{\mathrm{eq,\,10\,m}}$ from the light vehicle at variable speed is computed utilizing the equation below:

$$L_{\mathrm{Aeq},10\,\mathrm{m}}(\mathrm{light}) = L_{\mathrm{AE},\ 10\,\mathrm{m}}(\mathrm{light}) + 101g\frac{N(\mathrm{light})}{T} = 71.1 + 101g\left(\frac{N(\mathrm{light})}{T}\right) \tag{6.5}$$

The second part computes the sound pressure level from the heavy vehicle considering the variable speed of the vehicles, and the computation can be mathematically represented by the equations below:

(a) $L_{\mathrm{AE},10\,\mathrm{m}}(\mathrm{heavy}) = 80.5 + 30\mathrm{lg}(v/50)$ for vehicle $50 \geq v \leq 90$ km/h(6.6)
(b) $L_{\mathrm{AE},10\,\mathrm{m}}(\mathrm{heavy}) = 80.5\mathrm{db(A)}$ for vehicle $30 \leq v < 40$ km/h(6.7)

The computed $L_{\mathrm{AE},10\,\mathrm{m}}$ from the vehicle is then combined using Eq. 6.4:

$$\begin{aligned} L_{\mathrm{Aeq},10\,\mathrm{m}}(\mathrm{heavy}) &= L_{\mathrm{AE}},10\,\mathrm{m}(\mathrm{heavy}) + 101g\frac{N(\mathrm{heavy})}{T} \\ &= 80.5 + 101g\left(\frac{N(\mathrm{heavy})}{T}\right) \end{aligned} \tag{6.8}$$

Finally, the computed $L_{\mathrm{Aeq},24}$ from light and heavy vehicles is combined to yield the final basic noise level, signified mathematically as

$$L_{\mathrm{Aeq},\ 10\,\mathrm{m}}(\mathrm{mixed}) = L_1 = 101g\left(10^{L_{\mathrm{Aeq}}(\mathrm{light})/10} + 10^{L_{\mathrm{Aeq}}(\mathrm{heavy})/10}\right) \tag{6.9}$$

Stage II – Distance correction (ΔL2)
Since the sound is energy that propagates in all directions and is inversely proportional to the distance from the perspective of the source and receiver, the noise tends to fade away with respect to distance, and this decrease in energy in terms of distance correction is then computed using the equation provided below:

$$\Delta L_{\mathrm{AV}} = \Delta L_2 = -101g\left(1 + \frac{\sqrt{a^2 + (h_{\mathrm{m}} - h_{\mathrm{b}} - 0.5)^2}}{10}\right) \tag{6.10}$$

where a represents the distance from the receiver normal to the road.
h_{b} signifies the height of the road (meters).
h_{m} denotes the height of the receiver sensor.

Stage III – Ground and barrier correction (ΔL3)
Here, in the present stage of noise computation, the distance between the source and the receiver is often hindered by objects such as buildings, which are considered screens. The computation of stage 3 is carried out in two parts, where part one calculates the effect of screening, whereas part two involves the influence of the ground. The absorption of sound energy by the ground surface between the road and

the receiver is primarily based on two types of surfaces, that is, soft or hard. The soft ground is signified by areas covered with grass, normal soil, and river and lake surfaces, whereas the hard ground is denoted by surfaces covered with asphalt, concrete and soil with no vegetation. The equations below present the computation steps for screen correction:

$$\Delta L_{\mathrm{MS}} = \Delta L_{\mathrm{S}} + \Delta L_{\mathrm{m}} \tag{6.11}$$

$$h_{\mathrm{e}} = \frac{\left(h_{\mathrm{v}} - h_{\mathrm{m}}\right) d_1 + \left(h_{\mathrm{v}} - h_{\mathrm{b}} - 0.5\right) d_2}{\sqrt{\left(d_1 + d_2\right)^2 + \left(h_{\mathrm{m}} + h_{\mathrm{b}} - 0.5\right)^2}} \tag{6.12}$$

$$x = 1.1 h_e \sqrt{\frac{d_2 + d_1}{d_1 \bullet d_2}} \tag{6.13}$$

$$\Delta L_{\mathrm{S}} = -25x \geq 2.4 \tag{6.14}$$

$$\Delta L_{\mathrm{S}} = -5 - 101g\left(1 + x + 17x^2\right) 0 \leq x \leq 2.4 \tag{6.15}$$

$$\Delta L_{\mathrm{S}} = -5 - 101g\left(1 - x + 17x^2\right) - 0.33 \leq x \leq 0 \tag{6.16}$$

$$\Delta L_{\mathrm{S}} = 0x < -0.33 \tag{6.17}$$

$$Z = 1 \qquad \Delta L_{\mathrm{S}} \leq -18 \tag{6.18}$$

$$Z = \frac{-\Delta L_{\mathrm{S}} - 5}{13} \; -18 \leq \Delta L_{\mathrm{S}} \leq -5 \tag{6.19}$$

$$Z = 0 - 5 < \Delta L_{\mathrm{S}} \tag{6.20}$$

Part two of the section involves ground correction, and the coefficient σ, which is used for computation of ground correction, is a function of coefficients involved in screen correction, that is, distance to road, height of the road and height of the receiver. It can be computed as

$$\sigma = \frac{d_2}{10h_m},\ h_m \geq 2, \text{if } h_m \leq 2 \text{ then put } h_m = 0 \tag{6.21}$$

Therefore, from the above equation, one can easily conclude that the position of the source and receiver in accordance with the ground is largely significant. For the soft ground surface, the computation of corrections is carried out using the listed equations:

$$\Delta L_m = -5(1-z)1g\left(\frac{s^2}{1+0.01s^2}\right)\ s \geq 1 \tag{6.22}$$

$$\Delta L_m = -4z1g(s)\quad 0.3 < s < 1 \tag{6.23}$$

$$\Delta L_m = 2z - 4z1g\left(\frac{0.3}{s}\right)\ 0.1 < s < 0.3 \tag{6.24}$$

$$\Delta L_m = 0 \qquad s < 0.1 \tag{6.25}$$

$$\sigma = \frac{d_2'}{10h_m} \tag{6.26}$$

$$d_2' = d_2 \times 10^{-0.3hv} \tag{6.27}$$

For the hard ground surface, the computation can be made using the following equations:

$$\begin{aligned} \Delta L_m &= 2z + 3z1g(s) && 0.2 \leq s \leq 10 \\ \Delta L_m &= 5z && s > 10 \\ \Delta L_m &= 0 && s < 0.2 \end{aligned} \tag{6.28}$$

Stage IV – View correction angle (ΔL4)

The different view angles of the receiver towards the road section contribute significantly to the sound pressure level received and can be computed using the equation delineated below:

$$\Delta L_a = 101g\left(\frac{a}{180}\right) \tag{6.29}$$

Stage V – Façade correction (ΔL5)

The correction is quite complex and requires multifaceted calculations such as:

(a) Correction due to vegetation cover
(b) Correction due to road gradient
(c) Correction due to single reflection from vertical surfaces
(d) Correction due to multiple reflections in crowded environments
(e) Correction due to scattering from detached objects

The computation of Stage V is largely significant when we are focused on assessing the noise in a small area or a specific area. Its application in large areas is not viable since it requires large sets of data, time and computational hardware.

MF II – System for Prediction of Acoustic Detectability (SPreAD)
The framework of SPreAD was conceptualized and developed nearly 30 years ago by U.S. Forest Service (USFS) and Environmental Protection Agency (EPA) for the prediction of acoustic impact on the wild land environment. It was developed to assess noise propagation in natural ecosystems, such as vegetation cover areas. The model incorporated a large number of environmental factors, such as wind, temperature, land use/land cover, humidity, seasonal conditions and noise source characteristics. Unlike other models that compute noise in a single frequency concerning humans, SPreAD computes sound propagation in multiple frequencies (400, 500, 630, 800, 1000, 1250, 1600 and 2000 Hz), which helps in understanding the impacts of noise on different wildlife animal responses at different sound frequencies. The model is flexible for observing noise from point, line or polygon sources. The framework of the model can be categorized into six sections that need to be assessed in sequential order as the output of the first module is used in the succeeding module for computation. The six sections are as follows:

Spherical Spreading Loss: The section computes the decrease in the sound energy with respect to distance from the sound source

Atmospheric Absorption Loss: This section discusses the computation of loss in the sound pressure due to the absorption caused by atmospheric variables such as wind, humidity, air temperature and elevation.

Foliage and Ground Cover Loss: Here, the decline in the sound level due to the effects of ground is taken into consideration. The loss in energy is due to ground cover and propagation due to vegetation cover. Primarily, it is the function of the type of land use/landcover (water, urban, cropland, vegetation, barren, fallow, shrubs) of the area under investigation with respect to the distance from the source.

Downwind and Upwind Loss: the section addresses the change in sound level caused by the direction and velocity of wind. The sound energy declines rapidly in the upwind and crosswind situations compared to the downwind situation and the seasonal conditions.

Terrain Effects: This computes the changes in the sound level due to barriers from hills or ridges. The section determines the location and areas of the landscape that are largely influenced by the ground, barrier and atmospheric effects.

Predicted Noise Propagation: Finally, the computation of sound propagation in all eight frequency bands.

It is noteworthy that the SPreAD model is a static model that yields spatial patterns and potential disturbances caused by sound. The flexibility of the model is that it can be integrated with traffic, recreational and other dynamic models to predict different noise disturbance scenarios.

The manual computation of each of the six sections of the model was converted to a Python script and integrated into the GIS platform as a toolbox in ArcGIS software. The toolbox is open source and is freely available.

MF III – Road Noise Prediction Model

The model predicts equivalent long-term noise caused by traffic volume from the perspective of point location in an infrastructural vicinity. The method predicts both in the existing and future scenarios. The output of the method makes it largely suitable for the planning and management of road projects and their impact assessment analysis. The method comprises six different successive stages (S):

S1 – segmenting the road into homogeneous acoustic sections of the line source.
S2 – determination of sound energy per meter for each section, individually.
S3 – discretizing every homogeneous road section into point sources.
S4 – determining the power of sound per meter for each point source.
S5 – estimation of diminution in propagation between each point source and receiver.
S6 – summing up the sound energy contribution from the various sections of road to yield the overall sound level at the receiver's end.

Since the emission of noise largely depends on the type of vehicle, namely, light and heavy vehicles, the implementation of the method breaks down the road sections into a series of point sources S_i ($I = 1$ to N_s).

The emission of sound from a point source is determined for a particular frequency j in accordance with the acoustic power level $L_{w/m}$ of a line source and can be represented as

$$L^{\mathrm{i}}_{w,i} = L^{\mathrm{i}}_{w/m} + 10\log_{10} d_i \tag{6.30}$$

where d_i is the distance between two sources. The distance is selected in a way that it follows the rules mentioned below:

$$d_i \le 0.5 \times d_{\min,i}$$

and

$$d_i \le 20\,\mathrm{m},$$

where $d_{\min,i}$ is the orthogonal distance between the point source S_i and the nearest receiver point $R_{\mathrm{nearest},i}$.

The energy level $L^j_{w/m}$ for each point source is computed for each vehicle category as

$$L^{\mathrm{i}}_{w,i} = \oplus \sum_{\mathrm{VC}} \left[L^{\mathrm{i}}_{\frac{W}{m},\mathrm{VC}} + 10\log_{10} Q_{\mathrm{VC}} + R^{\mathrm{i}}_{\mathrm{VC}} \right] \tag{6.31}$$

$$L_{\mathrm{A}} \oplus L_{\mathrm{B}} = 10\log_{10}\left(10^{\frac{L_A}{10}} + 10^{\frac{L_A}{10}} \right) \tag{6.32}$$

Concerning road vehicles, the emission of power per meter of road lance is computed by the breaking contribution of rolling noise ($L^j_{r,W/m,\mathrm{RV}}$) and mechanical noise ($L^j_{m,W/m,\mathrm{RV}}$), which is largely dependent on the velocity and pace of the vehicle and is represented as

$$L^{\mathrm{i}}_{w/m,\mathrm{VC}} = L^{\mathrm{i}}_{r,w/m,\mathrm{VC}} \oplus L^{\mathrm{i}}_{m,\frac{w}{m},\mathrm{VC}}. \tag{6.33}$$

The sound level ($L^j R_{k,i}$) at a receiver (R_k) from a point source (S_i) is characterized by a power level ($L^i W_{,i}$) and can be evaluated using the equation given below:

$$L^{\mathrm{i}}_{R_k,i} = L^{\mathrm{i}}_{w,i} - A_{\mathrm{div}\,R_k,i} - A^j_{\mathrm{atm}\,R_k,i} - A^j_{\mathrm{dif}\,R_k,i} - A^j_{\mathrm{grd}\,R_k,i} \tag{6.34}$$

where the attenuation refers to geometrical spreading (A_{div}), atmospheric absorption (A_{atm}), horizontal diffraction around the vertical edges of obstacles (A_{dif}) and the ground effect (A_{grd}).

The natural attenuation of noise during propagation over a distance d_i can be expressed as

$$A_{\mathrm{div}\,R_k,i} = 20\log_{10}(d_i) + 11 \tag{6.35}$$

The atmospheric absorption (A_{atm}) is a function of the frequency-dependent absorption coefficient $\alpha_{\mathrm{air},}$ signified as

$$A^j_{\mathrm{atm}\,R_k,i} = \alpha_{\mathrm{air}} \frac{\mathrm{d}_i}{1000}. \tag{6.36}$$

The horizontal diffraction A_{diff} around vertical structures relies on the path length difference δ (in meters) and is given by the equation given below:

$$\left\{ \begin{array}{ll} 10\log_{10}\left(3 + \frac{40}{\lambda} C''\delta\right) & \text{if } \frac{40}{\lambda} C''\delta - 2 \\ 0 & \text{otherwise,} \end{array} \right. \tag{6.37}$$

where λ represents the wavelength of the centre frequency and C is a coefficient for multiple diffractions, such as

$$C'' = \begin{cases} \dfrac{1 + \left(\dfrac{5l}{e}\right)^2}{\dfrac{1}{3} + \left(\dfrac{5l}{e}\right)^2} & \text{if } n_{\text{dif}} = 1(\text{single diffraction}), \\ 1 & \text{if } n_{\text{dif}} > 1(\text{multiple diffraction}) \text{ and } e > 0.3\,\text{m}, \end{cases} \tag{6.38}$$

where denotes the distance between the first and last diffractive edge. The path difference δ is computed as a corner-to-corner propagation method with an offset of a few centimeters in relation to the wall.

In addition to potential specular reflections from vertical surfaces, the corrected power level of the sound source according to the absorption coefficient is given as

$$L_{W_{Si}}^{(n_{\text{ref}})} = L_{W_{Si}}^{(n_{\text{ref}}-1)} + n_{\text{ref}} \times 10 \log_{10}\left(1 - \alpha_{\text{vert}}\right). \tag{6.39}$$

6.3 Anticipated Results

The results of the methodological frameworks discussed above yield the identification of locations with different levels of noise pollution. Their integration with the GIS domain helps in the identification and visualization of different noise level scenarios in real time, and their integration also helps in the development of mitigation and planning measurements. Since the models yield similar results, the efficiency and efficacy of the model rely on their methodological framework.

The Nordic model yields the noise pollution scenario up to 300 meters, beyond which it does not work. One of the strengths of the model is its inclusion of atmospheric variables such as wind direction, speed and temperature as inputs, which significantly affect the intensity and magnitude of the sound energy. Primarily developed for monitoring noise in urban centres along roads, it is not in other landscape environments. Moreover, the prediction is primarily made based on the single sound frequency oriented towards the human environment. The model is quite complex and utilizes a large number of datasets, which is its strength and weakness.

In contrast, the SPreAD model is a wholesome model that is very flexible and can be integrated into any environmental landscape, that is, grasslands, forest, urban and agriculture, to study the impact and effects of noise. It also assesses sound power in eight different frequencies used by humans to animals. Another power of the model is that it utilizes a number of multifaceted factors affecting sound, such as wind, temperature, humidity, land use/land cover, elevation and sources of noise. Moreover, the model has been successfully integrated into GIS software (ArcGIS) as a toolbox and is very easy to use. Compared to the other noise prediction models where assessment is made based on the point source, the SPreAD model uses points, lines and polygons as noise sources, making it a widely usable and efficient model.

Furthermore, the road noise prediction model is a good model for the assessment of point source noise pollution in an urban landscape. The major pros of the model are its capacity to predict the noise level scenario both in the existing time periods and in the future. The efficient output of the model makes it viable and can be largely utilized for the planning of transport infrastructures in an urban landscape and for the development of mitigation measures to curb the impact of noise in various areas. The major cons of the model are that it does not take into consideration the land use/land cover categories that have a significant impact on sound propagation and attenuation.

6.4 Conclusion

This study focuses on the impact of noise on the ecology and environment. Currently, with the advancement of human civilization, various human-induced problems have upstretched with detrimental effects on humans, animals and the environment. Among them, pollution is considered one of the major problems that affect the quality of life on the surface of the earth, be it humans or animals on land or water. Among the various pollution types, noise pollution is one of the major problems for humans, primarily for those residing in urban centres and the other forms of life in their vicinity. Numerous methods and models have been developed in the last five to six decades for monitoring and predicting noise levels. In this study, we have discussed three different mathematical noise prediction models that are efficient and yield promising results in terms of noise level prediction in urban landscape ecosystems. With the integration of these noise models with GIS, their strength has significantly improved as the models provide the spatial distribution of noise levels in an area and help in the identification of areas that require attention in terms of mitigation measures. However, the framework and quality along with the type of datasets utilized play a significant role in the generation of precise noise level maps.

From the methodological point of view, it can be inferred that the SPreAD model might provide comparatively much better results, as it considers all parameters that influence the sound energy in a landscape. This is due to its multifaceted data set utilization; it is viable in multiple environments and is flexible in terms of usage integration. On the other hand, Nordic might be another potent model; however, its complexity and computation are time-consuming and require hardware to process a huge set of information. Finally, the road noise prediction model is efficient and easy to use with fewer dataset requirements. Additionally, its ability to predict the levels of noise in future scenarios makes it promising for the planning of the infrastructure and growth of urban centres. Finally, it can be advised that there exist numerous noise monitoring models that can be utilized owing to the availability of datasets and resources, which is significant in the study of noise prediction. Here, we discussed some of the promising noise prediction models regardless of data availability and resources.

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Chapter 7
Urban Areas and Air Pollution: Causes, Concerns, and Mitigation

Shivali Gupta and Rakesh Kumar

Abstract Urbanization has proven to be a catalyst for global economic growth. However, the concomitant progress in economic development has led to a degradation in air quality within urban settlements, primarily attributable to copious anthropogenic sources of pollutant emissions. Air pollution has numerous negative impacts on the well-being of humans and the environment. This includes the deleterious impacts on climate change as well as the emergence of serious cardiovascular and respiratory diseases. This chapter, therefore, discusses urban air pollution, encompassing the causal factors, associated concerns, and various strategies employed to mitigate its adverse effects. These strategies involve regulatory, technological, and behavioural responses, which are imperative to effectively address the issue of air pollution. Therefore, the examination of the complex interplay between urbanization across varying stages of development and air pollution is integral in attaining ambient air quality targets with respect to upcoming economic advancement and sustainable progression.

Keywords Anthropogenic Sources · Air pollution · Climate change · Human health · Sustainable development · Urbanization

7.1 Introduction

Rapid industrialization has facilitated a significant surge in both urbanization and economic expansion, especially in the developing world. "Urbanization refers to the process of population growth in urban areas, accompanied by a multitude of transformations that entail moving away from rural lifestyles. Such changes impact various aspects of industry structure, living standards, employment opportunities, and public services in the urban context". The process of urbanization is the result of population growth, which leads to modifications in the size, structure, and growth of

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cities (Liang & Gong, 2020). Urban areas or agglomerations exhibit a high degree of population density and are characterized by a comprehensive network of built environment infrastructure. The elevated rates of economic growth within metropolitan regions serve as a driving force attracting individuals on account of the heightened availability of employment prospects, educational resources, and an improved standard of living (Ho, 2012). Approximately fifty per cent of the global populace currently dwells in metropolitan regions, with a projected substantial upsurge in this figure in the upcoming years (World Bank, 2022). Although urbanization has contributed significantly to the global economy, it has also resulted in various challenges to environmental sustainability. One of the most critical challenges is the degradation of air quality in rapidly expanding urban areas (Wang et al., 2020). The United Nations Environment Programme et al. (2002) estimated that approximately 1.1 billion individuals worldwide are exposed to air that fails to meet health standards. Urban air pollution is a critical issue leading to a substantial number of fatalities annually, with Chen et al. (2022) reporting that over two million individuals succumb to its deleterious effects. Air pollution arises from the accumulation and sustained presence of specific substances, commonly known as air pollutants, within the ambient air, resulting in detrimental consequences on both the health of humans and the natural environment. Air pollution has become a significant concern due to its contribution to social inequality, health conditions, and environmental degradation, which includes the occurrence of acid rain, eutrophication, urban smog, and possibly even climate change (Ahmad et al., 2015). Numerous sources, such as the manufacturing segment, combustion engines, biomass combustion, and other related sources of particulate emissions, have led to an exponential increase in anthropogenic air pollutants. The matter of significant concern pertains to the issue (Leung, 2015).

Any airborne physical, chemical, or biological substance of natural or anthropogenic origin that negatively alters the atmosphere's natural properties and results in adverse impacts on the health of human beings or other biosphere components is referred to as an air pollutant. Air pollutants can be gaseous pollutants [nitrogen dioxide (NO_2), volatile organic compounds (VOCs), sulphur dioxide (SO_2), ozone (O_3), and carbon monoxide (CO)], particulate matter (PM), that is, PM_{10} (aerodynamic diameter $\leq$10 μm) and $PM_{2.5}$ (aerodynamic diameter $\leq$2.5 μm), persistent organic pollutants (dioxins), or heavy metals (lead, mercury) (Agarwal et al., 2019). The dissimilarities among various categories of atmospheric pollutants are manifested through their unique chemical composition, distinct emission patterns, reaction dynamics, levels of environmental persistence, transportation capabilities over short or prolonged distances, and disparate impacts on the natural surroundings (Fino, 2018). The effects of aerosols on both human health and climate change are well documented in the academic literature. These particulate matter substances serve as critical radiative forcing agents, possessing the ability to generate either positive (warming effect) or negative (cooling effect) radiative forcing. The degree to which aerosols influence radiative forcing is dependent upon their microphysical properties, such as optics and size, as well as their specific composition. The impact of aerosols on circulation systems and the consequent deterioration of environmental quality have been extensively studied and documented in the scientific literature (Banerjee & Srivastava, 2011; Ramanathan & Carmichael, 2008). Some gaseous air pollutants have the capacity to absorb long-wave radiation, thereby making a significant contribution to climate change. The transport of air pollutants through the atmosphere can extend over considerable distances and traverse across continents, thereby increasing the complexity of regional air quality. Consequently, the investigation of the origins and ultimate occurrence of these gases within the atmosphere holds paramount significance (Agarwal et al., 2019; Mhawish et al., 2017). As reported by Bikis and Pandey (2021), the adverse effects of transportation-related air pollution are experienced by 40% of urban residents in Addis Ababa. Various sources, traversing route, and ramifications of airborne contaminants have been represented in Fig. 7.1.

There are multiple causes of intricate air pollution in urban areas, including emission sources, such as traffic or industrial processes, along with meteorological phenomena, such as insolation, wind patterns, temperature, and relative humidity. Furthermore, chemical transformations contribute significantly to the generation and evolution of air pollution through the occurrence of various chemical reactions and dry depositions (Ho, 2012). Pollution processes are inherently dependent upon the prevailing meteorological conditions as well as physical and chemical characteristics of contaminants, which together are vital in shaping overall pollution dynamics as well as the transportation, dispersion and eventual sink of air pollutants (Vallero, 2014b).

Henceforth, to mitigate air pollution and preserve human health and ecological balance, it is imperative that priority is given to the management of urban air quality.

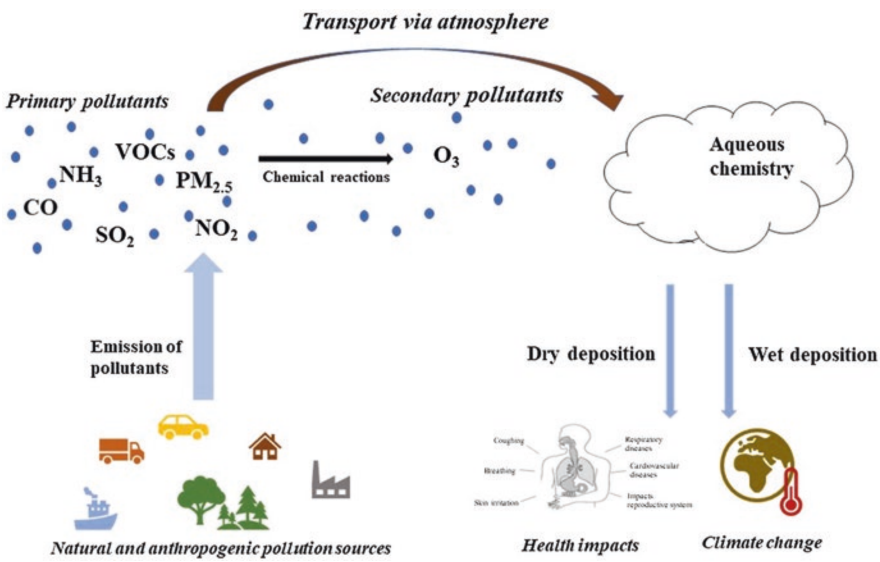

Fig. 7.1 Sources, pathways, and effects of air pollutants

An imperative requirement for rigorous scientific assessment pertaining to the assessment of the ramifications that urbanization on the quality of atmospheric composition. This chapter provides an overview of urban air pollution, encompassing factors causing such pollution, adverse effects pertaining to health and the environment, and possible remedial actions to reduce air pollution and counter the detrimental association between urbanization and pollution for the promotion of sustainable urban developmental practices.

7.2 Air Pollutant Types

The effects of air pollutants are subject to differential impacts on individuals, contingent upon factors such as concentration, toxicity, and duration of exposure (Leung, 2015). Air pollutants are categorized into two types, namely, primary pollutants and secondary pollutants, depending on their source of origin. Primary pollutants refer to the contaminants emitted directly from their source into the environment, specifically into the atmosphere. Examples of these primary pollutants include SO_2, CO, and CO_2. The term “secondary pollutants” pertains to particles generated because of chemical interactions between materials in a mixed gas phase that are exposed to solar radiation or due to reactions between primary pollutants (Agarwal et al., 2019; Banerjee et al., 2015; Kumar et al., 2016), for instance, the formation of ozone, which is a secondary pollutant (Ahmad et al., 2015).

The air pollutants are further divided into outdoor pollutants and indoor air pollutants (Fig. 7.2). Outdoor air pollutants are composed predominantly of NOx, SO_2, O_3, CO, PM, and hydrocarbons (HCs). In metropolitan regions, these emissions originate predominantly from motor vehicles, with additional contributions stemming from power generation facilities, industrial boilers, incineration operations, petrochemical manufacturing plants, aviation, marine transportation, and related sources. The variability in atmospheric conditions depends upon geographical location and the directionality of prevalent air currents. Urban areas exhibit reduced significance in the contribution of long range sources of pollution owing to the extended distance from such sources (Leung, 2015). The reduction in air dispersion in the urban environments can be attributed to the presence of densely located buildings which inhibits air circulation (Cheng et al., 2009; Li et al., 2009). Conversely, proficient urban planning can mitigate the challenges related to the accumulation of air pollution by means of the wide dispersion of pollutants (Leung, 2015; Li et al., 2009).

Indoor air pollutants mainly include CO, O_3, SO_2, NOx, radon, PM, VOCs, semi-volatile organic compounds, and microorganisms. The presence of these contaminants is prevalent in both interior and exterior environments, and certain sources of origin for these pollutants may exist in external contexts (Leung, 2015). Sick building syndrome (SBS) is a prevailing adverse effect that triggers acute health symptoms, including irritation, allergies, and other related conditions. The aetiology of the syndrome remains largely unknown, albeit it may exhibit a time-limited

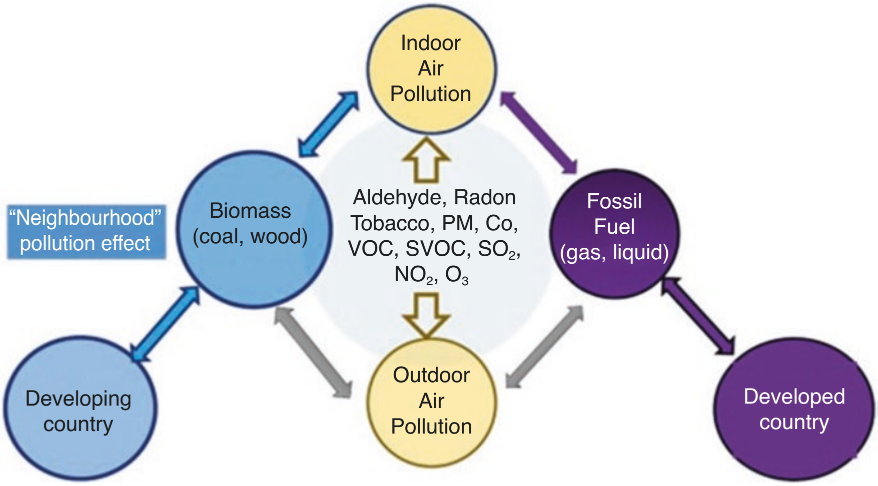

Fig. 7.2 Indoor and outdoor air pollution and its sources. (Source: Rosário Filho et al., 2021)

propensity in which cessation of exposure to the occupational or environmental setting could lead to its resolution. According to Wargocki et al. (2000), enhanced ventilation can reduce SBS and improve indoor air quality. Radon is a radioactive, odourless, and colourless gas that is known to be a significant contributor to the incidence of lung cancer in numerous countries. It is considered an indoor air pollutant that is commonly found in stony construction materials or inadequately ventilated basements of residential homes. The quality of indoor air is contingent upon specific indoor activities, including smoking, cleaning, and employing wood burning for the purposes of heating and cooking (He et al., 2004; Leung, 2015). He et al. (2004) assessed the concentrations and emission rates of particulates in indoor environments resulting from various indoor activities and sources. The findings of the study revealed that cooking-related activities could increase the PM number concentration by a factor ranging between 1.5 and 27 times. Additionally, the urban heat island effect has been observed to create numerous challenges for individuals especially residing in tropical regions with high atmospheric temperatures (Memon et al., 2009). The urban heat island phenomenon is exacerbated in metropolitan regions as a consequence of global climate change, resulting in prolonged periods of indoor occupancy and escalated reliance on air conditioning systems. Consequently, increased exposure of humans to indoor biological and chemical pollutants may potentially generate deleterious consequences on public health (Leung, 2015).

Air pollutants are further classified as hazardous air pollutants and criteria air pollutants, although both types of pollutants are "hazardous" (Vallero, 2014a).

Hazardous Air Pollutants

Hazardous air pollutants, commonly called "air toxics", are the chemical substances recognized to induce cancer and other chronic illnesses in individuals, including reproductive complications and birth abnormalities, even at very minimal concentrations. Hazardous air pollutants typically exhibit spatial limitations within localized regions, commonly referred to as “hot spots”. These regions are predominantly found in industrial and urban areas, which may exhibit high concentration of hazardous pollutant like benzene or other chemical associated with a specific industrial activity (Vallero, 2014a).

Ecotoxicity, which is alternatively referred to as ecosystem toxicity, characterizes the potential threat that a substance may impose on divergent organisms inhabiting an ecosystem. Chemical hazards encompass several potential harms, including the risk of fire, chemical reactivity, and corrosivity. Hazards may potentially have biological attributes, such as biohazards, and physical attributes, including radioactivity. Biohazards are a category of biological agents that comprise various microorganisms, such as bacteria and viruses, as well as fragments of larger organisms, such as pollen and spores. Physical hazards can also be a consequence of air pollution, for example, an increase in melanoma cases because of increased exposure to UV radiation brought on by air pollutants that reach the stratosphere and react with ozone. The critical determinants of a compound's potential hazard are its intrinsic toxicity, mobility within environmental media and tissues, durability, and tendency to amass in living tissue (Vallero, 2014a).

Criteria Pollutants

The criteria pollutants are those that are used to determine the quality of air in a region based on common standards. The criteria pollutants refers to prevalent air pollutants that possess the potential to adversely impact the health or well-being of the general public (Vallero, 2014a). The National Ambient Air Quality Standards (NAAQS) have been set up for each of the criteria air pollutants. In general, for the criteria air pollutants, the acceptable levels of exposure can be determined and for which an ambient air quality standard has been established e.g. particulate matter, ground-level ozone, sulphur dioxide, nitrogen dioxide, carbon monoxide and lead. Particulate matter (PM) refers to solid or liquid particles suspended in air and is one of the most important criteria pollutants monitored throughout the world. Particulate matter is further classified based on their aerodynamic diameter, as fine ($PM_{2.5}$) or coarse (PM_{10}) particles. PM is notorious for its propensity to induce severe health impacts, reduce visibility, and exacerbate climatic perturbations through radiative forcing.

Ground-level ozone (O_3) is a colourless gas known to provoke deleterious effects on both the environment and human well-being, specifically on vegetation and wildlife. Exposure to this pollutant can result in short-term effects such as respiratory distress, whereas long-term issues may arise, including chronic respiratory conditions such as asthma, bronchitis, and emphysema (Vallero, 2014a). Ground-level O_3 is also a primary ingredient of smog, another important air pollutant in the urban regions.

NO_2 is generated by numerous sources during the combustion process of fuel at elevated temperatures. NO_2 exhibits reactivity with various atmospheric constituents, resulting in the generation of a number of hazardous pollutants. Specifically, in the presence of water vapour, NOx undergoes reaction with ammonia and other relevant compounds, it forms fine particulates and favors the formation of ground-level O_3 upon reaction with VOCs. Studies have shown that even short term exposure to NO_2 can be detrimental to human health. For instance, an exposure for a duration of less than 24 hours has been documented to contribute to negative respiratory consequences, including the exacerbation of asthma episodes and inflammation of the airways among individuals without pre-existing respiratory conditions (Vallero, 2014a).

SO_2 is another important air pollutant which possesses the capacity to induce respiratory irritation, inflict damage upon crops through foliar stress, and cause degradation of materials when it encounters acidic aerosols. Additionally, atmospheric SO_2 has been found to be responsible for reduction in atmospheric visibility affecting road, rail and air traffic. Sulphur dioxide and other sulphur oxides undergo chemical reactions within the atmosphere, resulting in the formation of acids, with sulphuric acid (H_2SO_4) being a prominent constituent of acid rain.

Carbon monoxide (CO) is a by-product of inefficient or incomplete combustion processes. Carbon monoxide has been shown to elicit diverse health effects by binding to haemoglobin, resulting in the formation of carboxyhaemoglobin (COHb). The accumulation of COHb in the bloodstream leads to a reduction in the availability of oxygen (i.e. hypoxia) due to the increased concentrations of COHb in the blood (Vallero, 2014a). Furthermore, the respiratory system, the central nervous system, and the development of the foetus may also experience additional effects from its exposure.

Lead, a metallic element, is utilized in a plethora of industries, and it is primarily procured through mining activities, smelting operations, battery recycling procedures, and waste incineration facilities. The detrimental impacts of lead exposure in the atmospheric environment on human health include the manifestation of lead poisoning, neurotoxicity, and numerous other deleterious effects.

7.3 Status in Cities

Air pollution is a grave environmental concern, particularly in urbanized regions where a large population is exposed to air quality levels that exceed the established emission thresholds. It has been projected that by 2025, urban areas will be inhabited by approximately 60% of the global populace. As per projections, the overwhelming majority (93%) of urban expansion will be observed in emerging nations, especially Asia and Africa which are projected to exhibit high growth rates (80%) (Sofia et al., 2020). Urban areas occupy <5% of the Earth's surface, yet they are accountable for generating as much as 80% of global CO_2 emissions (Ghosh & Maji, 2011). According to estimates from the World Health Organization (WHO), the inhalation of $PM_{2.5}$ particles contributed to the premature deaths of 4.2 million people worldwide as of 2016 caused by ambient air pollution (Fino, 2018).

Urban form, which pertains to the spatial configuration, composition, and compactness of urban land uses, will experience significant transformations in the future as a result of the extensive urbanization (Liang & Gong, 2020). Small cities having high residential density promotes the usage of public transportation and walking (Liang & Gong, 2020; Rodriguez et al., 2016). According to a study of 83 urban regions around the world, those with closely spaced built-up areas release less NO_2 (Bechle, 2011) and are thus effective at reducing air pollution, while dispersed cities can decentralize industrial polluters, enhance the efficiency of fuel and reduce transportation congestion (Glaeser & Kahn, 2003), enabling the decentralization of jobs, which reduces pollution emissions. A dispersed city's greater open spaces promote air dilution. However, compact cities are frequently associated with greater urban heat island effects influencing the availability and advection of air pollutants (Liang & Gong, 2020). The behavioural aspects of the people residing in compact cities appear to be an important factor in determining air pollution levels (Piracha & Chaudhary, 2022). Indicators of urbanization included population and development level and scale of the city, which have direct effects on the prevalence of air pollution. Increased building construction in cities led to a decrease in vegetation areas as well as reduced plant adsorption capacity for air pollutants, along with higher concentrations of particulate matter and dust in the air (Chen et al., 2022). Thus, the conflicting findings reveal the intricate interaction between air pollution and urban form, suggesting that an erratic association may be present in cities at various levels of urbanization and at different times. As a result, any planning strategy intended to reduce air pollution should take into account the current state of development and adapt its future plan accordingly (Liang & Gong, 2020).

Although air pollution is a global problem, as it affects all places, considerable variation in air pollution levels is observed in different regions. For illustration, the $PM_{2.5}$ annual average concentration in the most polluted cities was approximately 20 times higher than that in the cleanest metropolis in a survey of 499 global cities (Liang & Gong, 2020). The average total number of O_3 and $PM_{2.5}$ days from 2008 to 2012 ranged from 3.81 days and 0.95 days in non-core counties to 47.54 days and 11.21 days in large central metropolitan counties, respectively (Strosnider et al., 2017). Therefore, to estimate variations in air quality caused by urbanization, more thorough analyses with improved modelling techniques may be needed.

7.4 Monitoring of Air Pollutants

Ambient air monitoring is the systematic and long-term measurement of air pollution levels and specific pollutant types in ambient air. The ambient air quality monitoring network entails the selection of locations, pollutant types, infrastructural facilities, duration, frequency and procedures of sampling, operation, and manpower (Haque & Singh, 2017). In 1984, India's Central Pollution Control Board (CPCB) launched National Ambient Air Quality Monitoring (NAAQM), later renamed the National Air Monitoring Programme (NAAQP), for the continual monitoring of air quality in major cities and industrial towns of the country.

To monitor air pollution, different methods, such as automatic, semiautomatic, and manual methods, are used. Automatic methods involve the use of equipment that directly measures pollution, allowing for real-time monitoring of air pollution. Semiautomatic approaches involve the collection of air quality samples from equipment at specific locations and then transporting and analysing these samples in the laboratory. Manual methods involve collecting samples manually, for example, CO monitoring. Developing an emission inventory (EI) is critical for describing pollutant emissions and regulating air quality. For modelling air pollution, many different scales are available, including microscales (street canyons), mesoscales (country, city), and global, regional, or continental scales. Numerous mesoscale models, including CHIMERE, METPOMOD, CMAQ, and TAPOM, are used to simulate the air quality of urban areas. EIs, land use, meteorological conditions, terrain, and borders are all input parameters into these air quality models (Ho, 2012).

GIS Tools in Air Pollution Studies

Geographical Information System (GIS) is a computer assisted program that maps and analyses the Earth and other geographical data. GIS applications combine distinct visualizations with databases that enable data acquisition, collection, storage, manipulation, modelling, analysis, retrieval, and display of georeferenced data (Ahmad et al., 2015). Information from sources such as remote sensing, including satellite and aerial images, earthbound surveys, and cartography, that is, maps, is used by GIS to construct overlapping layers that may be accessed and edited interactively in one spatial structure (Kamińska et al., 2004).

GIS can be used to analyse trends and environmental effects brought on by human activities, as well as to help predict potential outcomes and plans at various governmental levels. GIS applications include creating dynamic databases and developing spatial correlations with the temporal distribution of epidemiological data. The application of GIS tools in monitoring, analysing, and modelling pesticide migration in the environment and its ultimate health impacts has increased. Studies related to public health and the environment using GIS analysis have produced significant findings that may ultimately aid in preventing excessive or uncontrolled exposure to xenobiotics. Such studies, however, still rarely employ GIS technology, especially in developing nations where there is little awareness of the technology's availability and advantages (Kamińska et al., 2004).

There are numerous ways to use data from real-world GIS database models for environmental investigations. Data inputs, database transformation (data query and data analysis), and data output are the three basic GIS components. Input data include points (e.g. for soil pit locations), linear features (e.g. for depicting networks of roads), aerial polygons (e.g. for depicting forest areas), and other sources, such as information from traditional maps and ground surveys (registered by GPS), provided they provide spatial information. Input data are typically in vector or raster format. GIS provides output as digital or analogue maps, tabular data, and reports that contain records on the outcomes and a list of the processes followed throughout database analysis. Primarily, GIS enables transforming the coordinate system of input data, converting raster images into vector images, and extracting, overlaying, and managing data (Kamińska et al., 2004).

GIS has wide applications in air pollution studies, including air quality assessments, pollution data visualization, and decision-making processes, and thus, regulates pollution and air quality (Sówka et al., 2020; Tecer & Tagil, 2013). GIS applications can be used to monitor air pollutant emissions from various sources, manage spatial and statistical data, and facilitate visualization of the relationship between environmental health and the number of times human activities result in poor air quality. GIS modelling and statistical analysis can be used to study and predict the effects of climatic factors on air pollution. Air pollution mapping helps identify sources of pollution, determine the concentration of pollutants, and control emissions. A number of GIS-based air pollution studies have been undertaken. For environmental modelling with GIS applications, air quality management systems (AQMSs) are used to locate monitoring stations, develop geospatial models, and support spatial decision-support systems. GIS applications can be used to create three-dimensional spatial records of pollutants in AQMSs (Ahmad et al., 2015). Bozyazi et al. (2000) performed GIS spatial analysis to determine Istanbul's air pollution levels in connection to land use, and their findings revealed that the city's air pollution levels were closely associated with land use type.

Surface modelling using spatial interpolation is an advanced GIS tool for location-oriented analysis. Sówka et al. (2020) found that the ordinary kriging method, which is a widely used technique for geospatial interpolation and estimation, enabled accurate spatial presentation of variation in $PM_{2.5}$ concentrations at sites not covered by measuring systems. According to Ung et al. (2002), "virtual stations" are also generated using GIS statistical interpolations. The thin plate spline approach of geographic databases and remotely sensed data from the LANDSAT Thematic Mapper sensor are combined to carry out this process. Additional measurements from virtual stations serve as input data for additional extrapolation and interpolation techniques. The method of "virtual measuring stations" has also been used in a study by Beaulant et al. (2008) to virtually densify the network of permanent measuring stations. The quality of interpolation is intended to be improved by increasing the amount of pollutant concentration data.

Geostatistics uses spatial correlation to solve estimation problems, presented using variogram models (Bozyazi et al., 2000). These methods have been applied to several issues, including mapping. By using GIS geostatistical analysis, the relationship between long-term exposure to air pollution and illness incidence rates (such as cancer and bronchitis) can be determined. Geostatistics finds application in providing predictions for unsampled locations, as exhaustive studies are costly and time-consuming (Pandey et al., 2013). GIS facilitates decision-making by preparing thematic maps of variations in pollutants, which also helps in analysing the cause of decreases or increases in value, determining the most afflicted localities and subsequently taking the appropriate remedial measures by decision makers (Vaddiraju, 2020).

GIS is useful in creating health risk maps, as it assists in establishing relationships between population density, distribution of air quality, and health risk. Spatial interpolation techniques can be used to create a health risk map that depicts the spatial distribution of respiratory symptoms and disorders (Pandey et al., 2013). Thus, GIS tools have various applications in monitoring pollutant emissions and serve as a powerful tool for conserving the quality of air.

7.5 Causes of Air Pollution

Air pollution can result from both natural and anthropogenic sources. Natural sources polluting air include dust storms, volcanic eruptions (emitting S, Cl, ash particulates), sea salt spray, wildfires (releasing smoke, CO), pollen dispersal, vegetation (giving off VOCs), and natural radioactivity (e.g. radon gas formed from radium decay). Population density, housing, traffic, and industry accumulation are anthropogenic causes that intensify air pollution in urban areas (Martínez-Bravo and Martínez-del-Río, 2019). Anthropogenic activities causing air pollution include transport, power plants, waste treatment, industrial processes, households, agriculture, construction, mining, and warfare that are associated with the combustion of fuels of different kinds (Ahmad et al., 2015).

Sources of air pollution are also divided into point sources and non-point sources. Sources involving the emission of pollutants from a single place are referred to as point sources. It typically involves a combustion or mechanical process. Anthropogenic examples of point sources include power plants with smokestacks, and natural examples include the eruption of a volcano. Non-point sources involve the release of pollutants over a wide area and are classified as linear and area sources. A linear source corresponds to the main communication pathways, for example, roads and railways. An area source involves the release of pollutants within a defined geographic area. Human examples include a sizable port complex or oil refinery run by several different enterprises. Natural examples are a large agricultural field and a forest with a variety of coniferous and deciduous trees (Shendell, 2019).

Furthermore, pollution sources can be stationary (fixed or a preset pollutant emitter, e.g. refineries and power plants) or mobile (non-stationary, e.g. vehicles) sources (Ahmad et al., 2015). Different fuels are used to operate mobile sources, such as compressed natural gas, unleaded gasoline, and diesel (high or low sulphur content). Mobile sources of air pollution are further divided into two categories: on-road and off-road mobile sources. A few examples of on-road mobile sources related to human activity include automobiles, and off-road mobile sources include construction and farming equipment such as tractors and trains (on-land); aircraft carriers, motor-driven boats, cargo vessels, and submarines (on-water); and helicopters and aeroplanes (in-air). A “mobile line source” is a highway or main primary road that runs through suburban or urban areas (Shendell, 2019).

7.6 Concerns of Air Pollution in Urban Areas

Health Effects

Air pollution is linked to a plethora of negative health effects, such as cardiovascular and respiratory disorders, diabetes, infertility issues, cancer, and neurological diseases. Thus, the estimation of pollution cost is an economic assessment of the probability of becoming ill or premature death (Ferrante et al., 2015). Human beings are subjected to airborne pollutants through inhalation via the nose or mouth, ingestion of food that has been found to be contaminated, exposure to ocular pollutants via the eyes, and contact with environmental pollutants through the dermal or skin layers, regardless of whether the skin is intact or has open cuts (Shendell, 2019). Research by the United States Environmental Protection Agency (USEPA) finds that certain health conditions, such as the respiratory effects of air pollution exposure, can be directly linked to their economic consequences, such as the costs associated with doctor visits, lost school and work days, hospital visits, and, ultimately, deaths (Fig. 7.3).

The presence of airborne contaminants is accountable for the onset and persistence of acute or chronic respiratory illnesses. Acute illnesses encompass a spectrum of conditions, ranging from minor irritations to inflammatory responses, allergic reactions, compromised lung function, and even eventual respiratory collapse, contingent upon the exposure extent. Chronic diseases, which encompass cardiovascular diseases, chronic obstructive pulmonary diseases, and various types of cancers such as lung cancer are prevalent health concerns worldwide. The phenomenon of oxidative stress, stemming from air pollutant exposure, has been established to substantially contribute to chronic diseases, as postulated by Vallero (2014c). Current research suggests that chronic exposure to air pollution may induce neurological disturbances through the processes of atherosclerosis and oxidative stress (Manisalidis et al., 2020). The critical factors pertaining to particulates are their size, soluble fraction, and density. One example may be seen in the case of ultrafine particles, whose aerodynamic diameter measures less than 100 nm. These minute particles possess the ability to infiltrate deep into the lungs, as their penetration depth is inversely proportional to their size. Vapour pressure, density, and solubility are significant variables in assessing gaseous pollutants. High vapour pressure air pollutants are more prone to remain suspended in the atmosphere due to their propensity to exist in a vaporous state compared to those compounds that exhibit lower vapour pressures. The respiratory system may be subjected to detrimental impacts by several principal air pollutants in the vapour phase, including sulphur oxides, CO, NOx, O_3, and PM (Vallero, 2014c).

Particulate matter in diverse manifestations has been linked to the development of cancer, particularly concerning the organic portion of aerosols. Chemical substances, such as polycyclic aromatic hydrocarbons (PAHs), are associated with the occurrence of respiratory system cancers, specifically lung cancer. For instance, the compound benzo(a)pyrene has been found to be a causative agent in these cancers (Ferrante et al., 2015). Additional PM-related alterations include genotoxicity,

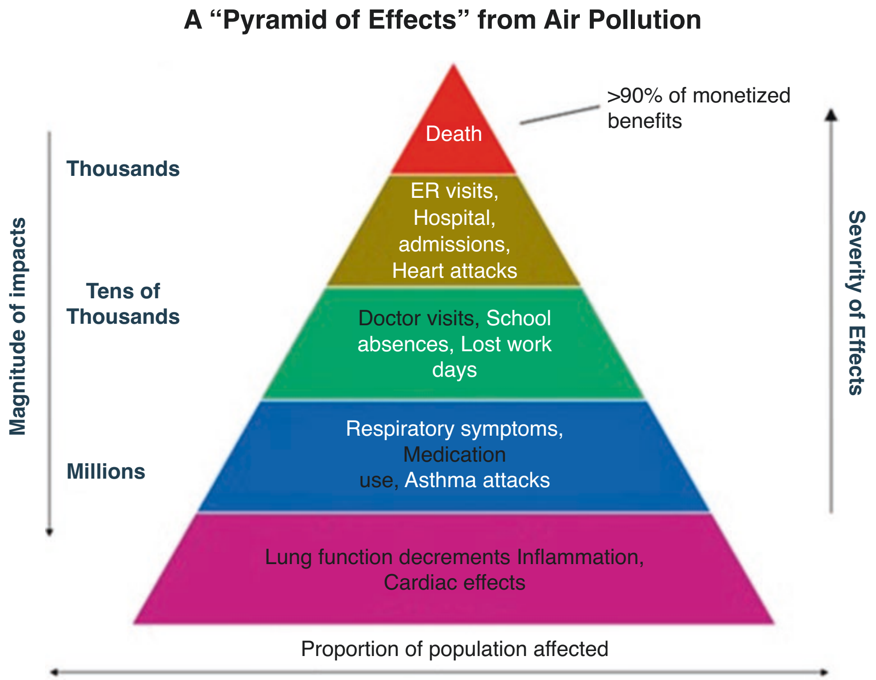

Fig. 7.3 Pyramid of effects from air pollution. (Source: United States Environmental Protection Agency, USEPA)

infertility, and low birth weight (Fortoul-van der Goes et al., 2015). Inhaling acute NO_2 concentrations causes respiratory distress, which has been linked to increased hospital emergency visits (Vallero, 2014a). Higher tropospheric O_3 concentrations are especially harmful to children, older adults, people doing heavy exercise or work who have elevated ventilation rates and therefore respiratory exposure dosages, and people already suffering from asthma or lung conditions. Since infants' lungs continue to develop postbirth and have prolific tissue that is more susceptible to environmental contaminants, infants are also vulnerable to higher ground-level O_3 concentrations (Vallero, 2014c). Black lung disease or pneumoconiosis is caused by coal dust. Silicosis is caused by rock dust from silica-containing rocks. Brown lung illness, also known as Byssinosis, has been linked to textile fibre exposure and may be caused by bacteria in cotton, making it a combination physical-chemical-biological air pollutants (Vallero, 2014c). Skin ageing, atopic dermatitis, eczema, urticaria, acne, dyschromia, and psoriasis may be caused by the absorption of air pollutants by human skin and are typically brought on by PM, oxides, and photochemical smoke upon exposure. Skin cancer has also been linked to pollutants (Eleni et al., 2014; Manisalidis et al., 2020). Suspended pollutant exposure also affects eyes, causing asymptomatic eye outcomes, irritation (Weisskopf et al., 2015), dry eye syndrome, or retinopathy (Manisalidis et al., 2020; Mo et al., 2019).

Air pollutants can harm the respiratory system's fluid dynamics directly (for example, by inflammation of airways) or indirectly (for example, by changing the immunological response). Air pollutants can cause lungs to become rigid by affecting surfactant chemistry and thus hindering inflation (Vallero, 2014c). Urban residents are more vulnerable to harmful health impacts caused by air pollutants due to extremely degraded air quality in urban areas produced mainly by heavy road emissions and myriad of other pollution sources. There is always a potential risk of industrial accidents that can lead to the spread of toxic fog and can prove devastating to the local populace. Overpopulation and unregulated urbanization, combined with industrialization, exacerbate the problem in emerging countries. Epidemiological studies have been carried out to verify the existence and quantification of adverse health consequences produced by air pollution, as well as to estimate dose–response relationships (Manisalidis et al., 2020). Statistical evaluations of monitoring and biomonitoring data also demonstrate a link between air pollution levels and morbidity and mortality rates. Furthermore, indoor, urban, and high-risk site outdoor pollution has different characteristics due to poor ventilation of houses, which permits the accumulation of different biological and chemical pollutants not found in comparable outdoor concentrations in severe pollution events. The concentration of heavy metals, which are often more prevalent and have a wide range of species in urban and industrial air pollution, is a significant difference between indoor and outdoor air pollution. In places with significant urban agglomerations, the incidence of neoplastic disorders is higher (Ferrante et al., 2015).

Metals that enter the respiratory system by direct interaction with DNA may result in chromosome abnormalities or gene mutations; these changes may promote cell proliferation and lead to the development of cancer (Cope et al., 2004). Depending on the amount absorbed, heavy metals such as lead can cause acute poisoning or chronic intoxication in humans (Manisalidis et al., 2020). Manganism, an extrapyramidal neurological condition that is characterized by bradykinesia, rigidity action tremor, and cognitive failure, may develop in workers exposed to airborne Mn. Cadmium affects the cardiovascular system and causes hypertension and atherosclerosis. Very low concentrations of mercury cause cardiovascular diseases and promote atherosclerosis. Mercury is also associated with neurotoxic effects (Alissa & Ferns, 2011). Even though these elements have serious harmful consequences, very scant knowledge is available specifically regarding the relationship between inhalation exposure and certain diseases (Fortoul-van der Goes et al., 2015). More research is needed to fully understand the damage mechanisms caused by pollutants to human health and to reduce exposure and mitigate its negative consequences.

Environmental Effects

Air pollution has adverse effects on the environment, including acid rain, smog, eutrophication, and damage to agriculture and ultimately ecosystems. According to Ashmore (2013), air pollutant problems may vary spatially, including regional problems such as acid deposition and tropospheric ozone caused by long-range pollutant transport or local environmental impacts of pollution, such as being limited to the area in the vicinity of a factory or a road.

Climate change, a consequence of environmental pollution, affects the geographical distribution of several infectious diseases (Manisalidis et al., 2020). Black carbon and ozone (short-lived climate pollutants) can exacerbate climate change, altering the frequency and duration of heat waves and cold spells, ultraviolet radiation exposure, precipitation patterns, etc. These changes can indirectly threaten urban lives and livelihoods (Mitchell et al., 2016). A warmer climate can affect surface pollutant concentrations by affecting the rate of atmospheric chemical reactions, biogenic VOC emissions, and atmospheric boundary layer height (Heal et al., 2013). Pollutant impacts may also vary temporally, for instance, the release of large pollutant concentrations accidentally, therefore causing immediate effects on biodiversity, which may further result in a delayed and gradual recovery, whereas other impacts may be the outcome of pollutant accumulation over years (Ashmore, 2013). Therefore, it is imperative to consider city pollution, regional pollution, and hot spot occurrences, which are defined by higher-than-average pollutant peaks followed by gradual restoration of normal limits while evaluating urban pollution (Ferrante et al., 2015).

The pathways followed by pollutants to enter ecosystems may be directly related to their impacts. Pollutants enter ecosystems as gases, particles, or both. Gaseous pollutants can be taken up through stomata or inhaled directly by animals. Pollutants may infiltrate ecosystems by rainfall, mist, or as particles in other instances. Gaseous pollutants such as NOx, SO_2, and NH_3 are also deposited as particulates, that is, nitrate, sulphate, and ammonium, through wet deposition and can not only impact organisms directly but also cause eutrophication and acidification of the environment over longer periods. Photochemical oxidants, such as O_3, are secondary pollutants formed in the presence of sunlight from chemical reactions involving VOCs and NOx. Direct uptake of O_3 by leaf tissue damages plant cells and reduces overall plant productivity. O_3 also causes substantial damage to a variety of materials, such as metals, paint, plastics, rubber, and fabrics. Metal deposition mainly occurs via rainfall or as particulate matter. Metals on deposition accumulate in soils or leach into freshwaters, which results in deleterious effects on soil organisms or plant roots at toxic concentrations. Persistent organic pollutants (POPs), another group of chemicals, raise concerns due to their possibility of large bioaccumulation in the food chain. The process of "global distillation", in which compounds volatilize in warmer portions of the Earth at ambient temperatures and become redeposited at cooler latitudes, provides evidence that the atmosphere can operate as a conduit to disperse these compounds. Their bioaccumulation in polar areas is therefore of considerable concern. For instance, it has been observed that fish from Antarctica, which is far from any immediate sources of pollution, have POP concentrations that are comparable to those found in fish from the North Sea (Ashmore, 2013).

Pollutant effects on organisms are intricate and dependent on a variety of variables. The amount of pollution, that is, dose ingested, is the most crucial of these variables. This will depend on pollutant concentration in the air and exposure duration to it. Acute toxicity is a short-term consequence of exposure to air pollution at higher concentrations, characterized by direct damage to exposed tissue and leaf damage. In contrast, chronic toxicity, which may be caused by exposure to air pollution over an extended period and at much lower concentrations, is typically characterized by changes in reproduction, growth, and physiology (Ashmore, 2013). Air pollutants rarely occur alone, and responses to mixtures of pollutants can result in synergistic or antagonistic effects. When the combined effect of two pollutants is larger than their individual effects, it is referred to as a synergistic response. For instance, when NO_2 and SO_2 are taken up together, they often have synergistic effects on vegetation. When the impact of a pollutant mixture is the same as that of individual pollutants or even has a lessened impact, it is called an antagonistic interaction. Furthermore, the deposition of one pollutant can affect the uptake and impacts of another pollutant over time. For instance, increased bioaccumulation of metals such as cadmium, mercury, and lead in fish and birds can be caused by freshwater acidification brought on by the deposition of nitrate and sulphate (Ashmore, 2013).

Therefore, estimating how much pollutant emissions should be reduced to ensure an acceptable degree of biodiversity protection is crucial. Not only are higher concentrations of air pollutants of concern but so are widely distributed contaminants with lesser quantities, the effects of which become apparent over many years. It is also essential to fully understand how pollution interacts with climatic, biological, and soil variables to precisely analyse the effects of pollution within an ecological context.

7.7 Challenges and Solutions

Challenges

Considerable challenges are posed to future urban resilience and public health protection by the climate change caused by air pollution, as urban populations would be subjected to greater temperatures than experienced at present (Milner et al., 2019). The physical and sociological characteristics of urban environments constantly change, which makes the intricate linkages between air pollution, metropolitan climate, and public health more difficult to understand and anticipate. Climatic conditions are further modified by emissions from vehicular traffic, vegetation, and urban structures, resulting in significant spatial gradients of heat and air pollution, which may eventually exacerbate health risks and social disparities in time and space. Changes in demographics or the built environment, whether planned or unplanned, may alter patterns of exposure to air pollution, temperature extremes, or other environmental hazards and may also aggravate deleterious impacts on the health of the urban population.

The growing population in urban centres is another cause creating complexities for city dwellers, such as housing shortages, lack of open spaces, traffic problems, slums, waste accumulation, and air pollution (Haque & Singh, 2017; Kumar & Singh, 2003; Singh et al., 1972). Urban air pollution impacts the urban poor more than the general population due to their greater susceptibility to diseases, as their health is below average, their housing quality is low, they lack knowledge about pollution, and they have less awareness of indoor pollution due to fuel burning for heating and cooking purposes, as is the case with slum dwellers, the most vulnerable section of urban society.

Inadequate monitoring and enforcement of regulations could result in more toxicity and higher emissions (Shendell, 2019). Additionally, little research has been undertaken to determine air pollution reduction caused by smart growth and other compact city design concepts (Piracha & Chaudhary, 2022). Therefore, to resolve the problems and conflicts among various economic, social, and environmental concerns at various levels, it is necessary to effectively regulate urban air pollution (Salmond et al., 2018).

Solutions or Mitigation Strategies

Reducing air pollution is essential for human health and environmental protection. Air pollution mitigation helps tackle climate change and forms the basis of sustainable development. The mitigation measures or solutions to curb air pollution and its consequent effects can be broadly grouped as regulatory measures, technological solutions, and behavioural changes.

Various regulatory steps or measures taken to mitigate air pollution include defining air quality legislation, various WHO air quality guidelines (AQGs) based on health-effect evidence, air quality standards, and the environmental policies established at the international level; for example, measures limiting emissions from vehicles, industries, and other sources, such as imposition of emission standards for vehicles such as limiting NOx emissions (Fino, 2018).

To regulate air quality, a number of laws have been enacted to govern air pollutant emissions in the atmosphere, such as the Clean Air Act 1956 introduced by the British Parliament in the aftermath of the Great Smog of London (1952), the U.S. Clean Air Act (CAA, 1963), administered by the United States Environment Protection Act (EPA), and the Air (Prevention and Control of Pollution) Act, 1981, in India to control and prevent air pollution nationwide. Ambient air quality standards (AAQS) have been adopted by the WHO (Table 7.1), many industrialized nations, and certain rapidly expanding economies (such as China and India) (Shendell, 2019). An air quality standard is defined as a specific level of air pollution adopted as enforceable by a regulatory authority. Standard formulation includes elements such as monitoring and measurement strategies, data handling processes, statistics, and quality control and assurance (Fino, 2018). The primary and secondary AAQS have been specified in the United States Federal Clean Air Act Amendments of 1990. The primary and secondary AAQS are given for certain pollutants, which vary depending on the emphasis placed on protecting human or ecological health as well as the quality of the environment. Primary AAQS is based on research related to human health (epidemiology, exposure assessments, toxicology, etc.). Secondary AAQS is established based on an emphasis on factors such as resource degradation, aesthetics, and visibility. Air quality standards are defined for specific time intervals, with specific measurement units and statistics (Shendell, 2019). As per resolution WHA68.8 adopted by the World Health Assembly, when using the WHO AQGs to develop standards, regulatory bodies and policy-makers must take social, cultural, and economic factors into consideration (Fino, 2018). The shipping industry and marine traffic contribute a significant proportion of global anthropogenic emissions. Shipping is intrinsically international; therefore, it is necessary to strictly implement uniform regulations at the global scale. Various measures have been taken, including the adoption of the MARPOL Convention and Emission Control Areas (ECAs) designation by the International Maritime Organization (Komar & Lalić, 2015). Furthermore, efforts that target transboundary air pollution need to be intensified and coordinated at local, national, and international levels. The Convention on Long-range Transboundary Air Pollution (CLTRAP) marked the beginning of a legally binding framework for addressing air pollution on a regional basis, adopted in 1979 by the UNECE (Fino, 2018).

Technological solutions to combat air pollution may include the usage of cleaner technologies in industries, renewable energy (energy generation), promoting hybrid vehicles with much less pollutant emissions, and growing urban vegetation that filters airborne PM. To reduce pollution emissions from automobiles, electric vehicles and hydrogen cell vehicles with no emissions (at tailpipe) must be used (Piracha & Chaudhary, 2022). The concept of a "smart city" is another important step that responds to the needs of inhabitants in a more efficient and sustainable manner (Cariolet et al., 2018).

The green infrastructure approach for cities such as growing plants can be used as barriers between people and air pollution from automobiles as well as to absorb air pollution (Piracha & Chaudhary, 2022). Barwise and Kumar (2020) discovered that certain biological characteristics of plants can effectively minimize transport-related air pollution and developed a framework for selecting plants to lessen exposure to air pollution. Overall, small leaf size, ideal vegetation height and density, and high leaf complexity are all factors in the elimination of transport-related air pollution, with taller vegetative barriers (between humans and traffic) being more beneficial in cases of open roads and shorter ones in cases of street canyons.

Table 7.1 Recommended 2021 AQG levels and 2005 air quality guidelines (WHO, 2021)

Pollutant	Averaging time	2005 AQGS	2021 AQGS
$PM_{2.5}$, μg/m^3	Annual	10	5
	24-hour[a]	25	15
PM_{10}, μg/m^3	Annual	20	15
	24-hour[a]	50	45
O_3, μg/m^3	Peak season[b]	–	60
	8-hour[a]	100	100
NO_2, μg/m^3	Annual	40	10
	24-hour[a]	–	25
SO_2, μg/m^3	24-hour[a]	20	40
CO, mg/m^3	24-hour[a]	–	4

Source: https://www.ncbi.nlm.nih.gov/books/NBK574591/table/ch3.tab 26/

[a]99th percentile (i.e. 3–4 exceedance days per year)

[b]Average of daily maximum 8-hour mean O_3 concentration in the six consecutive months with the highest 6-month running-average O_3 concentration

Building materials and design also have a significant influence on decreasing air pollution by using light-sensitive titanium dioxide to make buildings serve as a photocatalyst that reacts with and neutralizes air pollutants in the presence of oxygen and water vapours, converting harmful nitrogen oxide into nitrates. Strategies to mitigate the negative health effects of the urban heat island effect include increasing the solar reflectance and emittance of roofs and pavements by light-coloured roofs and increasing green areas to reduce heat capture (Piracha & Chaudhary, 2022). Minimizing emissions and increasing natural sinks of air pollutants is another solution to meet environmental challenges. Eco-friendly and sustainable practices are needed to reduce air pollution. According to Weyens et al. (2015), phytoremediation is an effective plant-based, economical, soil-stabilizing, sustainable, and environmentally friendly process to reduce air pollutants attributable to the gas-exchange mechanism in plants exchanging gases with ambient air. Through various mechanisms, plants and allied microbes absorb contaminants, both organic and inorganic, from the surrounding air and break down or detoxify them. However, uncertainties regarding the suitability and potential of particular species for specific pollutants still prevail, which necessitates future research in this field. Additionally, the slow removal process of phytoremediation, allowing the build-up of pollutants over a confined area, is another barrier to its widespread use (Agarwal et al., 2019).

Lifestyle changes such as the use of energy-efficient appliances, and public transport or bicycles for shorter distances are some behavioural responses to the mitigation of air pollution. Various governments and non-governmental organizations around the world have implemented low-carbon measures to direct sustainable urbanization practices towards improved health, such as the Istanbul Declaration of the North Atlantic Treaty Organization and the UN's Millennium Declaration. Urbanization had positive effects on global health in general. However, the health benefits of urbanization could be reversed by air pollution. To promote sustainable growth, the government should strike a balance between air pollution regulation and urbanization (Wang, 2018). Environmental governance should be processed concurrently with economic and urban development. It is necessary to raise public awareness along with the multidisciplinary approach by scientific professionals. More research on air pollution, including forecasting air pollutant quantities, especially the impacts of air quality indicators and long-term monitoring in different weather conditions, is required for sustainable development and formulation of government policies.

7.8 Conclusions

Urban populations experience multiple exposures to air pollution, resulting in severe health effects in terms of morbidity and premature deaths. The ever-increasing size of the population; lack of knowledge and awareness about air pollution; low housing quality in poor sections of urban society; indoor pollution, which has emerged as a major issue; and inadequate monitoring of emissions are some of the challenges that exacerbate urban air pollution problems. Deleterious environmental and health concerns due to urban air pollution must be addressed by adopting various mitigation strategies, such as renewable energy, green infrastructure, and low-carbon emissions, and by the introduction and stringent implementation of policies and air quality legislation. Understanding the perplexing relationship between air pollution and urban forms and tackling air pollution in conjunction with climate and public health issues can result in substantial progress towards sustainable urbanization.

Conflict of Interest The authors have no conflicts of interest.

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Chapter 8
Constructing the Dynamics of Water Quality Parameters Using Geospatial Technology and In Situ Observations

Neeta Kumari, Kiran Kadave, Susmita Marandi, Soumya Pandey, and Gaurav Kumar

Abstract Water quality assessment is a critical aspect of maintaining the health of aquatic ecosystem. The escalating issue of water pollution poses a significant threat to human well-being, necessitating the need for water quality evaluation. Geospatial technology, particularly GIS tools, plays a vital role in monitoring and mapping water quality over larger spatial and temporal scales. This chapter explores the integration of geospatial technology and in situ observations to enhance the understanding of water quality dynamics in aquatic ecosystems. Geospatial technology, including remote sensing from satellites, offers broad-scale coverage and continuous monitoring, providing data on various optical and thermal properties of water bodies. In situ observations involve direct measurements taken at specific locations, providing ground truth data for calibration and validation. This chapter delves into the potential of machine learning and artificial intelligence (AI) techniques to process and analyze vast and diverse data sets, improving predictive modelling and parameter retrievals. It discusses challenges such as spatial and temporal resolutions, atmospheric interference, and data integration, along with solutions for data assimilation, sensor network optimization, and real-time monitoring. Overall, this chapter provides valuable insights into the integration of geospatial technology and in situ observations, offering practical guidance for researchers and water resource managers seeking to construct accurate and comprehensive water quality dynamics in aquatic ecosystems.

Keywords Geospatial technology · In situ observations · Water quality dynamics · Remote sensing · Machine learning · Sustainability

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8.1 Introduction

Water quality assessment is of utmost importance for various reasons. It is crucial for the protection of human health. Clean and safe water is essential for drinking, cooking, and personal hygiene (Dinka, 2018). Assessing water quality helps identify potential contaminants, such as bacteria, viruses, and chemical pollutants, ensuring the provision of safe drinking water to communities and reducing the spread of waterborne diseases (Liang et al., 2006). In addition, water quality assessment plays a vital role in environmental conservation. Healthy water ecosystems are essential for supporting biodiversity, sustaining aquatic life, and maintaining ecological balance. By monitoring and managing water quality, we can identify pollutants, excess nutrients, and other stressors that can harm aquatic organisms, destroy habitats, and disrupt the delicate balance of ecosystems (Crain et al., 2009; Peters et al., 1997). This helps protect vulnerable species and preserve biodiversity. Additionally, water quality assessment is essential for the protection of recreational areas. Many water bodies serve as popular recreational areas where people engage in swimming, boating, fishing, and other water-based activities. Assessing water quality in these areas ensures the safety and enjoyment of individuals by identifying potential risks, such as high bacterial contamination or toxic algal blooms, and enabling timely warnings or appropriate management actions (Chorus & Welker, 2021; WHO, 2021). Moreover, water quality assessment is crucial for agricultural and irrigation management. Agriculture relies heavily on water resources for irrigation and livestock needs. Assessing water quality helps ensure that water used in agriculture is free from contaminants that may affect crop growth, livestock health, or soil quality (Molden, 2013; Saad & Gamatié, 2020). Assessments also aid in identifying and managing nutrient runoff from agricultural activities, minimizing the impacts on downstream water bodies. Industries and commercial establishments also benefit from water quality assessment (Kneese & Bower, 2013). Many industries require water for their operations, and monitoring water quality is essential to ensure compliance with environmental regulations and prevent the release of pollutants into water bodies.

By assessing water quality, industries can implement appropriate treatment measures and reduce their environmental footprint. Groundwater resources are also protected through water quality assessment. Groundwater serves as a vital source of drinking water and irrigation for many regions. Assessing water quality helps identify potential contaminants and pollutants that can infiltrate groundwater sources (Schmoll, 2006). By monitoring and managing water quality at the surface and subsurface levels, we can protect and sustain the quality of groundwater resources. Additionally, water quality assessment plays a crucial role in climate change adaptation (Taylor et al., 2013). Climate change can have significant impacts on water quality, including alterations in temperature, precipitation patterns, and the frequency of extreme weather events. Water quality assessment helps understand the impacts of climate change on water bodies and enables adaptive management strategies to mitigate adverse effects and ensure the resilience of aquatic ecosystems (Creighton et al., 2016). Finally, water quality assessment provides valuable data and information for policymakers, water resource managers, and stakeholders. This information assists in the development of effective regulations, policies, and management strategies to address pollution sources, prioritize water quality improvement efforts, and allocate resources efficiently. In conclusion, water quality assessment is vital for protecting human health, preserving ecosystems, and ensuring sustainable water resource management. It serves as a foundation for effective water management, environmental conservation, and public health protection.

8.2 Role of Geospatial Technology In Situ Observations in Understanding Water Quality Dynamics

The role of geospatial technology and in situ observations is paramount in understanding the dynamics of water quality. Geospatial technology, which encompasses geographic information systems (GIS), remote sensing, and spatial analysis, provides powerful tools for capturing, analysing, and visualizing spatial data related to water quality (Ritchie et al., 2003; Thakur et al., 2017; Yang et al., 2022). In situ observations, on the other hand, involve direct measurements and sampling at specific locations, providing ground truth data. Together, these approaches offer valuable insights into the complex dynamics of water quality and contribute to effective monitoring and management strategies.

Geospatial technology plays a crucial role in water quality assessment by integrating various data sources and enabling comprehensive spatial analysis (Griffith, 2002; Usali & Ismail, 2010). Remote sensing, using satellite or airborne sensors, provides large-scale and frequent measurements of water quality parameters (Topp et al., 2020). It allows for the collection of spectral data, capturing the reflectance of light from water bodies, which can be correlated with specific water quality indicators. By analysing remote sensing data, such as imagery and derived indices, patterns and trends in water quality can be identified over extensive areas and multiple time periods (Bierman et al., 2011). This helps in detecting changes, locating pollution hotspots, and understanding the spatial distribution of water quality parameters. Additionally, GIS facilitates the integration and visualization of diverse data sets, such as water quality measurements, hydrological information, land use patterns, and pollutant sources (Volk et al., 2008). Through spatial analysis, GIS enables the identification of relationships and correlations between water quality parameters and environmental factors. By overlaying and analysing different layers of information, GIS can identify potential sources of pollution, model pollutant transport, and assist in decision-making for water resource management.

In situ observations complement remote sensing data by providing detailed, localized information on water quality parameters (Becker et al., 2019). These observations involve field measurements and sample collection at specific sites.

In situ data collection enables the calibration and validation of remote sensing measurements, improving the accuracy and reliability of water quality assessments. In situ observations provide precise measurements of physical, chemical, and biological parameters, such as temperature, dissolved oxygen, nutrient concentrations, and the presence of specific organisms (Gholizadeh et al., 2016). These direct measurements help validate remote sensing data and provide ground truth information for accurate interpretation.

Combining geospatial technology with in situ observations allows for a more comprehensive understanding of water quality dynamics (Park et al., 2020). The integration of remote sensing data and in situ measurements helps overcome the limitations of individual approaches, providing a holistic view of water quality parameters at different spatial and temporal scales. It enhances the accuracy of water quality models and predictions, enabling better decision-making and resource allocation. Furthermore, geospatial technology and in situ observations are valuable tools in assessing the impacts of human activities, climate change, and land use on water quality. By monitoring changes in water quality over time, it is possible to identify trends and assess the effectiveness of pollution control measures. This information assists in the development of targeted strategies for mitigating pollution sources, protecting ecosystems, and ensuring sustainable water resource management.

8.3 Objective of This Chapter

The objective of this chapter is to provide a comprehensive overview of the construction of water quality dynamics using geospatial technology and in situ observations. It aims to highlight the significance of integrating these approaches for a better understanding of water quality parameters, their spatial and temporal variations, and their implications for environmental management and decision-making.

8.4 Fundamentals of Water Quality Parameters, Their Significance, and Implications

Water quality refers to the chemical, physical, and biological characteristics of water that determine its suitability for various uses and its impact on ecosystems and human health (Carr & Neary, 2008). Assessing water quality involves analysing different parameters that provide insights into the overall condition of the water body. These parameters can vary depending on the specific context and purpose of the assessment.

Physical Parameters

Temperature Water temperature plays a crucial role in determining the metabolic rates, behavior, and distribution of aquatic organisms. It affects dissolved oxygen levels, nutrient availability, and overall ecosystem dynamics. Changes in water temperature can disrupt the delicate balance of aquatic ecosystems, affecting the growth and reproduction of aquatic species. Temperature variations may lead to shifts in species composition, changes in habitat suitability, and altered ecological processes.

Turbidity Turbidity refers to the clarity or cloudiness of water caused by suspended particles. It provides insights into the presence of sediments, organic matter, or pollutants. High turbidity can indicate erosion, sedimentation, or runoff from construction sites, agriculture, or land development. It affects light penetration, which can inhibit aquatic plant growth and disrupt aquatic food chains. Monitoring turbidity helps identify sediment sources, assess water quality degradation, and mitigate impacts on aquatic ecosystems.

Chemical Parameters

pH pH measures the acidity or alkalinity of water. It influences chemical reactions, nutrient availability, and the physiology of aquatic organisms. Extreme pH levels can be harmful to aquatic life. Acidic conditions (low pH) can result from acid mine drainage or industrial discharges, while alkaline conditions (high pH) can occur in areas with limestone geology or excessive algal activity. Monitoring pH levels helps detect acidification or alkalization, assess impacts on aquatic life, and guide water treatment processes.

Dissolved Oxygen (DO) Dissolved oxygen is vital for the survival of aquatic organisms, as it supports their respiration and metabolism. Adequate DO levels are necessary for maintaining healthy aquatic ecosystems. Insufficient DO levels can lead to hypoxia or anoxia, causing stress or death to aquatic organisms. Low DO can result from pollution, eutrophication (excessive nutrient enrichment), or temperature changes. Monitoring DO levels helps identify water bodies at risk and assess the impacts of pollution or excessive nutrient input.

Nutrients Nutrients, including nitrogen and phosphorus, are essential for aquatic plant growth and ecosystem productivity. However, excessive nutrient input can lead to eutrophication, an overgrowth of algae and aquatic plants, which negatively impacts water quality. High nutrient levels can result from agricultural runoff, wastewater discharge, or improper fertilizer use. Eutrophication can lead to algal blooms, oxygen depletion, and the degradation of aquatic habitats. Monitoring nutrient levels helps identify nutrient sources, manage agricultural practices, and implement nutrient reduction strategies.

Chemical Oxygen Demand (COD) and Biochemical Oxygen Demand (BOD) COD and BOD indicate the amount of oxygen required for the degradation of organic matter, representing the pollution level. Higher COD and BOD values suggest the presence of high concentrations of organic compounds, such as sewage, industrial effluents, or agricultural runoff. Elevated levels of organic pollutants can lead to oxygen depletion in water bodies and negatively impact aquatic ecosystems. Oxygen depletion can be harmful to aquatic organisms, leading to hypoxic or anoxic conditions, which can result in fish kills and the disruption of the entire aquatic food chain.

Biological Parameters

Biotic Index Biotic indices use the presence and abundance of specific organisms to assess water quality and ecosystem health. By analysing the composition of biological communities, the impact of pollution and environmental conditions on aquatic ecosystems can be evaluated.

Presence of Indicator Species Certain species can indicate pollution levels or specific environmental conditions. The identification and monitoring of these indicator species allow for the detection and assessment of pollution levels, helping to target and prioritize management actions to improve water quality and protect ecosystem integrity.

Microbiological Parameters

Microbiological parameters, such as coliform bacteria and pathogens, indicate the presence of microbial contaminants and potential health risks. High levels of coliform bacteria or the presence of pathogens in water can indicate faecal contamination from sewage or animal waste (Cabral, 2010). This poses a risk to human health, causing waterborne diseases. Monitoring microbiological parameters helps ensure the safety of drinking water sources and recreational waters.

Toxic Substances

Heavy Metals Monitoring heavy metal concentrations (e.g., lead and mercury) is crucial due to their toxicity and persistence in water. Continuous exposure to elevated levels of heavy metals through drinking water or the consumption of contaminated fish and seafood can lead to various health issues, including neurological disorders, kidney damage, respiratory problems, developmental issues in children, and even cancer. Once in water, heavy metals can contaminate sediments, disrupt aquatic ecosystems, and bioaccumulate in organisms, leading to harmful effects on aquatic plants, animals, and microorganisms (Sonone et al., 2020).

Pesticides and Herbicides Monitoring agricultural runoff for the presence of these chemicals helps assess potential water contamination. Long-term exposure to these chemicals may have adverse health effects, such as developmental issues, reproductive problems, and increased cancer risks.

Radiological Parameters

Radionuclides Monitoring radioactive elements in water is important to ensure compliance with safety standards. Radionuclides in water can pose significant health risks to humans if ingested or absorbed through the skin (Naja & Volesky, 2017). Some radionuclides emit ionizing radiation, which can damage cells and increase the risk of cancer and other health effects.

Water quality parameters are measured through field sampling and laboratory analysis. Regular monitoring of these parameters provides data on trends, identifies pollution sources, and guides water resource management and pollution control efforts. Advances in technology, such as remote sensing and sensor networks, enable continuous monitoring and real-time data collection, enhancing water quality assessment and management. It is important to note that acceptable water quality standards and guidelines may vary depending on the intended use of water, such as drinking water, recreational activities, or ecosystem preservation.

8.5 Importance of In Situ Observations in Understanding Water Quality Dynamics

In situ observations play a crucial role in understanding water quality dynamics due to their direct and real-time nature. They provide valuable data obtained directly from the water body, offering a comprehensive and accurate assessment of water quality parameters (Glasgow et al., 2004). The importance of in situ observations in understanding water quality dynamics can be summarized as follows:

Accurate and Reliable Data In situ observations provide precise and reliable data, as measurements are taken directly at the location of interest. This eliminates uncertainties associated with data interpretation and ensures accurate assessments of water quality conditions.

Real-Time Monitoring In situ observations enable real-time monitoring of water quality, allowing for immediate detection of changes and variations. These real-time data can be crucial in identifying short-term fluctuations and understanding dynamic processes within the water body.

Spatial Variability Water quality can vary significantly across different locations and depths within a water body. In situ observations capture spatial variability, providing insights into the heterogeneity of water quality parameters. This information is essential for understanding local impacts and designing targeted management strategies.

Validation of Remote Sensing Data In situ observations serve as ground truth data for remote sensing measurements. By validating remote sensing data with in situ data, the accuracy and reliability of remote sensing-based water quality assessments can be enhanced.

Impact Assessment In situ observations allow for the assessment of the immediate impacts of pollution events or changes in environmental conditions. This rapid response capability is valuable in identifying potential pollution sources and promptly addressing water quality issues.

Long-Term Trends In situ observations can be conducted over extended periods, enabling the monitoring of long-term trends in water quality parameters. These longitudinal data help identify gradual changes or trends in water quality and support the evaluation of the effectiveness of management measures over time.

Water Resource Management In situ observations provide critical information for water resource management and decision-making. Understanding water quality dynamics helps in formulating effective strategies for pollution control, ecosystem conservation, and sustainable water use.

8.6 Sampling and Measurement of In Situ Data

In situ data collection for water quality assessment involves various sampling techniques and measurements to obtain accurate and representative information about the condition of water bodies. Grab sampling entails collecting discrete water samples at specific locations, providing instantaneous data for various parameters. Integrated sampling, on the other hand, involves continuous measurements as instruments are lowered through the water column, offering insights into variations with depth. Composite sampling combines multiple grab samples from different locations to create a representative sample, allowing for a comprehensive assessment of overall water quality. Passive sampling employs specialized devices or materials to absorb pollutants over time and is suitable for monitoring contaminants with low concentrations or for long-term studies. Continuous monitoring systems use automated instruments or data loggers to continuously measure parameters in real time, enabling the identification of short-term fluctuations and trends. Vertical profiling involves taking multiple grab samples at different depths, which is useful for studying changes in water quality with depth in stratified water bodies.

Measurements of key water quality parameters include physical (temperature, turbidity), chemical (pH, dissolved oxygen, nutrients), biological (biomass, algal blooms), and microbiological (coliform bacteria, pathogens) aspects. Temperature and turbidity are measured using thermometers and turbidimeters, respectively. For chemical parameters, pH meters, dissolved oxygen meters, and colorimetric methods for nutrients are employed. Biological parameters are assessed through field observations, plankton nets, or fluorometers for chlorophyll-a content. Microbiological parameters, such as coliform bacteria and pathogens, are measured using specialized testing kits to detect microbial contamination. By employing these techniques and measurements, in situ observations provide valuable insights into water quality dynamics, supporting effective water resource management and ensuring the protection of aquatic ecosystems and human health.

8.7 Geospatial Technology for Water Quality Assessment

Remote sensing plays a crucial role in water quality assessment by providing valuable information about water bodies from a distance without direct contact or physical sampling (Chawla et al., 2020). This technology uses sensors mounted on satellites, aircraft, drones, or other platforms to capture and measure various properties of water, allowing for continuous monitoring, spatial coverage, and temporal analysis. Remote sensing provides a powerful and cost-effective tool for water quality assessment, enabling timely and informed decision-making for sustainable management of water resources and protection of aquatic ecosystems. Some of the key roles of remote sensing in water quality assessment are given below.

Spatial and Temporal Monitoring Remote sensing allows for frequent and wide-area monitoring of water bodies, enabling the assessment of water quality over large geographic regions and across different time intervals. This helps in identifying long-term trends and seasonal variations and detecting sudden changes in water quality.

Detection of Pollutants Remote sensing can identify and quantify various pollutants, such as suspended sediments, chlorophyll-a (an indicator of algae and phytoplankton abundance), dissolved organic matter, and nutrients such as nitrogen and phosphorus. Monitoring these pollutants helps assess the overall health of aquatic ecosystems and potential impacts on human health.

Algal Bloom Monitoring Harmful algal blooms (HABs) can have detrimental effects on water quality and marine life. Remote sensing helps in the early detection and tracking of algal blooms, allowing authorities to take timely measures to protect public health and aquatic ecosystems.

Bathymetry and Bottom Characterization Remote sensing can measure the depth of water bodies (bathymetry) and provide information about the bottom composition. These data are essential for understanding habitat suitability, sediment distribution, and erosion patterns.

Identification of Land–Water Interactions Remote sensing can analyze the interaction between land and water, such as identifying sediment runoff from land-based activities and urban runoff and identifying potential pollution sources.

Water Temperature Estimation Remote sensing can provide data on water surface temperature, which is vital for understanding the thermal dynamics of water bodies, as temperature affects water quality and ecosystem dynamics.

Identification of Turbidity and Sediment Transport Remote sensing can estimate water turbidity, which is an essential parameter for understanding sediment transport, erosion, and the impact of land-use changes on water quality.

Emergency Response and Disaster Management Remote sensing can be used during environmental disasters such as oil spills or industrial accidents to assess the extent of contamination and guide response efforts.

Data Integration and Modelling Remote sensing data can be integrated with other environmental data, such as meteorological information, river flow data, and water quality measurements from field surveys, to create comprehensive models for water quality prediction and management.

8.8 Satellite Sensors and Their Capabilities for Water Quality Monitoring

Satellite sensors are essential tools for water quality monitoring due to their ability to capture large-scale, continuous data over vast areas. They can measure various optical and thermal properties of water bodies, providing valuable information for assessing water quality (Gholizadeh et al., 2016; Mushtaq et al., 2015, 2021). Some of the commonly used satellite sensors and their capabilities for water quality monitoring are presented below. These satellite sensors, among others, contribute to a comprehensive understanding of water quality by providing data on various parameters, such as chlorophyll-a, suspended sediments, turbidity, temperature, and water surface properties. Integrating data from different sensors enhances the accuracy of water quality assessments and supports effective management and conservation efforts for water resources. Table 8.1 presents the commonly used satellite sensors.

Moderate Resolution Imaging Spectroradiometer (MODIS) MODIS is onboard both the Aqua and Terra satellites and provides data at moderate spatial resolutions (250 m, 500 m, and 1 km). It measures ocean color, including chlorophyll-a concentration, which indicates the presence of phytoplankton and algae and thus the level of primary productivity and potential harmful algal blooms. MODIS can also estimate the concentration of suspended sediments and colored dissolved organic matter, providing insights into water clarity and turbidity.

Visible Infrared Imaging Radiometer Suite (VIIRS) VIIRS is mounted on the Suomi NPP and NOAA-20 satellites, offering similar capabilities to MODIS. It measures ocean color, chlorophyll-a, and suspended sediment concentrations, contributing to water quality assessment.

Sentinel-2 Part of the European Space Agency's Copernicus program, Sentinel-2 provides high-resolution (10–60 m) multispectral data. Its red-edge and near-infrared bands allow for accurate estimation of chlorophyll-a and other water quality parameters, even in coastal and turbid waters.

Landsat Landsat satellites provide moderate to high spatial resolution (30 m) multispectral data. Although not specifically designed for water quality, Landsat data can be used to assess water quality parameters such as chlorophyll-a, suspended sediments, and turbidity.

Hyperspectral Sensors Hyperspectral sensors, such as the airborne visible/infrared imaging spectrometer (AVIRIS), can provide high-resolution data with hundreds of narrow spectral bands. These sensors offer more detailed information on water constituents, allowing for improved identification and quantification of various water quality parameters.

Advanced Very High-Resolution Radiometer (AVHRR) AVHRR provides thermal infrared data that can be used to estimate water surface temperature essential for understanding thermal dynamics, which influence aquatic ecosystems and water quality.

Synthetic Aperture Radar (SAR) SAR sensors, such as those on Sentinel-1, can be used to monitor water surface roughness, detect oil spills, and track changes in coastal zones.

Table 8.1 List of the more commonly used spaceborne sensors in water quality assessments

Category	Satellite—sensor	Launch date	Spectral bands (nm)	Spatial resolution (m)	Swath width (km)	Revisit interval (day)
High resolution	Digital Globe WorldView-1	18 September 2007	Pan	0.5	17.7	1.7
	Digital Globe WorldView-2	8 October 2009	8 (400–1040)-1 Pan (450–800)	1.85–0.46	16.4	1.1
	NOAA WorldView-3	13 August 2014	8 (400–1040)-1 Pan (450–800)-8 SWIR (1195–2365)	1.24–3.7–0.31	13.1	1–4.5
	Digital Globe Quickbird	18 October 2001	4 (430–918)-1 Pan (450–900)	2.62–0.65	18	2.5
	GeoEye Geoeye-1	6 September 2010	4 (450–920)-1 Pan (450–800)	1.65–0.41	15.2	<3
	GeoEye IKONOS	24 September 1999	4 (445–853)-1 Pan (526–929)	3.2–0.82	11.3	~3
	SPOT-5 HRG	4 May 2002	3 (500–890)-1 Pan (480–710)-1 SWIR (1580–1750)	2.5 and 5–10–20	60	2–3
	CARTOSAT	5 May 2005	Pan (500–850)	2.5	30	5
	ALOS AVNIR-2	24 January 2006	4 (420–890)-1 Pan (520–770)	2.5–10	70	2

Moderate resolution	Landsat-8 OLI/ TIRS	11 February 2013	5 (430–880)-1 Pan (500–680)-2 SWIR (1570–2290)-1 cirrus cloud detection (1360–1380)-2 TIRS (10,600–12,510)	30–15–100	170	16
	Landsat-7 ETM+	15 April 1999	6 (450–1750)-1 Pan (520–900)-1 (2090–2350)-1 (1040–1250)	30–15–60	183	16
	Landsat-5 TM	1 March 1984	5 (450–1750)-1 (2080–2350)-1 (1040–1250)	30–120	185	16
	Landsat-5 MSS	1 March 1984	4 (450–1750)-1 Pan (1040–1250)	80	185	18
	EO-1 Hyperion	21 November 2000	242 (350–2570)	30	7.5	16
	EO-1 ALI	21 November 2000	9 (433–2350)-1 Pan (480–690)	10–30	185	16
	Terra ASTER	18 December 1999	3 VNIR (520–860)-6 SWIR (1600–2430)-5 TIR (8125–11,650)	15–30–90	60	16
	PROBA CHRIS	22 October 2001	19 in the VNIR range (400–1050)	18–36	14	7
	HICO	10 September 2009	128 (350–1080)	100	45–50	10

(continued)

Table 8.1 (continued)

Category	Satellite—sensor	Launch date	Spectral bands (nm)	Spatial resolution (m)	Swath width (km)	Revisit interval (day)
Regional-global resolution	Terra MODIS	18 December 1999	2 (620–876)-5 (459–2155)-29 (405–877 and thermal)	250–500–1000	2330	1–2
	Envisat-1 MERIS	1 March 2002	15 (390–1040)	300–1200	1150	Daily
	OrbView-2 SeaWiFS	1 August 1997	8 (402–885)	1130	2806	16
	NIMBUS-7 CZCS	24 October 1978	6 (433–12,500)	825	1556	6
	ERS-1 ATSR-1	17 June 1991	1 SWIR (1600), 1 MWIR (3700), 2 TIR (10,850–12,000), Nadir-viewing Microwave Sounder with channels at 23.8 and 35.6 GHz	1000 (MW sounder: 20 km)	500	3–6
	ERS-2 ATSR-2	22 April 1995	3 VIS-NIR (555–865), 1 SWIR (1600), 1 MWIR (3700), 2 TIR (10,850–12,000)	1000	500	3–6
	ENVISAT AATSR	1 March 2002	3 VIS-NIR (555–865), 1 SWIR (1600), 1 MWIR (3700), TIR (10,850–12,000)	1000	500	3–6
	Suomi NPP VIIRS	28 October 2011	5 I-bands (640–1145), 16 M-bands (412–12,013), DNB (500–900)	375–750	3060	1–2 times a day
	NOAA-16 AVHRR	21 September 2000	6 (650–1230)	1100–4000	3000	9

Source: Gholizadeh et al. (2016)

8.9 Retrieval Algorithms for Deriving Water Quality Parameters from Remote Sensing Data

Retrieval algorithms for deriving water quality parameters from remote sensing data are mathematical procedures that convert the radiometric measurements obtained by satellite sensors into meaningful and quantifiable information about the constituents and properties of water bodies. These algorithms use the relationship between the observed electromagnetic radiation (reflectance or radiance) and the inherent optical properties of water to estimate various water quality parameters (Mouw et al., 2015). The retrieval process can be complex due to the influence of atmospheric effects, sensor characteristics, and inherent variability in water constituents. The retrieval algorithms can vary based on the sensor used, water body type (e.g., coastal, open ocean, inland waters), and environmental conditions (Mushtaq & Nee Lala, 2017). Validation of the retrieved water quality data through in situ measurements and intercomparison with other sensors or retrieval methods is crucial to ensure accuracy and reliability (Bailey & Werdell, 2006). Additionally, as technology advances, more sophisticated algorithms and machine learning approaches are continuously being developed to improve water quality parameter retrieval from remote sensing data. An overview of the retrieval process and some commonly used algorithms for specific water quality parameters are given below:

Water-Leaving Radiance and Atmospheric Correction The first step in water quality retrieval is to remove the atmospheric effects from the satellite-measured radiance to obtain the water-leaving radiance, which only represents the contribution of water and its constituents. Atmospheric correction methods, such as the dark-object subtraction (DOS) method, atmospheric correction using a model (e.g., 6S, MODTRAN), and empirical line methods, are commonly used for this purpose.

Chlorophyll-a Concentration Chlorophyll-a is a pigment found in algae and phytoplankton, and its concentration is an essential indicator of water quality and ecosystem health. Common algorithms for chlorophyll-a retrieval include the blue–green algorithm, OC3 (Ocean Color 3), and OC4 (Ocean Color 4). These algorithms use specific bands in the blue and green regions of the electromagnetic spectrum to estimate chlorophyll-a concentrations (Fig. 8.1a, b).

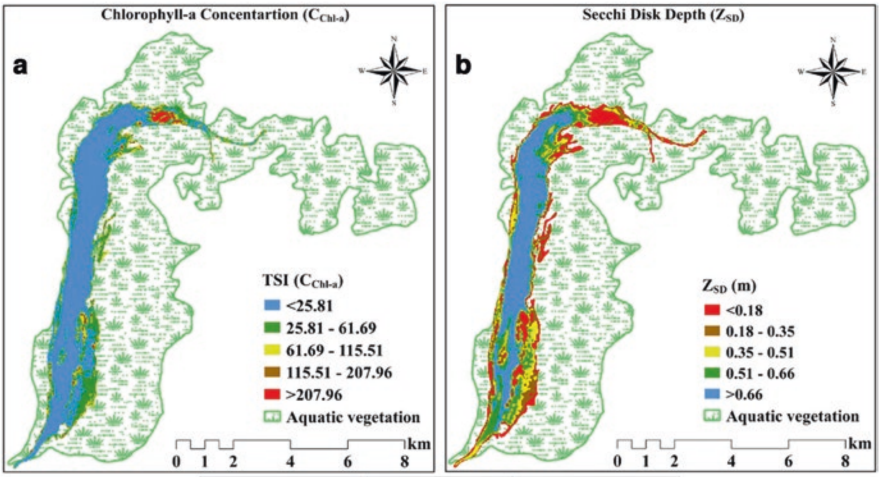
Suspended Sediments and Turbidity Suspended sediments and turbidity affect water clarity and light penetration. Since suspended matter is the primary cause of water turbidity, fluvial suspended sediment concentrations have frequently been determined using turbidity measurements. The suspended particulate matter (SPM) concentration can be estimated using algorithms such as the NIR-red band ratio, the NIR-green band ratio, or the turbidity index. These algorithms leverage the relationship between the spectral reflectance and the concentration of suspended particles in water. In a turbidity study in an ice-marginal lake at the Bering Glacier, Alaska, simple and multiple linear regression analyzes were performed using various bands, such as Landsat 7 ETM-F (Enhanced Thematic Mapper), which is used to find the best turbidity predictor in glacial lakes. The red portion of the electromagnetic spectrum, such as Landsat 7 ETM+ Band 3, and the near-infrared portion of the electromagnetic spectrum, such as Band 4, were used in the final algorithm to predict turbidity concentration (Liversedge, 2007). Maps based on algorithms that show turbidity are used in inter- and intraannual sediment analysis. Various researchers can use this information in the prediction of important glacial events for ex-surge events or outburst floods.

Colored Dissolved Organic Matter (CDOM) CDOM refers to the fraction of organic matter in water that absorbs light and imparts a brownish or yellowish color. Heterogeneous organic compounds that are naturally water soluble make up colored dissolved organic matter (CDOM). It absorbs visible and ultraviolet light. In situ folic acid production from the decomposition of seaweed is a primary production byproduct. The addition of industrial and domestic effluents contributes to an increase in CDOM concentrations in coastal waters. Due to seawater mixing and photodegradation, the optical characteristics of CDOM are altered in coastal environments. Algorithms for CDOM retrieval, such as the CDOM absorption model, use the relationship between the absorption of light by CDOM at specific wavelengths and its concentration.

Water Temperature Water temperature can be estimated using thermal infrared bands from sensors such as MODIS, VIIRS, or Landsat. Planck's law-based algorithm relates the radiance measured at specific thermal infrared wavelengths to water temperature.

Secchi Disk Depth The Secchi disk depth is a simple and widely used measure of water transparency. It can be estimated using algorithms that relate the Secchi disk depth to the water-leaving radiance or to the inherent optical properties of water, such as absorption and scattering coefficients (Fig. 8.1).

Total Suspended Matter (TSM) TSM includes both organic and inorganic particles suspended in water. Suspended matter is connected to total primary output by green plants, heavy metal input, and micropollutants. Researchers have discussed the connection between reflectance and suspended sediment. Suspended sediments cause surface water to radiate more in the visible and near-infrared ranges of the electromagnetic spectrum. Surface water radiance is influenced by sediment type, texture, color, sensor view, and sun angles, as well as water depth. The amount of suspended matter in inland water can be estimated and mapped using remote sensing techniques, which also provide temporal data. Algorithms for TSM retrieval often use a combination of reflectance bands from different parts of the spectrum and incorporate information on the specific absorption and scattering properties of the suspended matter (Mao et al., 2012). Many satellite platforms, including Landsat, SPOT (Satellite Pour Observation de la Terre), IRS (Indian Remote Sensing), CZCS



Descriptive statistics	C_{Chl-a} (µg/L)	Z_{SD} (m)
Minimum	1.79	0.02
Maximum	350.10	0.82
Mean	28.71	0.50

Fig. 8.1 Chlorophyll-a (**a**) and Secchi disk depth map (**b**) developed by Mushtaq et al., 2022 for Wular Lake using satellite and in situ derived algorithm. (Source: Mushtaq et al., 2022)

(Coastal Zone Color Scanner), and Sea-viewing Wide Field of View Sensor, have been used for remote sensing studies of suspended materials (SeaWiFS) (McKinna et al., 2011). These investigations have demonstrated a significant correlation between brightness and reflectance from a single band or a combination of bands in satellite or aerial platforms and suspended materials.

Phytoplankton Functional Types (PFTs) Eutrophication in a water body can be measured in terms of the amount of chlorophyll present in the algal plankton cells. One of the photosynthetic substances that affect the color of water is chlorophyll. There is a wealth of information available on employing remote sensing to map chlorophyll-a, a crucial measure for determining the quality of water and an indicator of algal concentration. Phytoplankton density has important implications for primary production and carbon cycle models. It also helps in the monitoring of the state of water bodies. During cyanobacterial blooms, large uncertainty persists in the detection of the amount of chlorophyll. Various assessments of chlorophyll in water are based on correlations between radiance and the narrow-band ratio. The various methodologies used for chlorophyll measurement are aircraft, Landsat, SPOT (Satellite Pour Observation de la Terre), SeaWiFS (Sea-viewing Wide Field-of-view Sensor) and CZCS (Coastal Zone Color Scanner) (Usali & Ismail, 2010). These methods use a variety of algorithms and wavelengths to map chlorophyll in oceans, estuaries, and freshwater. Advanced algorithms, such as the phytoplankton absorption and backscattering properties (PABP) algorithm, use hyperspectral data and models to distinguish different phytoplankton functional types based on their absorption and scattering properties.

Hyperspectral Imaging in Water Quality Monitoring

Hyperspectral imaging uses hyperspectral sensors. These are advantageous when high-precision and accurate concentrations of water quality parameters are required without any contact with the water. Accurate nonpoint pollution source detection is a difficult engineering problem. This technology has applications in various water-related analyses or imaging, such as from surface to water and from air to groundwater quality monitoring. Currently, hyperspectral images can be obtained by using DJI ground flight control software, and one such study has considered the range of 500–900 nm. There were 11 types of water quality parameter bands selected for the best combinations (Liu et al., 2021). Remote sensing helps in identifying the major parameters using their optical properties. Optical water indicators help in monitoring water quality parameters in a profitable manner. The data accumulated from water bodies determine the application of optical indicators.

8.10 Integration of In Situ Observations with Remote Sensing Data

Integration of in situ observations with remote sensing data is a powerful approach that combines the strengths of both methods to improve the accuracy and reliability of water quality assessments. In situ observations involve direct measurements taken at specific locations within a water body, while remote sensing provides broader coverage and continuous monitoring over large areas. By integrating these two sources of data, researchers and water resource managers can obtain a more comprehensive understanding of water quality dynamics (Ali et al., 2022; Yuan et al., 2022; Zhao et al., 2022) (Fig. 8.2).

Here are some key aspects of how in situ observations and remote sensing data can be integrated:

Calibration and Validation In situ observations play a crucial role in calibrating and validating remote sensing data. Calibration involves establishing the relationship between the satellite sensor's measurements (e.g., radiance or reflectance) and the actual water quality parameters measured in the field (e.g., chlorophyll-a concentration, turbidity, or suspended sediments). Validation involves comparing the remotely sensed data with in situ measurements to assess the accuracy of the retrieval algorithms and to identify potential biases or uncertainties.

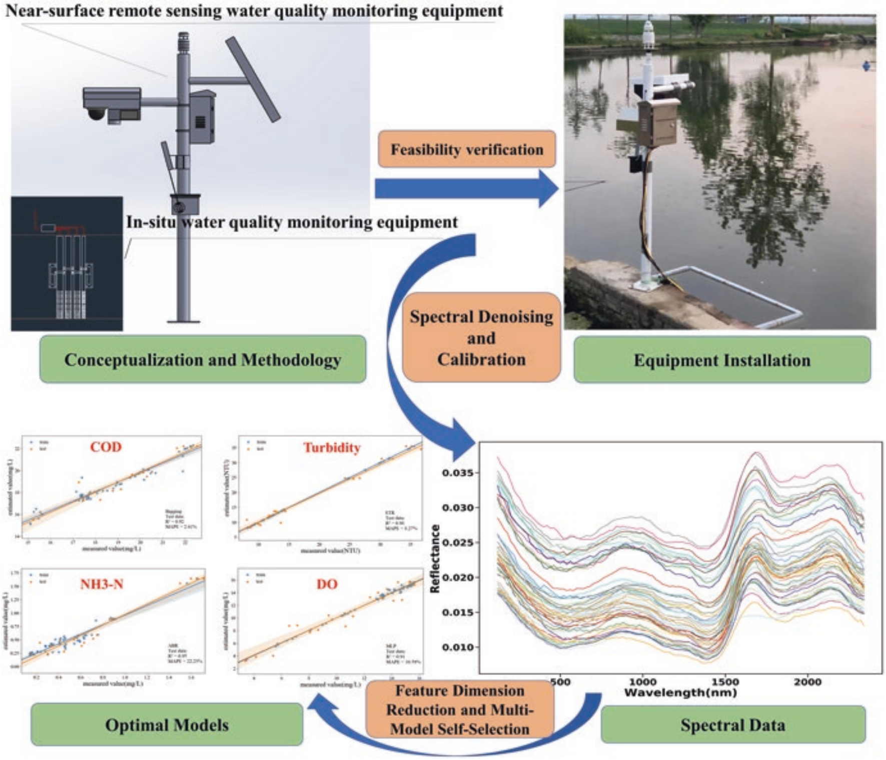


Fig. 8.2 The retrieval of water quality parameters based on near-surface remote sensing and the machine learning algorithm by Zhao et al., 2022 (Source: Zhao et al., 2022)

Training Data for Machine Learning Machine learning algorithms can be trained using in situ data to develop more accurate and robust water quality retrieval models from remote sensing data. By incorporating in situ measurements as training data, machine learning models can learn from the ground truth and improve their performance in estimating water quality parameters over a broader area.

Site-Specific Information In situ observations provide site-specific information, such as water quality data at specific locations or during particular events (e.g., algal blooms, storm events). This information can be used to validate and refine remote sensing-based water quality estimates for those specific areas or time periods.

Identifying Spatial and Temporal Patterns Remote sensing data offer extensive spatial and temporal coverage, allowing the identification of water quality patterns over large regions and across different time scales. By integrating in situ observations, researchers can validate these patterns and gain a deeper understanding of the spatial distribution and temporal variability of water quality parameters.

Data Assimilation in Models In hydrodynamic and water quality models, in situ data can be assimilated with remote sensing data to improve model accuracy and reliability. Data assimilation techniques merge both data sources, optimizing the model simulations and providing more realistic representations of water quality dynamics.

Monitoring Network Optimization Integrating in situ observations with remote sensing data can help optimize the design of in situ monitoring networks. By identifying critical areas or regions where in situ measurements are most needed, resources can be allocated more efficiently to enhance water quality monitoring efforts.

Emergency Response and Management During environmental emergencies (e.g., oil spills, harmful algal blooms), in situ observations can provide real-time, ground-truth data to validate and complement remote sensing data, supporting timely and effective response and management actions.

By integrating in situ observations with remote sensing data, water quality assessments can benefit from a more comprehensive and accurate understanding of aquatic ecosystems, leading to improved decision-making for sustainable water resource management and conservation.

8.11 Potential for Integrating Machine Learning and Artificial Intelligence in Water Quality Modelling

Integrating machine learning and artificial intelligence (AI) in water quality modelling has the potential to revolutionize the field and greatly improve the accuracy and efficiency of water quality assessments and predictions. Machine learning algorithms can learn from data and identify complex patterns, making them well-suited for handling the vast and diverse data sets involved in water quality monitoring (Xiao et al., 2022) (Fig. 8.3).

Enhanced Predictive Modelling Machine learning algorithms can analyze historical water quality data, along with other environmental variables (e.g., meteorological data, land use, and hydrological parameters), to build predictive models. These models can forecast future water quality conditions, helping water resource managers and policymakers make informed decisions and implement proactive measures.

Improved Retrieval of Water Quality Parameters from Remote Sensing Data Machine learning can be used to develop more robust retrieval algorithms that leverage the spectral information from remote sensing data to accurately estimate water quality parameters, such as chlorophyll-a concentration, turbidity, and suspended sediment levels.

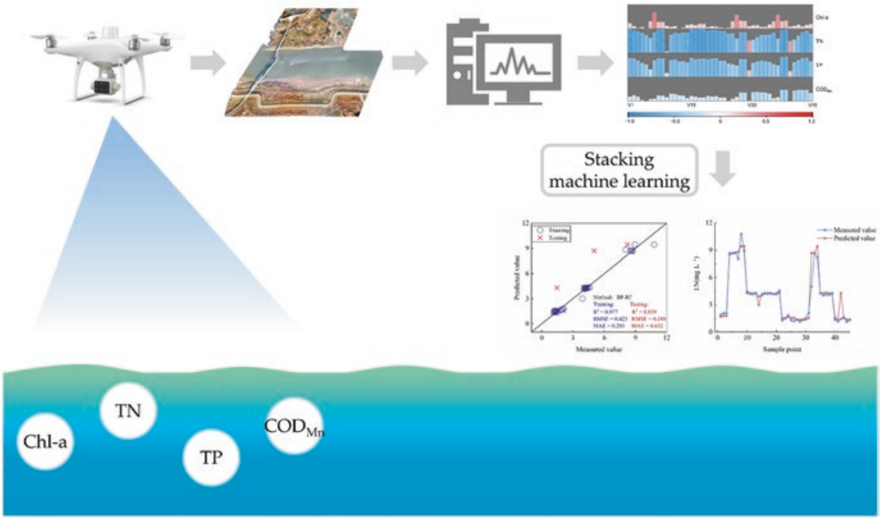


Fig. 8.3 Overview of UAV multispectral image-based water quality monitoring using stacked ensemble machine learning algorithms by Xiao et al., 2022. (Source: Xiao et al., 2022)

Data assimilation and Model Calibration AI techniques can assimilate data from multiple sources, including in situ observations, remote sensing data, and model simulations, to optimize model parameters and improve model accuracy. This data assimilation process helps to incorporate real-time observations and reduces uncertainties in water quality predictions.

Detection of Anomalies and Event Detection Machine learning algorithms can be used to identify anomalies or unusual events in water quality data, such as harmful algal blooms or pollution incidents. By detecting these events early, appropriate management actions can be taken promptly to mitigate potential impacts.

Sensor Network Optimization AI can optimize the design and deployment of in situ sensor networks. Machine learning algorithms can determine the optimal locations for sensors based on water quality patterns, reducing the number of required sensors while maintaining adequate coverage.

Real-Time Monitoring and Decision Support Integrating AI with sensor networks enables real-time data analysis, allowing for prompt response to changing water quality conditions. AI-driven decision support systems can aid in adaptive management and emergency response.

Automatic Data Quality Control Machine learning algorithms can automatically detect and correct errors in water quality data, ensuring the reliability and consistency of the data sets used in modelling.

Uncertainty Analysis AI can be utilized to quantify and manage uncertainties associated with water quality models. By understanding the uncertainty in predictions, decision-makers can make more informed choices when managing water resources.

Autonomous Water Quality Monitoring AI-powered autonomous platforms, such as drones or autonomous underwater vehicles, can be deployed to collect water quality data in remote or hazardous areas, providing valuable information for modelling and monitoring efforts.

Integrating machine learning and AI in water quality modelling offers tremendous potential for advancing our understanding of water systems and supporting effective water resource management (Sit et al., 2020). However, it is essential to ensure the availability of high-quality and diverse data sets, address ethical concerns, and maintain human oversight in decision-making to responsibly harness the full benefits of these technologies.

8.12 Limitations and Challenges in Constructing Water Quality Dynamics Using Geospatial Technology and In Situ Observations

Constructing water quality dynamics using geospatial technology and in situ observations comes with several limitations and challenges that need to be carefully addressed to ensure accurate and reliable assessments. One of the main limitations is the spatial and temporal resolution of geospatial technology, such as remote sensing. Satellite sensors with moderate to coarse spatial resolutions may not fully capture the spatial variability of certain water quality parameters at smaller scales, while short-term water quality events or processes can be missed due to limited temporal resolution. Additionally, remote sensing data are susceptible to atmospheric interference, which can introduce errors in the retrieved water quality parameters despite applying atmospheric correction methods. In situ observations also have limitations, including sensor drift, calibration issues, and spatial coverage constraints, which can impact the accuracy and representativeness of measured data.

Furthermore, validating remote sensing data with in situ observations poses challenges, as in situ data may not always coincide in time and location with satellite overpasses, leading to temporal and spatial discrepancies. The complex and dynamic nature of water bodies and their constituents presents another challenge, as interactions between different water constituents can lead to nonlinear relationships, making accurate parameter retrievals difficult. Moreover, data integration and harmonization from multiple sources can be challenging due to differences in spatial and temporal resolutions, data formats, and measurement units.

Financial and logistical challenges also arise in maintaining and operating both geospatial technology and in situ monitoring networks. The costs associated with establishing and maintaining in situ observations, especially in remote or hard-to-reach areas, can be substantial. Similarly, accessing and processing remote sensing data may require specialized infrastructure and expertise. Last, data accessibility and sharing can be hindered by factors such as data ownership, privacy concerns, and data format compatibility. Overcoming these challenges requires collaborative efforts among researchers, governments, and organizations. Advances in sensor technology, calibration techniques, and data integration methods will further improve our ability to construct accurate water quality dynamics using geospatial technology and in situ observations. Continuous research and innovation in this field are crucial for sustainable water resource management and the preservation of aquatic ecosystems. By addressing these limitations and challenges, we can make significant strides in understanding and managing water quality for the benefit of both humans and the environment.

8.13 Conclusion

Water quality is a very important factor that affects the health of aquatic ecosystems as well as human health. The most concerning environmental issue is the rising level of water pollution because it has a direct or indirect impact on flora and fauna health. Therefore, water quality assessment is now a top priority. The integration of geospatial technology and in situ observations is a powerful approach that holds significant promise in advancing our understanding of water quality dynamics in aquatic ecosystems. The combination of remote sensing data with ground truth measurements from in situ observations enables comprehensive and accurate assessments of water quality parameters. GIS tools play a vital role in monitoring and mapping water quality across different spatial and temporal scales. With the assistance of GIS technology, water quality parameters such as suspended matter, turbidity, phytoplankton, chlorophyll, and dissolved organic matter can be effectively tracked and analyzed. Additionally, GIS, in conjunction with remote sensing technology, allows for the creation of thematic maps that aid in determining groundwater potential zones. Spectral reflectance values from in situ water quality measurements provide valuable insights into the specific bands or wavelengths corresponding to various water quality parameters. The integration of hyperspectral imaging and ground truthing data further enhances water quality monitoring, enabling a comprehensive and accurate assessment of water quality dynamics. By leveraging GIS tools and remote sensing data, researchers and water resource managers can make informed decisions and implement effective strategies to ensure the sustainable management of water resources and the preservation of aquatic ecosystems. The integration of geospatial technology and in situ observations is a transformative step toward achieving our common goal of safeguarding the health and vitality of our water systems in an increasingly complex and interconnected world.

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Chapter 9
Urban Air Quality Monitoring and Modelling Using Ground Monitoring, Remote Sensing, and GIS

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Abstract This chapter explores the advancements in urban air quality studies, focusing on the utilization of ground monitoring systems, remote sensing, and GIS techniques in urban air quality monitoring and modelling. It provides an overview of the importance of monitoring urban air quality, the challenges associated with it, and the need for comprehensive and integrated approaches to address this issue. This chapter highlights the role of ground monitoring stations, remote sensing technologies, and GIS in assessing and managing urban air pollution. It also discusses the application of these techniques in modelling air quality and predicting air pollutant concentrations. By integrating these techniques, researchers and practitioners can enhance their understanding of air pollution patterns, develop effective pollution control strategies, and promote sustainable urban development. The case studies and applications discussed in this chapter serve as valuable examples for decision-makers and environmental managers looking to improve air quality in urban areas.

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Keywords Air quality · Dispersion models · DSS · GIS · Ground monitors · Remote sensing

9.1 Introduction

Urban air quality is a vast subject with different socioeconomic aspects in different parts of the world – and even within a specific region. Urban air pollution (UAP) is a significant global concern in developed and developing countries. The swelling urban population and increased motorized city traffic have resulted in severe air pollution affecting the surrounding environment and human health. The WHO has estimated more than two million deaths per annum along with various respiratory illnesses due to increasing UAP in developing countries (WHO, 2014). Originally, outdoor air pollution remained, by and large, a purely urban process, and historical records and literature testify that the difficulties were extensive. One of the significant sources of UAP is the road transport sector. In addition, industrial, commercial, and domestic activities likewise contribute to UAP. Over 70–80% of pollution in megacities in emerging nations is credited to vehicular emissions triggered by many older vehicles united with poor vehicle upkeep, inadequate road infrastructure, and low fuel quality (Wang et al., 2010). The criteria pollutants accountable for worsening urban air quality are oxides of sulphur dioxide (SO_2), nitrogen oxides (NO_x), particulate matter (PM), carbon monoxide (CO), and volatile organic compounds (VOCs). Resuspension of road dust due to traffic movement and tire and brake wear is also significant sources of ambient PM concentrations in urban areas (Amato et al., 2014).

Pollutants in ambient air have concentrations that are distributed heterogeneously in urban areas, fashioning hot spots in the dominant business district, signalized roadways, and traffic intersections. Additionally, meteorological and topographical variations in urban areas lead to complex temporal and spatial variations in pollutant concentrations. The spatial measure of urban air quality mapping differs from micro, medium to macrolevels. The hurdles in the source-control process of air quality management recommended developing a combined, risk supervision effect-based urban air quality management process. The data from traditional monitoring stations are vital because they can be used for law enforcement purposes and are accepted by the courts. However, the construction and upkeep of reference air quality monitoring stations are costly. Moreover, these large structures are often hard to locate and require the authorization of the local authority. It should be noted that they only provide air quality data from a fixed location, which may not represent local air quality. Urban air quality maps, therefore, depend heavily on air quality modelling with only a few valid data points. Spatial density monitors allow us to better understand the state of quality air of a place beyond a better granularity of the data.

This can be accomplished with the use of remote sensing and geographic information systems (GIS) in air quality modelling, as it offers significant advantages in understanding and visualizing the state of air quality in urban areas. Remote sensing technologies, such as satellite imagery and aerial sensors, provide a wide coverage area, allowing for the monitoring of air quality over expansive urban regions. Remote sensing provides the capability for real-time or near-real-time air quality monitoring. This continuous data collection is crucial for promptly identifying sudden changes or pollution events, aiding in timely responses to mitigate potential health and environmental impacts. On the other hand, geographic information systems (GIS) play a crucial role in air quality modelling by facilitating the spatial analysis and visualization of data. GIS platforms can combine data from various sources, such as remote sensing, ground monitors, meteorological data, and land-use information, to create detailed air quality maps and models. These models can be used to simulate potential scenarios and evaluate the effectiveness of different mitigation strategies.

9.2 Ground Monitoring Techniques

Determining and controlling atmospheric pollutant emissions, comprehending pollutant dispersion, and monitoring emission levels or concentrations in ambient air are necessary for protecting the atmosphere. Therefore, ground-based air quality monitoring networks are essential. These networks are made up of monitoring stations that are judiciously positioned throughout various regions to provide real-time data on air pollutant concentrations, meteorological, and other parameters. The primary goal of these networks is to record the concentration levels of atmospheric pollutants to define air quality limits and mitigation plans in the event where high amounts of contamination are identified. Table 9.1 presents an overview of measurement techniques and permissible limits of criteria pollutants (CPCB: NAAQMS/36/2012–13) along with major emission sources and health impacts. Criteria pollutants are a set of common air pollutants that are regulated by environmental agencies due to their detrimental effects on human health and the environment (US EPA, 2015). The six primary criteria pollutants, as defined by the United States Environmental Protection Agency (EPA), include carbon monoxide (CO), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), particulate matter (PM), lead (Pb), and ground-level ozone (O_3) (US EPA, 2022). These pollutants are continuously measured and monitored by thousands of monitoring stations spread across specific countries or regions. These monitoring stations are maintained by various governmental and nongovernmental organizations that further collect, archive, and distribute the air quality dataset (Fig. 9.1). The system gathers data from a variety of monitoring stations, including federal, state, local, and tribal authorities, as well as industry sources, to provide a comprehensive picture of air quality across the

Table 9.1 Criteria pollutants and monitoring techniques

S.No.	Pollutants	Sources	Ambient concentration		Methods of measurement	Health effects
			Time weighted average	*NAAQS standard*[a]		
1.	Sulphur dioxide (SO_2) in µg/m^3	Primary emission (fossil fuel burning)	Annual[b]	50	1. Improved West and Gaeke 2. Ultraviolet fluorescence	Respiratory diseases Cardiovascular problems Premature death
			24 hours[c]	80		
2.	Nitrogen dioxide (NO_2) in µg/m^3	Primary emission (fossil fuel burning) Secondary formation	Annual[b]	40	1. Modified Jacob and Hochheiser 2. Chemiluminescence	Respiratory problems Increased risk of respiratory infections Aggravation of asthma symptoms
			24 hours[c]	80		
3.	Particulate matter ($PM_{2.5}$) in µg/m^3	Primary emission (anthropogenic sources)	Annual[b]	40	1. Gravimetry 2. TEOM 3. Beta attenuation	Respiratory and cardiovascular problems
			24 hours[c]	60		
	Particulate matter (PM_{10}) in µg/m^3	Primary emission (natural sources)	Annual[b]	60		
			24 hours[c]	100		
4.	Ozone (O_3) in µg/m^3	Photochemical formation	8 hours[c]	100	1. UV photometry 2. Chemiluminescence 3. Chemical method	Respiratory issues Skin cancer
			1 hour[c]	180		
5.	Lead (Pb) in µg/m^3	Primary emission (fossil fuel burning and waste incineration)	Annual[b]	0.50	1. AAS/ICP method 2. ED – XRF	Neurological and developmental issues
			24 hours[c]	1.0		
6.	Carbon monoxide (CO) in mg/m^3	Primary emission (incomplete combustion)	8 hours[c]	02	Non-dispersive infra-red (NDIR) spectroscopy	Carbon monoxide poisoning and death
			1 hour[c]	04		

Source: NAAQMS/36/2012–13

[a]Permissible limit for industrial, residential, rural, and other areas (except ecologically sensitive areas)

[b]Annual arithmetic mean of a minimum of 104 measurements in a year at a particular site taken twice a week 24 hours at uniform intervals

[c]24 hourly, 8 hourly, or 1 hourly monitored values, as applicable, shall be complied with 98% of the time in a year. 2% of the time, they may exceed the limits but not on 2 consecutive days of monitoring

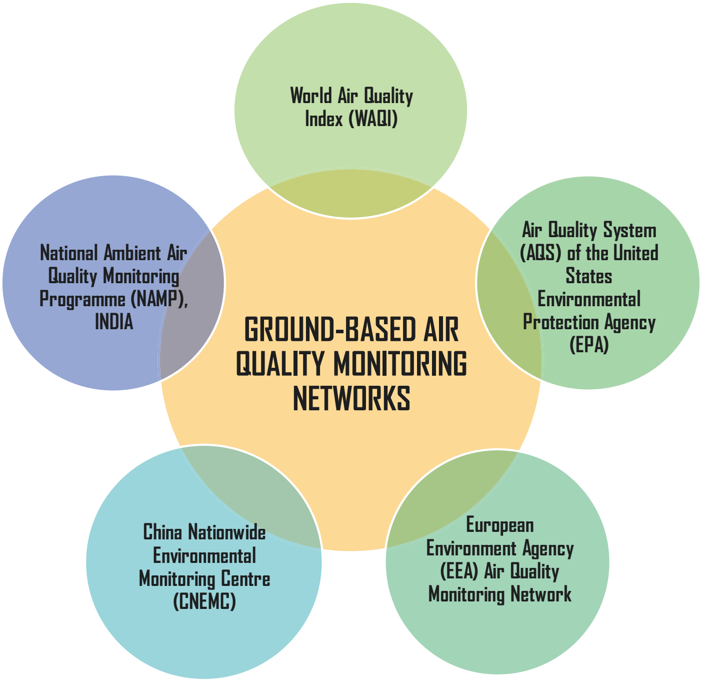

Fig. 9.1 Various ground-based air quality network across the globe

country or region. The information gathered is widely used by researchers, policy-makers, and the general public to access and analyse data on air pollution and its effects on human health and the environment. Furthermore, the air quality index (AQI) is utilized by government agencies, environmental organizations, and researchers to convey the air quality status to local communities (Table 9.2). The AQI serves as a measure of air pollution levels and the corresponding health hazards within a particular region.

Data Analysis and Interpretation

In air pollutant studies, data analysis methods are crucial for interpreting and understanding the collected data. A few of the common data analysis methods used in air studies are:

Descriptive Statistics Descriptive statistics provide a summary of the data collected in a clear and concise manner. This includes measures such as the mean, median, mode, standard deviation, and range (Table 9.3). Descriptive statistics help in understanding the central tendency, dispersion, distribution, and shape of the air

Table 9.2 Air quality index scale

Index values	Category	Cautionary statements	$PM_{2.5}$ (μg/m^3)	PM_{10} (μg/m^3)
0–50	Good	None.	0–15.4	0–54
51–100	Moderate	Unusually sensitive people should consider reducing prolonged or heavy exertion.	15.5–40.4	55–154
101–150	Unhealthy for sensitive groups	Sensitive groups should reduce prolonged or heavy exertion.	40.5–65.4	155–254
151–200	Unhealthy	Sensitive groups should avoid prolonged or heavy exertion; everyone else should reduce prolonged or heavy exertion.	65.5–150.4	255–354
201–300	Very unhealthy	Sensitive groups should avoid all physical activity outdoors; everyone else should avoid prolonged or heavy exertion.	150.5–250.4	355–424

Source: US EPA (2022)

Table 9.3 An example of a statistical table of the air quality dataset

	$PM_{2.5}$	PM_{10}	NO_2	CO	O_3	SO_2
Count	290,621	227,747	292,359	268,197	290,539	292,462
Mean	58.78	88.05	45.79	0.96	55.69	8.98
Std	66.11	89.29	32.06	1.00	53.82	11.70
Min	2.0	5.0	1.0	0.1	1.0	1.0
25%	16.0	37.0	20.0	0.4	2912.0	2.0
50%	39.0	70.0	39.0	0.7	45.0	5.0
75%	77.0	113.0	66.0	1.2	79.0	11.0
Max	1004	3000	300	15	504	307

Source: Zhang et al. (2019)

pollutant dataset. It aims to uncover patterns, trends, and relationships within a dataset, providing valuable insights into the underlying phenomena.

Time Series Analysis Time series analysis is used to study the variation in air pollutant concentrations over time. It involves analysing patterns, trends, and seasonality in the data. Techniques such as autocorrelation analysis, moving averages, and decomposition methods can be employed to identify long-term trends and cyclic patterns. This technique reveals how the frequency content of pollutant concentrations changes over time and can help identify short-duration pollution events (Fig. 9.2).

Spatial Analysis Spatial analysis is used to examine the spatial distribution of air pollutants. This involves analysing data collected from different monitoring stations or using modelling techniques to interpolate and visualize pollutant concentrations across a geographic area. Geographic information systems (GIS) and spatial interpolation methods such as kriging or inverse distance weighting are commonly used for spatial analysis. An example of spatial analysis is presented in Fig. 9.3. From

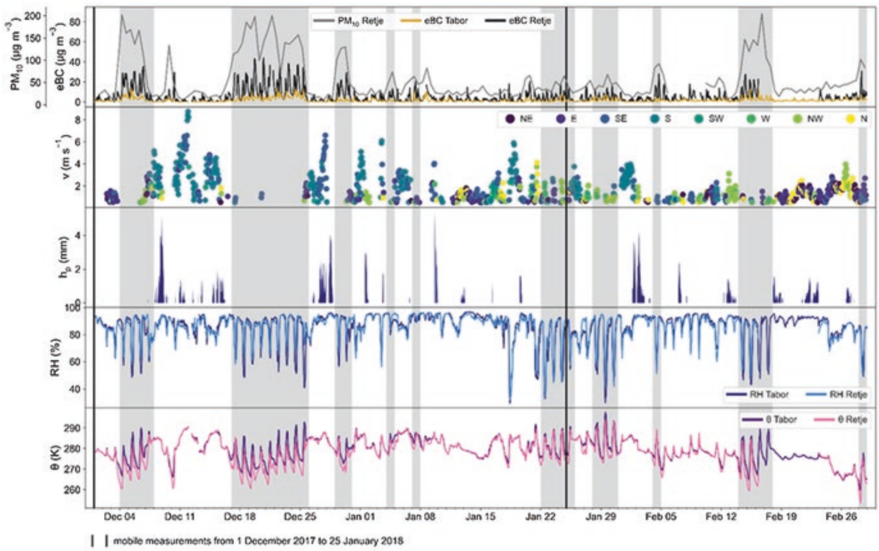

Fig. 9.2 Time series of meteorological and air quality data for the winter period (December 1, 2017–March 1, 2018) for a site in Europe. (Source: Glojek et al., 2022)

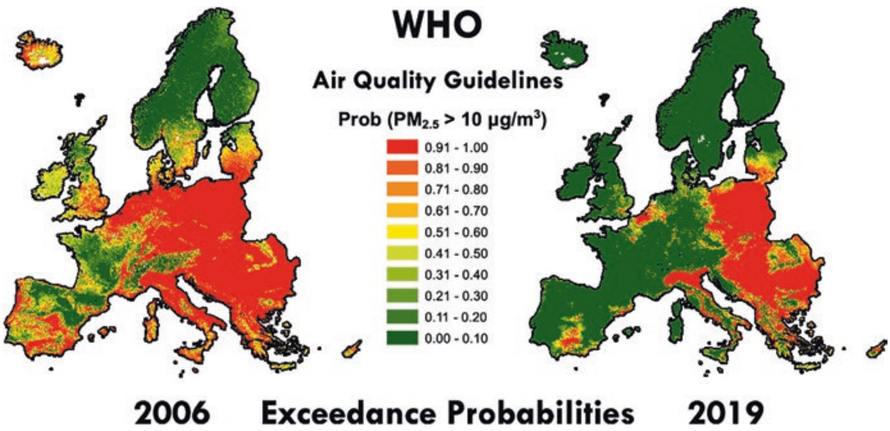

Fig. 9.3 Map depicting the likelihood of $PM_{2.5}$ exceeding the permissible limit set by the World Health Organization (WHO) across Europe for 2006 and 2019. (Source: Beloconi & Vounatsou, 2021)

2006 to 2019, the spatial plots exhibit a noticeable reduction in the likelihood of $PM_{2.5}$ levels surpassing the acceptable threshold established by the World Health Organization throughout Europe (Beloconi & Vounatsou, 2021).

Regression Analysis Regression analysis is employed to understand the relationships between pollutants and various influencing factors, such as meteorological

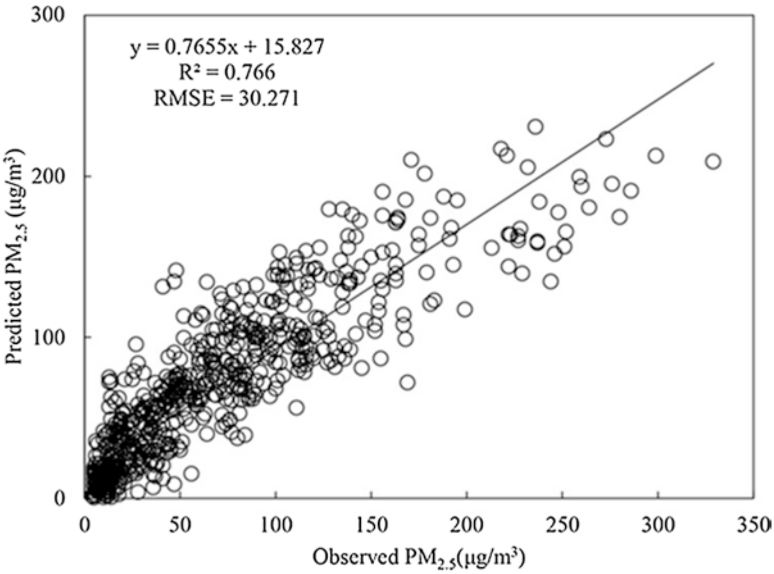

Fig. 9.4 The scatter distributions for the fitting and cross-validation of Beijing City $PM_{2.5}$ data predicted via multivariate linear regression model for 2015. (Source: Zhao et al., 2018)

variables, traffic density, or industrial emissions. Multiple regression analysis can help identify the significant predictors and quantify their impact on pollutant concentrations. Researchers use regression analysis to predict a targeted pollutant concentration and validate the results with an observational dataset (Fig. 9.4).

Principal Component Analysis (PCA) PCA is a multivariate statistical technique used to identify underlying patterns and correlations among a large number of air pollutant variables. It reduces the dimensionality of the data by transforming the variables into a new set of uncorrelated variables called principal components. PCA aids in identifying major pollutant sources and understanding their contributions to overall pollution.

Cluster Analysis Cluster analysis is used to group similar air pollution data points together based on their characteristics (Fig. 9.5). It helps identify distinct pollution patterns or sources that can assist in developing pollution control strategies. Various clustering algorithms, such as k-means, hierarchical clustering, or self-organizing maps (SOM), can be applied in this analysis.

Source Apportionment Source apportionment methods aim to identify and quantify the contributions of different pollution sources to the overall air pollutant concentrations. Techniques such as chemical mass balance (CMB) and positive matrix factorization (PMF) can be used to determine the source profiles and estimate source contributions. An example of source apportionment analysis is presented in Fig. 9.6.

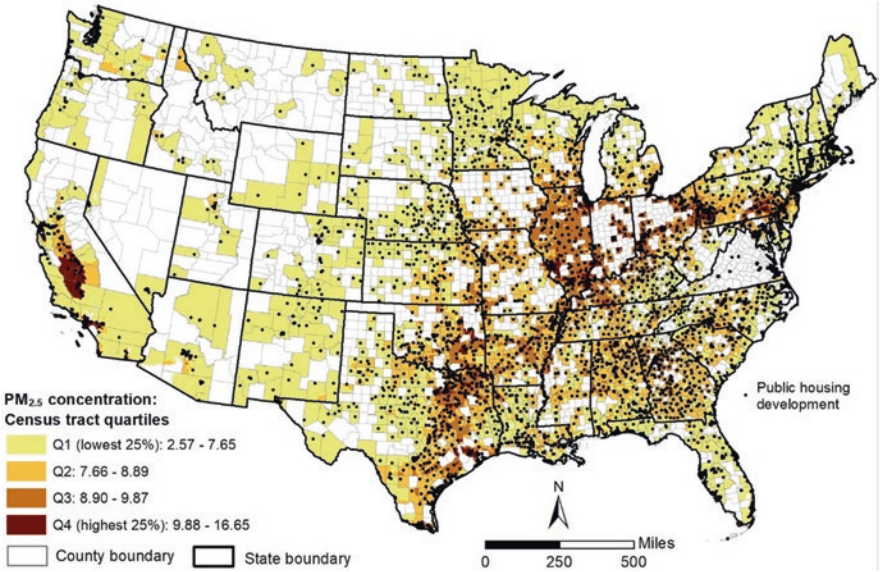

Fig. 9.5 Census tracts in continental US counties with public housing by annual average particulate matter ($PM_{2.5}$) concentration in micrograms per cubic meter (μg/m^3), 2011–2015. (Source: Chakraborty et al., 2022)

This research collected $PM_{2.5}$ samples from six locations in Delhi during both summer and winter seasons, spanning a period of 40 days at each site. The collected samples underwent chemical speciation analysis, including ions, metals, organic compounds, and elemental carbons. To determine the sources of pollution, the researchers applied the chemical mass balance technique. The results of the source apportionment analysis revealed that secondary aerosols, biomass burning (BMB), vehicles, fugitive dust, coal and fly ash, and municipal solid waste burning were identified as significant contributors to the observed pollution levels (Nagar et al., 2017).

Application of Observational Air Quality Dataset in Research

Ground monitoring data of air quality play a crucial role in research related to environmental science, public health, and policy development. Here are some key uses of ground monitoring data in research.

Identifying Pollution Sources By analysing pollutant concentrations and their spatial distribution, researchers can identify specific pollution sources. For this, instruments are strategically placed all over the area of interest. A handful of techniques employed for identifying pollutant emission sources using observational datasets

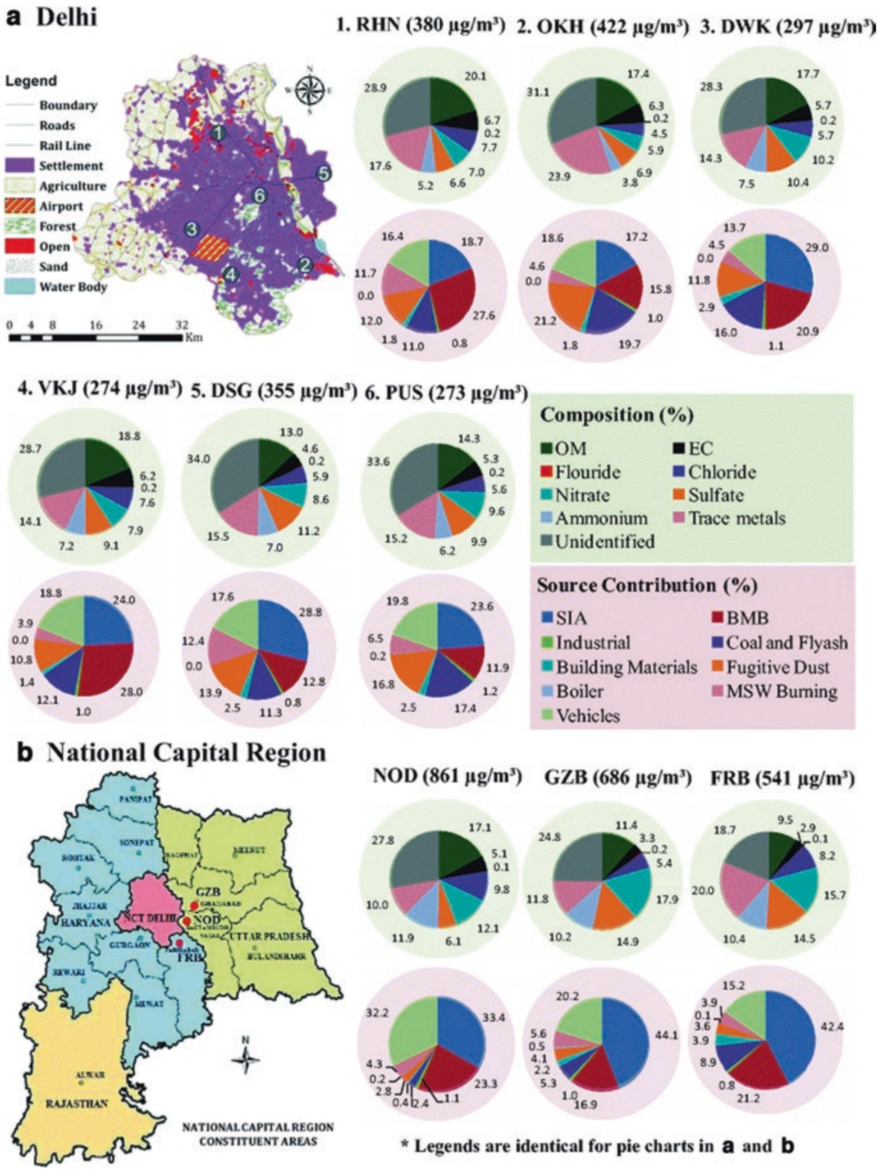

Fig. 9.6 Chemical composition and source apportionment of $PM_{2.5}$ in (**a**) Delhi during winter and summer at the six sites and (**b**) National Capital Region at three sites during winter. (Source: Nagar et al., 2017)

are source apportionment (Argyropoulos et al., 2012; Liu et al., 2017), correlation and regression analysis (Slezakova et al., 2013), backwards trajectory analysis (Singh et al., 2020), and dispersion modelling. Of the aforementioned techniques, the most widely used is the "*source apportionment technique*." This technique is used not only to identify but also to quantify the contributions of different pollution sources to a particular environmental pollutant using observational datasets coupled with source receptor models such as chemical mass balance (CMB) or positive matrix factorization (PMF). For instance, Argyropoulos et al. (2012) performed source apportionment for PM_{10} at two sites located on Rhodes Island (Greece) in the Eastern Mediterranean utilizing chemical mass balance (CMB) receptor modelling. The results indicated that vehicular emissions were the primary contributors to PM_{10}, accounting for 40.9% and 39.2% during the warm season and 36.8% and 31.7% during the cold season at the two monitoring sites, respectively. Another significant source of ambient PM_{10} was secondary sulphates, predominantly composed of ammonium and calcium sulphates (18% and 16.5%, respectively, at the two sites). Another example is the source apportionment of atmospheric pollutants by using PMF and ME2 models at Tianjin (Liu et al., 2017). Five source categories were identified with secondary sources, contributing approximately 25.4–26.1% of the pollution. Vehicle exhaust accounted for approximately 23.3–25.4% of the pollution, while coal combustion contributed approximately 16.5–18.2%. Crustal dust was responsible for approximately 13.2–14.0% of the pollution, and biomass burning accounted for approximately 9.1–10.2% of the pollution. Ground monitoring data allow researchers to identify and track the sources of air pollution in a specific area. This information is crucial for developing targeted mitigation strategies and policies.

Model Validation and Improvement Ground monitoring data play a crucial role in the validation and enhancement of air quality models. It enables researchers to assess and fine-tune their models by comparing them to actual measurements, ensuring that the predicted pollutant concentrations align with the observed values. This iterative process is vital for enhancing the precision and dependability of air quality models, as they are fundamental in predicting future levels of air pollution and evaluating the potential consequences of different scenarios.

Studying Spatial and Temporal Trends Ground monitoring data collected over extended periods allow researchers to analyse long-term trends in air quality. This includes studying seasonal variations, year-to-year changes, and spatial patterns in pollution levels. Such studies provide insights into the underlying causes and drivers of air pollution, facilitating targeted interventions and policy development. For example, during the global pandemic (COVID-19) outbreak, large-scale lockdown implementation resulted in cleaner air quality in many parts of the world. This fact came into limelight due to the spatiotemporal trend analysis of different air pollutants in countries such as Italy (Deng et al., 2022), China (Bhatti et al., 2022), and India (Pal et al., 2022). Another example is the long trend analysis of air pollutants, which provides a comprehensive idea of how much the "air pollutant" has increased or decreased in a certain time frame or over a region of interest. One such study was conducted to analyse the trends of particulate matter in a southern Indian industrial area, and there was a clear and consistent upwards trend in the 24-hour average $PM_{2.5}$ concentrations, showing an annual increase of 0.43 μg/m^3 (Peter et al., 2023).

Health Impact Assessments and Economic Losses The link between air pollution and a variety of unfavourable health consequences and effects on the economy is increasingly broad in the Indian states. Ground monitoring data combined with health data and demographic information enable researchers to conduct health and economic impact assessments. As part of the Global Burden of Disease Study (GBD) 2019, exposure to ambient particulate matter pollution, home air pollution, and ambient ozone pollution, as well as their associated deaths and disability-adjusted life years in each state of India, were calculated. Using the cost-of-illness technique, the economic effect of air pollution as the cost of lost productivity owing to premature mortality and morbidity attributed to air pollution for every state in India was examined (Pandey et al., 2021). In 2019, air pollution in India was responsible for 167 million (confidence interval: 1.42–1.92) or 17.8% (15.8–19.5) of all fatalities in the nation. The bulk of these fatalities, 98 million (0.77–1.19), and household air pollution, 61 million (0.39–0.86), were caused by ambient particulate matter pollution. From 1990 to 2019, the mortality rate from home air pollution fell by 64.2% (52.2–74.2), but the death rate from ambient particulate matter and ozone pollution increased by 115.3% (28.3–344.4) and 139.2% (96.5–258.2), respectively. In India, economic losses due to premature mortality and illness caused by air pollution totalled US $28.8 billion (21.4–67.34) and $8.0 billion (5.9–10.3), respectively, in 2019. The overall loss, $368 billion (27.4–47.7), was 13.6% of India's GDP. The economic loss as a percentage of the state gross domestic price (GDP) among various states is 3.2 times, ranging from 0.67% (0.47–0.91) to 2.15% (1.60–2.77), with the lowest per capita GDP, i.e. Uttar Pradesh, followed by Bihar, Rajasthan, and Madhya Pradesh, had the largest losses. In 2019, Delhi, followed by Haryana, was the state with the largest per capita economic losses associated with air pollution, with a variation of 5.4 times among all states (Pandey et al., 2021).

Filling the Policy Gaps Delhi, the nation's capital, felt the most severe air pollution among all of India's cities. The negative effects are severe, which results in a decline in life expectancy (health) and high expenses to the government to address the environmental crisis (Sharma et al., 2018). To overcome all the losses, laws and legislation must be modified with each passing day. As a result, multiple ground-based (CPCB) analyses along with satellite-based earth observations were performed to study the air quality index (AQI) of Delhi. Due to poor AQI, "Anti-pollution policy measures" were framed, which included the Graded Response Action Plan (GRAP), Odd-Even Scheme, and National Clean Air Program (Chatterji, 2021).

Overall, ground monitoring data on air quality provide a solid foundation for research, enabling scientists to investigate the causes and effects of air pollution, evaluate interventions, and guide policy decisions to protect public health and the environment.

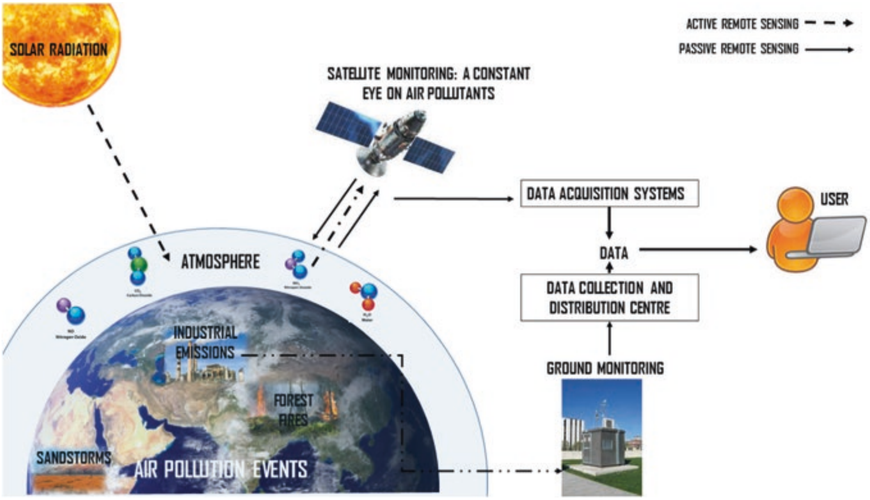

Fig. 9.7 A schematic representation of atmospheric data acquisition using the remote sensing technique

9.3 Remote Sensing and Satellite/Sensors for Air Quality Monitoring and Assessment

Remote sensing is a valuable tool for assessing air quality, allowing us to gather information about the composition and condition of the Earth's atmosphere from a distance (Fig. 9.7). It involves the use of various sensors and instruments mounted on satellites, aircraft, or ground-based platforms to collect data on different aspects of the atmosphere, such as pollutant concentrations, aerosol properties, and meteorological parameters. Satellite-based remote sensing is particularly useful for air quality assessment on a regional or global scale. Satellites equipped with specialized sensors can provide continuous and wide-ranging observations of the Earth's atmosphere and thus are capable of filling the spatial gaps of ground monitoring resources (The California Air Resources Board, 2023). Remote sensing data are often combined with other sources of information, such as meteorological data and air quality models, to provide a comprehensive assessment of air quality. This integration allows for a better understanding of pollutant sources, transport patterns, and their impacts on human health and the environment. Additionally, remote sensing can help in the identification of air pollution hotspots, monitoring long-term trends, and assessment of the effectiveness of air quality management strategies.

There are several satellites that provide air pollutant datasets by measuring various atmospheric parameters. The selection of satellite data to address specific air quality issues depends on data accuracy and spatial and temporal resolution, among other factors. Here are some notable sensors/satellites known for their air pollutant monitoring capabilities (summarized in Table 9.4).

Table 9.4 Satellite/sensors providing continuous measurements for air quality assessment

Sensor/satellite	Agency name	Spatial resolution	Approximate repeat time	Parameters measured
CALIPSO	NASA	30 m × 30 m	16 days	Cloud & aerosol
Aqua satellite {AIRS}	NASA	13.5 km	Daily	CO, CO_2, O_3, CH_4
Aura satellite {OMI}	NASA	13 × 24 km^2	Daily	O_3, HCHO, NO_2, SO_2
Aura satellite {TES}	NASA	5 × 8 km^2	6 days	O_3, CH4, CO
Envisat satellite {SCIAMACHY}	ESA	30 × 60 km^2	6 days	O_3, HCHO, NO_2, SO_2, CO, CO_2, CH_4
MetOp satellite {IASI}	ESA	12 km	12 hours	O_3, CO, CH_4, BrO, SO2
GOME-2	ESA	40 × 80 km^2	Daily	O_3, HCHO, NO_2, BrO, SO_2
Terra {MOPITT}	NASA	22 × 22 km^2	3 days	CO
Terra+Aqua {MODIS}	NASA	1 × 1 km^2	Daily	AOD, O_3
GOME	ESA	40 × 320 km^2	3 days	O_3, HCHO, NO_2, BrO, SO_2
GOSAT (2008)	JAXA	10 km	3 days	CO_2, CH_4
Sentinel 5 {TROPOMI}	ESA	Up to 5.5 km × 3.5 km	1 day	Total columns of O_3, So_2, NO_2, CO, HCHO, vertical profiles of O_3, cloud & aerosol
Nimbus-4 (BUV)	NASA	11.3° × 11.3°	10 days	TCO

Source: (Palmer, 2008; Abad et al., 2019)

TES (Tropospheric Emission Spectrometer) The TES instrument is an infrared Fourier transform spectrometer that is installed on the NASA Aura satellite, which was launched on 15 July 2004. It has a spectral resolution of 0.06 cm^{-1}. The satellite passes over specific locations at approximately 13:30 and 01:30 local time (Schoeberl et al., 2006). The TES instrument conducts a global survey with a repeating cycle of 16 days. Its measurements cover a footprint of 5 km × 8 km at nadir, allowing for approximately 180 daytime retrievals per month over North America after eliminating cloud contamination (optical depths <1.0) and applying TES retrieval quality control flags. Due to its high spectral resolution and reliable signal-to-noise ratio (Shephard et al., 2008), the TES instrument successfully detected tropospheric ammonia from space, providing measurements over Southern California and China for the first time (Beer et al., 2008).

MOPITT (Measurement of Pollution in the Troposphere) The MOPITT remote sensing instrument was launched on the EOS Terra satellite in December 1999, with the purpose of quantifying and monitoring the movement of pollution in the troposphere (Deeter et al., 2003). Operational since March 2000, MOPITT has nadir-viewing channels that enable the monitoring of carbon monoxide and methane. The instrument has an instantaneous field of view of 22 by 22 km when observing from nadir.

OMI (Ozone Monitoring Instrument) The Ozone Monitoring Instrument (OMI) is carried by the Aura satellite, part of the Earth Observing System launched by the National Aeronautics and Space Administration (NASA) in July 2004 (Levelt et al., 2006). OMI operates as a solar backscatter spectrometer specifically designed for ultraviolet/visible (UV/VIS) measurements in the nadir direction. It offers nearly worldwide coverage within a single day, achieving a spatial resolution of approximately 13 km by 24 km. The instrument is capable of detecting various trace gases, such as ozone (O_3), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), formaldehyde (HCHO), bromine monoxide (BrO), and chlorine dioxide (OClO), as well as aerosol characteristics. Its unique features include the ability to measure essential trace gases on a global scale daily with a compact footprint.

AIRS (Atmospheric Infrared Sounder) The AIRS instrument, launched on the EOS Aqua spacecraft in May 2002, is a cross-track scanning infrared spectrometer (Pagano et al., 2003). Positioned in a polar orbit at an altitude of 705 km, the satellite provides global coverage twice a day as it crosses the equator at approximately 1:30 am and 1:30 pm local time (Xiong et al., 2008). With 2378 channels spanning 649–1136, 1217–1613, and 2169–2674 cm^{-1}, AIRS offers high spectral resolution. Its field of view (FOV) is 1.1°, corresponding to a nadir footprint of 13.5 km on the Earth's surface, while the scan angles span ±48.95° (Aumann et al., 2003). In conjunction with AMSU, AIRS is utilized in the current retrieval system to obtain atmospheric temperature-humidity profiles, cloud and surface properties, and minor gases within a 45 km FOV (Susskind et al., 2003). While it is feasible to utilize AIRS alone for these retrievals, the presence of clouds can have a stronger impact on the results (Susskind et al., 2006).

MODIS (Moderate Resolution Imaging Spectroradiometer) MODIS was launched by NASA (National Aeronautics and Space Administration) on 18 December 1999. Subsequently, on 4 May 2002, it was installed on the Earth Observing System (EOS) satellites, Terra and Aqua (Barnes et al., 2003). Comprising 36 spectral bands, MODIS offers spatial resolutions ranging from 250 m to 1 km, and it revisits the same location every 1–2 days (Payra et al., 2023). The Terra and Aqua satellites follow polar orbital paths, with both passing over the equator at specific local times. Terra passes at 10:30 am, moving from north to south, while Aqua passes at 01:30 pm, moving from south to north (Sandu et al., 2010).

VIIRS (Visible Infrared Imaging Radiometer Suite) VIIRS is a sensor incorporated in the joint mission of NASA and NOAA called Soumi NPP, which was successfully launched on 28 October 2011. Its purpose is to orbit the Earth in a sun-synchronous, polar orbit (Xiong et al., 2013). The VIIRS sensor employs a total of 22 spectral channels, spanning from 0.412 to 12 μm (Moyer et al., 2018). With a spatial resolution ranging from 375 to 750 m, it provides complete coverage of the

Earth twice daily (Oudrari et al., 2014). The equatorial crossings of the Soumi NPP occur at both 1:30 am (nighttime overpass) and 1:30 pm (daytime overpass) at the same local time (Miller et al., 2012).

TROPOMI (TROPOspheric Monitoring Instrument) TROPOMI, launched on 13 October 2017 as part of the Sentinel-5 Precursor (S5P) satellite, is a passive-sensing hyperspectral nadir-viewing imager. S5P operates in a near-polar sun-synchronous orbit at an altitude of 817 km, passing over the same location at approximately 13:30 local time every 17 days (KNMI, 2017). TROPOMI uses a nonscanning push broom configuration, with a 108-degree instantaneous field of view and a measurement period of approximately 1 second. This configuration enables a swath width of approximately 2600 km, an along-track resolution of 7 km, and global coverage on a daily basis (KNMI, 2017). TROPOMI's spectrometers include ultraviolet (UV), UV–visible (UV–VIS), near-infrared (NIR), and shortwavelength infrared (SWIR) bands (Ialongo et al., 2020). The addition of NIR and SWIR bands in TROPOMI distinguishes it from its predecessor, OMI (Veefkind et al., 2012).

Application of Remotely Sensed Dataset in Research: A Case Study

The rise in anthropogenic activities and industrialization decreased the air quality of a place and impacted biotic and abiotic components directly or indirectly. For the assessment of harmful elements in the ambient area over spatial and temporal extents, satellite data proved to be a good source of dataset along with site measurements to check the reliability and validity of the dataset. For example, here, a case of ozone variability is analysed over Indian land mass by using Copernicus Atmosphere Monitoring Service Reanalysis (CAMSRA). The observation was during the premonsoon and monsoon months, and the spatial distribution of surface ozone displays greater (lower) concentrations of approximately 40–60 ppb (15–20 ppb) over northern and western India. During May, there is a noticeable rise across the northern area, particularly over the Indo-Gangetic Plains (IGP), which is due to solar radiation (SR), temperature, low-level circulation, and boundary layer height (BLH) fluctuations. CAMSRA-based surface ozone showed increasing trends in all four areas (north, east, west, and south India) as well as in India overall (0.069 ppb/year), with the eastern region showing the strongest increases. Furthermore, to develop more understanding of the analysis tool used, principal component analysis (PCA) demonstrates that a large proportion of the variation ranges from 30% to 50%. The findings show that changes in precursors or climatic circumstances have a considerable impact on surface ozone concentrations in India (Kunchala et al., 2022). Therefore, satellite data or modelled data are proven to be crucial tool for understanding and managing global air pollution because they provide broad coverage, continuous monitoring, spatial information, multispectral data, integration with models, and policy assistance for air quality management.

9.4 Geographic Information Systems (GIS) in Air Quality Monitoring

Geographic information systems (GIS) have revolutionized the understanding and analysis of spatial data. By combining location-based information with powerful analytical tools, GIS provides a framework for capturing, storing, manipulating, analysing, and presenting geographic data. The integration of air quality data with geographic information systems (GIS) has become a crucial aspect of environmental monitoring and management. Researchers have studied the concentration and spatial distribution of air contaminants using spatial simulations. The combination of these two powerful technologies enables a comprehensive understanding of the spatial distribution of air pollutants, their sources, and their impact on human health and the environment. This section explores the significance of integrating air quality data with GIS and the challenges associated with this integration.

Significance of Integrating Air Quality Data with GIS

Integrating air quality data with geographic information systems (GIS) offers several significant benefits. Here are some of the key advantages of this integration.

Spatial Analysis GIS has primarily offered effective techniques that evaluate the geographical point pattern of air contaminants, identify the connection between air quality and health risk, and improve visualization and analysis possibilities. By incorporating air quality data into GIS platforms, it becomes possible to visualize, query, and analyse the distribution and trends of pollutants across different geographical regions. This integration allows for a better understanding of the spatial patterns and hotspots of pollution sources, facilitating effective decision-making and targeted interventions. Although monitoring stations depict the air quality in a certain area, managing air quality requires spatial variation (Kumar et al., 2016). Therefore, with the aid of GIS tools, the most appropriate approach can be chosen from interpolation techniques such as the inverse distance weighting (IDW) method, kriging, nearest-neighbour, and splitting, based on the data that are available and the accuracy of the forecast of the concentration of the unknown points.

Data Visualization GIS offers powerful visualization techniques to represent air quality data in the form of maps, charts, and graphs. By presenting data in a visual format, GIS enables efficient communication of air quality issues and supports the development of effective mitigation strategies. For example, Lee and Bae (2021) presented a new approach that integrates ground-based observation of recorded air quality data with a dispersion model to determine the $PM_{2.5}$ level and a GIS platform to display results to evaluate the effects of emissions from a local primary emission source in a local rural village.

Data Integration Integration of air quality data with GIS allows for the incorporation of various data sources, including meteorological data, land use data, and population density data. By combining these datasets, analysts can identify correlations between air quality and other spatial variables. For instance, by overlaying air quality data with land use data, it is possible to identify areas with high pollution levels due to industrial or residential activities. Maantay et al. (2008) created novel methods to simulate air dispersion from stationary sources for five pollutants, PM_{10}, $PM_{2.5}$, NO_x, CO, and SO_2, using an air dispersion model, AREMOD, and a GIS program called ArcGIS.

Challenges and Limitations

The integration of air quality data with GIS offers numerous benefits for understanding and managing air pollution. By leveraging the spatial analysis capabilities of GIS, policymakers, researchers, and the general public can gain valuable insights into air quality patterns, identify pollution sources, and develop effective strategies for mitigating the adverse impacts of poor air quality. Overcoming challenges related to data quality, standardization, and accessibility will be crucial for maximizing the potential of this integration and fostering sustainable environmental management.

Data Quality and Standardization Integration of air quality data from different monitoring sources requires ensuring data quality and standardization. Variations in monitoring methods, equipment, and calibration can introduce inconsistencies and hinder accurate analysis. Establishing standardized protocols for data collection, validation, and sharing is crucial to maintain data integrity and facilitate meaningful integration with GIS.

Data Accessibility and Interoperability Air quality data are often collected by multiple agencies and organizations, resulting in data fragmentation and limited accessibility. Integrating these disparate datasets with GIS requires efforts to promote data sharing, standardize formats, and develop interoperable systems. Collaborative initiatives and open data policies can help overcome these challenges and enable comprehensive integration of air quality data with GIS.

GIS-Based Decision Support Systems for Air Quality Management

Air quality management is a complex task that requires the integration of various data sources, analytical tools, and decision-making processes. Geographic information systems (GIS) provide a powerful framework for developing decision support systems (DSS) that facilitate effective air quality management (Diah, 1997). In Fig. 9.8, the benefits of GIS-based DSS for air quality management are depicted.

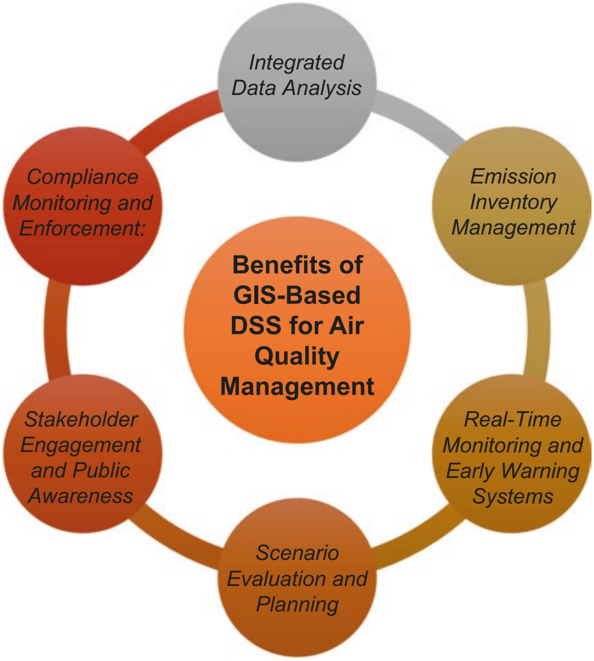

Fig. 9.8 Benefits of GIS-based DSS for air quality management

These GIS-based DSSs combine spatial data, modelling techniques, and visualization tools to support decision-making processes, policy development, and the implementation of targeted interventions. The integration of air quality monitoring, emission inventory, modelling, mapping, and the impact of air quality impact assessment of several control strategies plays an important role in decision support systems. Decision support systems support the evaluation of action plans by using information to the public about past and present air quality levels. The local authorities of major European cities, i.e. Lisbon, Stockholm, Geneva, Vienna, Milano, Peris, Berlin, and Oslo, used the decision support system (SMHI, 2009). Similarly, the decision support system is used in different parts of the world, i.e. the Austrian AirWare (Fedra & Haurie, 1999), Norwegian AirQUIS (Bøhler et al., 2002), and Swedish EnviMan (Tarodo, 2003) systems. The key components and benefits of GIS-based DSS for air quality management are discussed below.

Spatial Data Integration GIS-based DSS integrates diverse spatial data sources, such as satellite imagery, ground-based monitoring stations, meteorological data, emission inventories, and population data, into a unified system. In the context of air quality management, integrating these datasets within a GIS-based DSS offers several advantages, such as comprehensive data analysis, improved spatial analysis, enhanced modelling capabilities, powerful data visualization, and effective communication of complex air quality information. By combining and analysing these data layers, DSS can identify spatial patterns, hotspots, and correlations between air pollution and other environmental factors.

Modelling and Analysis Tools GIS-based DSS employs various air quality models, such as the Gaussian plume model or the Community Multiscale Air Quality (CMAQ) model, to predict pollutant concentrations at different locations (Byun & Schere, 2006). These models may include dispersion models that estimate pollutant dispersion patterns, emission models that calculate pollutant emissions from different sources, and health impact models that assess the effects of air pollution on human health. These models utilize spatial data, including emission inventories, meteorological conditions, and topographical features, to simulate pollutant dispersion patterns. Integration of these models within GIS allows for dynamic visualization and analysis of model outputs.

Decision-Making and Scenario Analysis GIS-based DSS provides decision-makers with tools to evaluate different scenarios and assess the potential impacts of interventions. DSS can incorporate policy guidelines, regulatory standards, and air quality objectives to help stakeholders make informed decisions. Decision support tools, such as multicriteria analysis and scenario analysis, allow for the evaluation of trade-offs and the selection of optimal strategies. Decision-makers can simulate and compare the effects of emission reductions, land use changes, or traffic management interventions on air quality indicators. They can also evaluate the potential outcomes of different air quality management strategies, which helps in selecting the most effective and sustainable measures for air quality improvement.

Visualization and Communication GIS-based DSS offers powerful visualization capabilities for examining the relationship between air quality and various factors, such as land use patterns, traffic emissions, and population density, and for presenting air quality data and model outputs in a user-friendly manner. Through spatial analysis techniques such as interpolation, overlay analysis, and hotspot detection, GIS-based DSS can identify pollution hotspots, assess the impact of emission sources, and evaluate the effectiveness of mitigation strategies. Maps, charts, graphs, and interactive dashboards enable stakeholders to visualize spatial patterns, trends, and the potential impacts of interventions. Effective visualization and communication of air quality information facilitate stakeholder engagement, public awareness, and informed decision-making.

Public Participation and Communication Engaging the public in air quality management is crucial for the successful implementation and acceptance of measures. GIS-based DSS can incorporate public participation tools, such as online mapping platforms and mobile applications, allowing citizens to contribute data, report pollution incidents, and provide feedback. This fosters a participatory approach and enhances communication between authorities, researchers, and the public.

9.5 Urban Air Quality Modelling

Air quality modelling refers to the simulation of the relationship between air pollutant emissions and atmospheric concentrations with physical and chemical atmospheric processes, meteorology, and other factors. These simulations are performed by a consortium of mathematical and numerical techniques. The need for modelling techniques in the field of air pollution and air quality studies developed from the limitations of ground monitoring systems and remote sensing techniques. Measurements of atmospheric pollution offer significant quantitative data regarding the levels of pollutants present and their deposition. However, such measurements are limited to describe the air quality at specific locations and specific points in time. On the other hand, modelling techniques offer a comprehensive deterministic portrayal of the air quality issue, encompassing an examination of various factors and origins such as emission sources, meteorological processes, and physical and chemical alterations (Daly & Zannetti, 2007). For the representation of real-world conditions, these models rely on extensive data collection and analysis, which are integrated with governing equations. The crucial input parameters for modelling the dispersion, transport, and chemical transformation of air pollutants along with urban air quality are meteorological factors (wind speed, temperature, atmospheric stability, etc.) and emission-related terms (potential sources, emission rates, stack height, etc.). Based on the inputs provided, these models are developed to analyse the primary pollutants released directly into the atmosphere, as well as the secondary pollutants formed through intricate chemical reactions within the atmosphere (US EPA, 2023). In 1990, Paolo Zannetti categorized air quality models into two types:

Physical models: Scaled-down representations of phenomena created in laboratories such as wind tunnels and water tanks.

Mathematical models: Analytical and numerical algorithms that describe the physical and chemical aspects of a problem.

Apart from the general category of the models mentioned above, several other types of air quality models are widely applied in research and policy development. Ranging from simple dispersion models to complex chemical transport models, there are numerous options available. Therefore, the appropriate selection and model application is a very crucial task. The assessment of models and their applications can be performed by a variety of factors, including the fundamental governing physical principles, the temporal and spatial coverage, the sources utilized, the components included, and the specific purpose they serve (European Environment Agency, 2020). These models play an important role in air quality management systems because they are widely used by agencies for controlling air pollution by identifying the source contributions to air quality problems and supporting the design of effective approaches to reduce harmful air pollutants. In addition, air quality models can also be used to forecast air pollutant concentrations from numerous sources after the implementation of a new regulatory program to estimate the effectiveness of the program in reducing harmful exposures to humans and the environment.

Modelling Approaches and Techniques

Typically, urban air quality models have a spatial scale that ranges from local to regional levels. These models serve as an effective tool to comprehend the issues in understanding the sources of urban air pollution and effective management of air quality by evaluating the relationship between air pollutant emissions and the resulting concentration in ambient air (Srivastava & Rao, 2011). The most commonly used air quality models are (1) conceptual models, (2) emission models, (3) meteorological models, (4) chemical models, (5) source-oriented models, and (6) receptor models. Below is an outline of various modelling methodologies and techniques commonly used in air quality modelling.

Eulerian and Lagrangian Models Eulerian models divide the atmosphere into a grid of cells or computational domains. They solve a set of mathematical equations that describe the conservation of mass, momentum, and energy within each cell. Eulerian models are widely used in air quality modelling and can simulate the complex interactions between emission sources, meteorology, chemistry, and dispersion processes. These models provide detailed spatial and temporal information about pollutant concentrations and are suitable for regional or urban-scale air quality assessments. Lagrangian models track individual air particles or "parcels" as they move through the atmosphere. These models simulate the movement of parcels based on the prevailing wind patterns, turbulence, and other factors. Lagrangian models are useful for studying the long-range transport of pollutants, including transboundary pollution and the transport of pollutants from distant sources. They can also incorporate the effects of complex terrain and atmospheric processes.

Box Models Box models are simple models that conceptualize the atmosphere by separating it into discrete "boxes," compartments, or cells. These models comply with mass conservation principles and assume uniform mixing conditions. Each box represents a different urban area component, such as roadways, buildings, and open areas. The transport of air pollutants into and out of the boxes, as well as their emission, is considered. Furthermore, box models integrate a variety of physical and chemical processes to simulate the behaviour of air pollutants, such as emissions, advection, dispersion, chemical reactions, deposition, and removal mechanisms. Box models' capacity to capture fluctuations in air pollution within metropolitan regions is a key advantage. Another advantage of these models is that they can simulate situations based on basic meteorological input while providing high spatial resolution and accounting for chemical interactions and numerous emission sources. However, it is critical to thoroughly consider the constraints and

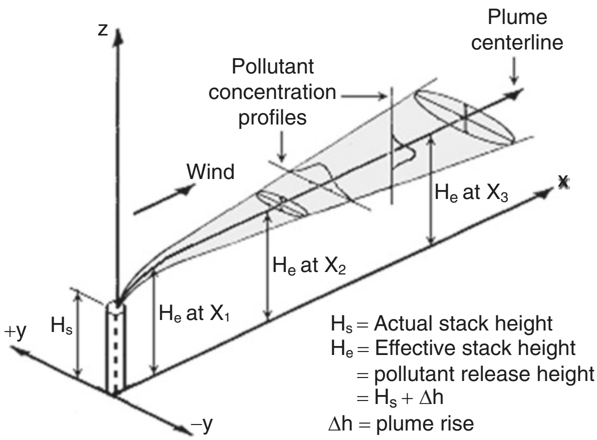

Fig. 9.9 A buoyant Gaussian air pollutant dispersion plume. (Source: Beychok, 2005)

uncertainties of box models to achieve dependable and accurate results when analysing urban air quality.

Gaussian Plume Models Gaussian plume models are widely used for simulating the dispersion of air pollutants from point sources. They consider the physical characteristics of the plume, such as buoyancy, wind speed, and atmospheric stability, to estimate the pollutant concentration downwind from the source. By considering these factors, the model can estimate the concentration of pollutants at various distances and heights from the source. Gaussian models assume that the plume disperses in a Gaussian-shaped pattern, with the highest concentration along the centreline and decreasing concentrations towards the edges. The Gaussian plume model assumes that the atmosphere is horizontally homogeneous and that the pollutant behaves as a passive scalar, meaning it does not affect the airflow. It also assumes that the pollutant is released continuously over a finite period and that the emissions are well mixed before reaching the receptor point. While these assumptions simplify the model, they provide reasonable estimates for many real-world scenarios. Figure 9.9 shows a buoyant Gaussian air pollutant dispersion plume. The width of the plume is determined by σ_y and σ_z, which are defined by stability classes (Pasquill, 1961; Gifford Jr., 1976).

The spatial dynamics of pollution dispersion are described by the following type of equation in a Gaussian model:

$$C(x, y, z; He) = \frac{Q}{2\pi u \sigma_y \sigma_z} \bullet \bullet \left[\exp\left(-\frac{y^2}{2\sigma_y^2}\right) \bullet \left\{ \exp\left(-\frac{(z-He)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+He)^2}{2\sigma_z^2}\right) \right\} \right]$$

where

$C(x, y, z)$: pollutant concentration at. point (x, y, z);
U: wind speed (in the x “downwind” direction, m/s);
Σ: represents the standard deviation of the concentration in the x and y directions, i.e. in the wind direction and cross-wind, in meters;
Q is the emission strength (g/s);
He: the effective stack height, see below.

Plume rise equations have been developed by Briggs (1975). The effective stack height (physical stack height plus plume rise) depends on the exit velocity of gas, stack diameter, average ambient velocity, stack gas temperature, and stability of the atmosphere.

Statistical Models Statistical models employ statistical techniques to establish relationships between air pollution concentrations and various influencing factors, such as meteorological variables, emission sources, and land use characteristics. By utilizing historical data, these models develop regression equations or statistical algorithms that can predict pollutant concentrations based on the input variables. These models are data-driven, and therefore, appropriate selection and quality assurance of the dataset is a crucial step. One commonly used statistical model in air quality analysis is the linear regression model. By fitting a regression model to the data, the contribution of each variable can be estimated, and their significance in explaining variations in air quality can be assessed. Another important statistical tool in air quality modelling is time series models, such as autoregressive integrated moving average (ARIMA) models. In recent years, the field of air quality modelling has witnessed advancements in the use of machine learning techniques. Machine learning algorithms, such as random forests, gradient boosting, support vector machines, and neural networks, have shown promising results in predicting air quality and identifying the key contributors to pollution. These models can handle complex interactions between variables and provide more accurate predictions than traditional statistical methods. Furthermore, ensemble modelling techniques have gained popularity in air quality research. Ensemble models combine multiple individual models, each with its own strengths and weaknesses, to obtain a more robust and accurate prediction. By incorporating different statistical models or machine learning algorithms within an ensemble framework, researchers can account for uncertainties and improve the reliability of air quality forecasts.

Receptor Models These models are observational techniques that use the chemical and physical characteristics of gases and particles measured at the source and receptor to both identify the presence of and quantify source contributions to receptor concentrations without considering the dispersion pattern of the pollutants (Srivastava & Rao, 2011). The fundamental principle behind receptor models is that different emission sources have unique signatures or profiles in terms of the chemical composition of the pollutants they release into the atmosphere. By analysing the chemical composition of the pollutants measured at monitoring sites, receptor models can attribute the contributions of different sources to the observed air pollution. Some examples of receptor models are CMB, PMF, PCA, MLR, UNMIX, etc.

Mathematically, the receptor model can be generally expressed in terms of the contribution from "*n*" independent sources to "*p*" chemical species in "*m*" samples as follows:

$$C_{ik} = \sum_{j=1}^{n} a_{ij} f_{jk}$$

Chemical Transport Models Chemical transport models (CTMs) are advanced Eulerian models that incorporate detailed atmospheric chemistry mechanisms. The primary objective of CTMs is to simulate the behaviour of various chemical species in the atmosphere, including gases and aerosols, as they are emitted into the air, transported by wind patterns, and undergo chemical reactions and deposition processes. These models incorporate a range of physical and chemical processes, including meteorology, emission inventories, atmospheric chemistry, and deposition mechanisms, to simulate the complex behaviour of pollutants. Meteorological data, such as wind speed, direction, and temperature, and emission inventories are essential inputs for CTMs. By integrating these components, CTMs generate spatial and temporal distributions of pollutants, allowing for the assessment of air quality on various scales, ranging from local to regional and even global. These models can be used to estimate pollutant concentrations at specific locations, identify pollution hotspots, and evaluate the effectiveness of emission reduction strategies and control measures. CTMs also enable the exploration of "what-if" scenarios to assess the potential impacts of changes in emissions, land use, and climate on air quality. However, it is important to note that CTMs are complex and rely on a significant amount of data, including accurate meteorological information, emission inventories, and chemical reaction rates. Uncertainties in these inputs can affect the accuracy of the model predictions. Therefore, CTMs are continuously refined and evaluated using observational data from air quality monitoring networks, satellite measurements, and field campaigns to improve their performance and reliability.

Coupled Models Coupled models integrate air quality models with other environmental or earth system models to capture the complex interactions between the atmosphere, land, and oceans. For example, coupling air quality models with meteorological models allows for the two-way interactions between meteorology and air pollution, providing more accurate predictions. Coupled models help understand the feedback mechanisms between air quality, climate change, and other environmental factors.

Calibration and Validation of Air Quality Models

Calibration and validation are crucial steps in the development and application of air quality models. These processes help ensure the accuracy and reliability of the models, allowing researchers and policymakers to make informed decisions regarding air pollution mitigation strategies and public health.

Calibration Calibration is the process of adjusting the model's parameters to improve its agreement with observed data. It involves comparing model predictions with measured pollutant concentrations or other relevant atmospheric variables. The goal is to minimize the differences between the model outputs and the observed data by adjusting the model's inputs or internal parameters. Calibration is typically performed using statistical optimization techniques, such as least squares or maximum-likelihood estimation. During calibration, modellers may adjust parameters related to emissions, atmospheric processes, or numerical algorithms used by the model. Emission factors, which quantify the amount of pollutant released per unit of activity, can be refined based on field measurements or detailed source testing. The representation of physical and chemical processes, such as atmospheric dispersion, chemical reactions, and deposition, may also be improved to better capture the observed pollutant behaviour. Therefore, to ensure accurate predictions, air quality models must be properly calibrated using empirical data. Various calibration techniques employed in air quality modelling are listed below.

(a) *Statistical Calibration Techniques*

- Ordinary least squares (OLS) regression
- Weighted least squares (WLS) regression.
- Maximum-likelihood estimation (MLE)

(b) *Bayesian Calibration Techniques*

- Markov Chain Monte Carlo (MCMC)
- Sequential Monte Carlo (SMC)

(c) *Parameter Estimation and Optimization Methods*

- Levenberg–Marquardt algorithm (Marquardt, 1963)
- Genetic algorithms (Goldberg, 1989)

(d) *Sensitivity Analysis*

- One-at-a-time sensitivity analysis (Saltelli et al., 2008)
- Morris method (Morris, 1991)

(e) *Data Assimilation Techniques*

- Kalman filtering (Kalman, 1960)
- Ensemble Kalman Filter or EnKF (Evensen, 2003)

By employing these calibration techniques, air quality models can be better equipped to inform policy decisions, assess environmental impacts, and mitigate the adverse effects of air pollution. The appropriate choice of calibration technique depends on the model's complexity, data availability, and computational resources. Implementing robust calibration practices enhances the reliability of air quality models and facilitates informed decision-making for effective air quality management.

Validation Once the calibration process is complete, the next step is validation. Validation aims to assess the model's performance by comparing its predictions against independent sets of observed data that were not used in the calibration process. This helps evaluate the model's ability to generalize and make accurate predictions for new scenarios or locations. Validation provides an important measure of confidence in the model's predictive capabilities. Validation datasets may include measurements from different monitoring networks, field campaigns, or satellite observations. Model evaluation metrics, such as correlation coefficients, mean error, or root mean square error, are commonly used to quantify the agreement between model predictions and observed data. Spatial and temporal analyses are performed to assess the model's performance across different locations, seasons, and time scales. A few validation techniques employed for assessing the accuracy of air quality models are listed below.

(i) Observational data comparison
(ii) Statistical Analysis
(iii) Sensitivity analysis
(iv) Ensemble modelling

Overall, the calibration and validation of air quality models are iterative processes that involve continuous refinement and improvement. They contribute to advancing our understanding of atmospheric processes, enhancing the accuracy of air quality predictions, and ultimately supporting evidence-based decision-making to protect public health and the environment.

9.6 Case Studies: Application of Modelling Approach for Air Quality Assessment

Case Study 1 – (Numerical Model) Gunwani et al. (2023) conducted an assessment of the weather research and forecasting model with chemistry (WRF/Chem) to determine its ability to simulate $PM_{2.5}$ using various meteorological initial/boundary conditions datasets and PBL parameterization schemes. The study focused on the Indo-Gangetic Plain during the winter period from December 2017 to January 2018. The model's simulations were performed with a horizontal grid resolution of 10 km and 47 vertical levels ranging from the surface up to 50 hPa. To drive the simulation, 21 class MODIS land-use data from previous studies were utilized (Ghude et al., 2020, 2022; Kumar et al., 2020; Jena et al., 2021; Sengupta et al., 2022). Datasets used for initial/boundary conditions were acquired from the

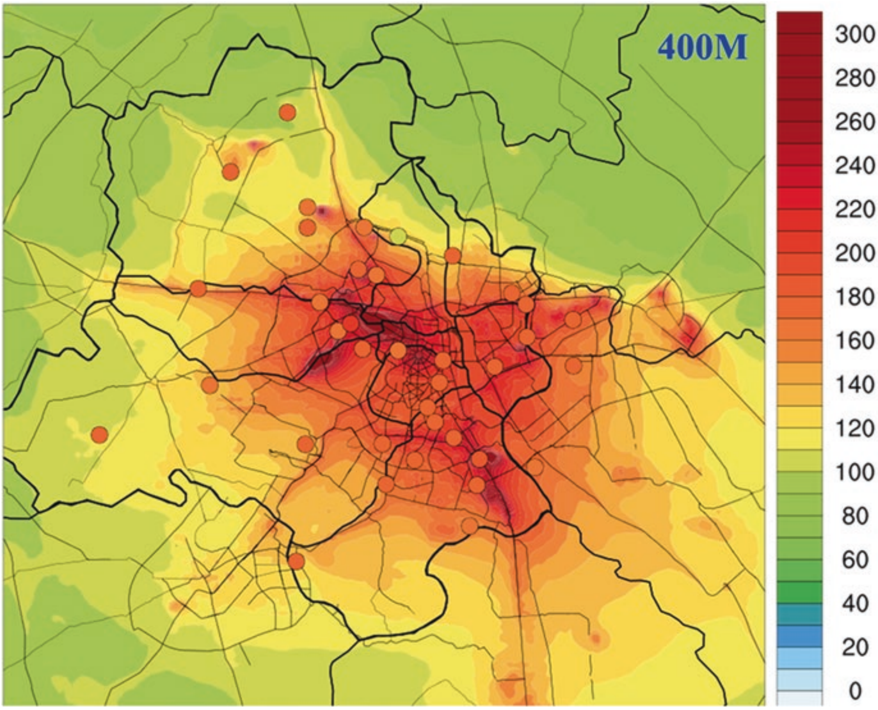

Fig. 9.10 Spatial distribution of averaged $PM_{2.5}$ concentrations at 400 m horizontal grid spacing (from day 1 forecast) overlaid with mean $PM_{2.5}$ observed at different monitoring stations across Delhi from 21 October 2019 to 1 February 2020 (Source: Jena et al., 2021)

National Centers for Environmental Prediction Final Analysis (NCEP-FNL), ERA-Interim, GDAS-GFS, and National Centre for Medium Range Weather Forecasting (NCMRWF), while the major PBL parameterization schemes applied were YSU – Yonsei University (Hong et al., 2006), MYJ – Mellor-Yamada-Janjić (Janjić, 1994), MYNN – Mellor-Yamada-Nakanishi-Niino (Nakanishi & Niino, 2004), ACM2 – Asymmetric Convective Model version 2 (Pleim, 2007) and Boulac (Bougeault & Lacarrere, 1989). The most favourable outcomes were observed when using initial/boundary conditions from ERA and GDAS datasets combined with local PBL parameterization schemes (MYJ and MYNN). Interestingly, the study found that $PM_{2.5}$ concentrations exhibited relatively less sensitivity to changes in initial/boundary conditions while showing a stronger sensitivity to variations in the PBL scheme.

Jena et al. (2021) introduced a novel and highly advanced air quality forecasting system with an unprecedented level of resolution (400 m grid spacing) (Fig. 9.10). The primary purpose of this system was to provide timely alerts to residents of Delhi and the National Capital Region (NCR) about potential acute air pollution episodes. This high-resolution system, evaluated during the period of October 2019 to February 2020, marks the first of its kind and showcases promising results. The forecasting system integrates near real-time aerosol observations from both ground-based and satellite platforms into the Weather Research and Forecasting model coupled with chemistry (WRF-Chem). This dynamic downscaling framework generates a 72-hour daily forecast for various air quality parameters. The assimilation of aerosol optical depth and surface $PM^{2.5}$ observations significantly enhances the accuracy of the initial conditions for surface $PM^{2.5}$, leading to an impressive improvement of approximately 45 μg/m^3 (approximately 50%). While the forecast accuracy shows a slight degradation over time, with the mean bias increasing from +2.5 μg/m^3 on the first day to −17 μg/m^3 on the third day, it remains notably skilful. The system excels in predicting both $PM^{2.5}$ concentrations and air quality index categories associated with unhealthy and very unhealthy conditions. The forecast's effectiveness has proven to be invaluable for decision-makers in Delhi, enabling them to make well-informed choices and implement necessary measures in response to potential air quality challenges. This pioneering high-resolution air quality forecasting system has demonstrated remarkable accuracy and skill in predicting $PM^{2.5}$ concentrations and air quality conditions. By assimilating real-time aerosol observations, it provides timely alerts to residents and supports decision-makers in effectively addressing air pollution issues in Delhi and the surrounding regions.

Case Study 2 – (Statistical Model) To estimate the daily concentration of ground-level $PM_{2.5}$ at a regional scale coinciding with satellite overpasses, a geographically weighted regression (GWR) model based on satellite data was developed by Song et al. in 2014. The dataset utilized for this study consisted of aerosol optical depth (AOD) measurements at a wavelength of 550 nm from the Collection 5.1 MODIS Dark Target level 2 aerosol retrievals over land product, obtained from the NASA LAADS Web. Ground-measured $PM_{2.5}$ data in the PRD region spanning from May 2012 to September 2013 were acquired from the Chinese Guangdong Environment Information Issuing Platform. Meteorological data, including boundary layer height, relative humidity, temperature, wind, and land use, were downloaded from the China Meteorological Data Sharing Service System (CMDSSS). External factors that can influence the relationship between $PM_{2.5}$ and AOD, such as those mentioned in the works of Gupta et al. (2006), Koelemeijer et al. (2006), Liu et al. (2007, 2009), Barman et al. (2008), and Schaap et al. (2008), were taken into consideration. The model's performance was assessed and validated using $PM_{2.5}$ data collected over the Pearl River Delta (PRD) region in China from May 2012 to September 2013. The evaluation demonstrated that the GWR model, with assimilated meteorological parameters, accounted for 73.8% of the variation in ground-level $PM_{2.5}$ concentration, outperforming two conventional statistical models: Model-I, a general linear regression model (56.4%), and Model-II, a semiempirical model (52.6%). The inclusion of vertical correction on satellite-derived AOD and relative humidity significantly enhanced the correlation between AOD and $PM_{2.5}$.

Case Study 3 – (Prediction Model) Chen et al. (2021) developed two random forest models to estimate daily $PM_{2.5}$ concentrations in Guangdong Province, China. Due to a significant portion of missing AOD data (over 80%), one model was created without using AOD as a predictor (referred to as the non-AOD model), while the other model incorporated AOD data (the AOD-based model). The study compared the predictive abilities of these two models and assessed whether AOD inclusion improved $PM_{2.5}$ predictions. Daily ground-based $PM_{2.5}$ measurements were collected from 148 monitoring sites within a 60 km buffer in Guangdong from January 2016 to December 2018. Additionally, daily MODIS MAIAC AOD data from NASA, providing a spatial resolution of approximately 1 km, were downloaded. Both random forest models were developed using the same dataset and underwent tenfold cross-validation to evaluate their performance. Surprisingly, the results showed that the non-AOD model and the AOD-based model demonstrated similar performance. The cross-validation R^2 (coefficient of determination) and RMSE (root mean square error) for the non-AOD model during 2016–2018 were 0.82 (8.4 μg/m^3), 0.81 (9.5 μg/m^3), and 0.78 (9.4 μg/m^3), respectively. For the AOD-based model, the corresponding values were 0.83 (8.2 μg/m^3), 0.82 (9.2 μg/m^3), and 0.80 (9.0 μg/m^3). The models demonstrated higher consistency in estimating $PM_{2.5}$ concentrations in areas close to monitoring sites compared to locations farther away and in southern coastal areas compared to northern regions. The non-AOD random forest model offers an advantage in that it is not affected by the missingness of AOD data. As a result, it can be reliably used for epidemiological studies to estimate individual-level exposure to $PM_{2.5}$ at a high spatial resolution, avoiding spatial or temporal gaps in the dataset. In conclusion, the study demonstrates that the non-AOD random forest model can be a valuable tool for accurately estimating $PM_{2.5}$ concentrations, especially in regions with limited AOD data availability. This approach holds great potential for enhancing individual-level exposure assessments and supporting epidemiological research on the health impacts of $PM_{2.5}$ pollution.

9.7 Conclusion

In conclusion, the integration of ground monitoring systems, remote sensing technologies, and Geographic Information Systems (GIS) techniques marks a significant advancement in urban air quality research. This combined approach offers multifaceted advantages spanning environmental science, public health, and policymaking. Ground monitoring data are pivotal for tracing pollution sources, validating models, and discerning spatial and temporal trends. Meanwhile, remote sensing and satellite sensors provide a comprehensive view of air quality, addressing gaps in coverage that ground-based methods might encounter. Sensors like TES, MOPITT, OMI, and others offer diverse capabilities for monitoring pollutants and meteorological parameters from a global perspective. GIS enhances spatial analysis, identifying pollution hotspots and enabling dynamic data visualization. Through data integration, including meteorological conditions and land use patterns, we gain insight into complex pollution-source interactions. Furthermore, GIS-based Decision Support Systems (DSS) utilize modelling tools to predict pollutant concentrations and intervention effects, facilitating informed decision-making. Case studies underscore diverse modelling approaches for air quality assessment. From numerical models like WRF/Chem to high-resolution forecasting systems and statistical models like GWR, each contributes to understanding pollution dynamics. These studies emphasize region-specific models, such as for the Indo-Gangetic Plain and Guangdong Province. Bridging scientific understanding with actionable insights empowers effective air pollution management. Overall, the fusion of ground monitoring, remote sensing, and GIS signifies a paradigm shift, enhancing our ability to analyse and mitigate urban air pollution. This holistic approach aids in identifying pollution sources, trends, and strategies for a healthier, sustainable future.

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Chapter 10
Assessment of Soil Contamination Using Remote Sensing and Spatial Techniques

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Abstract Soil contamination poses an enormous challenge to environmental and human health, necessitating effective assessment and management. Assessing the contamination of soil using remote sensing and spatial techniques has become an important area, as it provides rapid and accurate information about the extent and distribution of contaminants in soil. This chapter aims to present some of the current state of knowledge and advancements in this field. Remote sensing techniques, including hyperspectral remote sensing, thermal remote sensing, and radar remote sensing, offer valuable tools for mapping and monitoring soil contamination over large areas, enabling efficient decision-making and resource allocation. Spatial techniques usually involve the analysis and integration of spatially referenced data to assess and visualize soil contamination patterns and include geographic information systems, geostatistics, geospatial modelling techniques, machine learning, and data mining. Advancements in remote sensing and spatial techniques have enhanced the accuracy and efficiency of soil contamination assessment and include the development of high-resolution satellite sensors, advanced image processing algorithms, and the integration of multisource data. However, several challenges persist in the form of spectral unmixing, the scale of mapping, the resolution of data, ground validation, and data integration. Remote sensing and spatial techniques thus provide valuable tools for assessing soil contamination by offering the ability to map contamination patterns over large areas, identify hotspots, and support decision-making processes. Recent advancements in the assessment of soil contamination using remote sensing and spatial techniques have contributed to improved accuracy, efficiency, and applicability of these methods.

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10.1 Introduction

Soil pollution is a significant environmental issue caused by human activities such as industrialization, agriculture, and urbanization. Contaminants found in the soil, such as heavy metals, organic compounds, and radioactive substances, can pose serious health risks to humans and animals. Soil degradation can occur through physical and chemical processes. As per the Soil Science Society of America (SSSA), contaminants are substances in the soil that exceed natural levels and threaten human health. Soil contamination, referred to as one of the contributing factors to soil degradation, refers to the accumulation of non-native components in the soil, unrelated to its natural formation, which negatively impacts plant growth and the health of animals and humans (Okrent, 1999). Physical processes involve changes in soil depth, particle size, structure, and compaction, while chemical processes involve alterations in soil properties, including its chemical constituents and reactions (Chuncai et al., 2014; Sahoo et al., 2012). Soil degradation primarily arises from deforestation, leading to increased CO_2 emissions, reduced storage of carbon above and below ground, and disruptions to soil-vegetation-atmosphere transfer (SVAT) processes (Cao et al., 2001). It impairs crucial ecosystem services and has implications for climate change (Vågen et al., 2016). Various sources contribute to soil pollution, including agrochemicals (fertilizers, pesticides, and herbicides), natural gas, petroleum hydrocarbons, and potentially toxic elements (PTEs). Between 2000 and 2017, there has been a steady rise in pesticide usage worldwide, with varying increases across different regions (Table 10.1), ranging from approximately 8% in Europe to 84% and 104% in Oceania and South America, respectively (FAO, 2019).

Table 10.1 Global use of pesticides between 2000 and 2017 (*Source*: FAO, 2019)

	Annual pesticide use (tonnes)		
Region	2000	2017	Increase (percentage)
Africa	61,698	79,787	29.3
Asia	1,621,207	2,159,990	33.2
Caribbean	6776	11,451	69.0
Central America	75,423	101,256	34.3
Europe	440,881	476,138	8.0
North America	469,672	498,618	6.2
Oceania	37,773	69,669	84.4
South America	349,710	71,682	104.9
World	3,063,140	4,113,591	34.3

Source: FAOSTAT, 2019

In the post-industrial era, there has been notable progress in economic growth and intensive industrial operations. Consequently, there is a persistent release of significant amounts of natural gas, petroleum hydrocarbons, and persistent toxic elements (PTEs) into various soil environments, including agricultural soils. The seepage of natural hydrocarbon leaks from fuel pipelines, and tank leakages are often sources of hydrocarbon and obnoxious gases in the soil (Noomen et al., 2006). Anthropogenic activities, including open-cast mining, contribute to the formation of spoil dumps containing acidic substances and PTEs. These deposits have a significant impact on hydrological, geological, and vegetation features, leading to alterations in their characteristics (Götze et al., 2016). The conventional techniques for the assessment of soil contamination are based on sampling and require several samples to be collected, and intricate laboratory procedures such as separation and preconcentration make them impractical for the purpose of mapping contaminated soil over extensive regions (Xian-Li et al., 2012). The emergence of geospatial technological approaches such as remote sensing and other spatial techniques has been recognized as an alternative and efficient method for mapping and monitoring various soil contaminants (Choe et al., 2008; Wu et al., 2005). The utilization of remote sensing, in conjunction with various geospatial techniques, has emerged as a vital tool for detecting pollution at different stages (Saghatelyan & Sahakyan, 2009; Wu et al., 2007) and ecological risk monitoring (Asmaryan et al., 2014), and these approaches aid in achieving a significant reduction in pollution levels across both natural and human-modified landscapes (Asmaryan et al., 2014; Saghatelyan & Sahakyan, 2009). Furthermore, the efficacy of proximal and airborne sensors, along with unmanned aerial vehicles (UAVs), has been demonstrated in accurately and quantitatively estimating the presence of contaminants (Choe et al., 2008; Vågen et al., 2016). The deployment of satellite-based hyperspectral and multispectral sensors has been expanded, and new sensors are being developed, promising a substantial increase in the availability of data for land monitoring purposes. This will result in the generation of extensive databases at a large scale (Buckingham & Staenz, 2008; Malenovský et al., 2012; Sánchez et al., 2015). This chapter provides an extensive compilation of knowledge and information acquired from diverse sources spanning several decades. Our focus will be on the utilization of remote sensing and spatial techniques in various domains to address soil contamination. Additionally, we will discuss the limitations and challenges associated with remote sensing of soil contamination, along with potential solutions to overcome them.

10.2 Remote Sensing

Assessment of soil contamination using remote sensing and spatial techniques has contributed to improved accuracy, efficiency, and applicability. These advancements have contributed to a more precise and comprehensive understanding of soil contamination, enabling better decision-making processes, effective land management, and targeted remediation efforts. However, continued research is necessary to address challenges such as data availability, scale mismatch, and validation procedures, ensuring the reliability and widespread adoption of these techniques in soil contamination studies. Some notable advancements include the following:

High-Resolution Satellite Sensors: The availability of high-resolution satellite sensors, such as WorldView, GeoEye, and Pleiades, has increased the spatial detail and precision of soil contamination assessments. These sensors provide imagery with pixel sizes as small as 30 cm, allowing for the detection of small-scale variations in contamination.

Hyperspectral Imaging: Hyperspectral sensors with increased spectral resolution have facilitated the identification and characterization of contaminants in soil. By capturing hundreds of narrow and contiguous spectral bands, hyperspectral imaging enables the detection of subtle differences in reflectance related to specific contaminants.

Unmixing Techniques: Spectral unmixing algorithms have advanced the analysis of hyperspectral data for soil contamination assessment. These algorithms can identify and quantify the contribution of different materials in a pixel, including contaminants and soil components, improving the accuracy of contamination mapping.

LiDAR (Light Detection and Ranging): The integration of LiDAR technology, which employs laser pulses to measure the distance between a sensor and the Earth's surface, has been utilized in conjunction with remote sensing to improve soil contamination assessment. By utilizing LiDAR data, it becomes possible to obtain precise details regarding terrain elevation, vegetation structure, and surface roughness. This information proves valuable in identifying potential sources of contamination and pathways.

Fusion of Multi-source Data: The integration of data from multiple sources, such as remote sensing, GIS, and ground-based measurements, has been increasingly used to improve soil contamination assessments. Combining information from different sensors and platforms enables a more comprehensive understanding of contamination patterns and their spatial relationships with environmental variables.

Machine Learning and Artificial Intelligence: Remotely sensed data have been leveraged in conjunction with machine learning algorithms, including random forests, support vector machines, and deep learning models, to automate the classification of contaminated areas. These algorithms possess the capability to learn intricate patterns and correlations among spectral data, soil properties, and contamination. As a result, they enable efficient and precise mapping of contamination.

Open Data and Citizen Science: The availability of open-access remote sensing data, such as those from NASA and ESA, has democratized soil contamination assessment. Citizen science initiatives have also emerged, where volunteers contribute ground-based measurements and observations for the validation and calibration of contamination maps.

Improved Data Processing and Analysis Software: The development of advanced data processing and analysis software, such as ENVI, ERDAS Imagine, and QGIS, has facilitated the integration, visualization, and interpretation of multidimensional remote sensing and spatial data. These tools provide a user-friendly interface for researchers and practitioners to conduct soil contamination assessments.

10.3 Spatial Techniques

Spatial techniques involve the analysis and integration of spatially referenced data to assess and visualize soil contamination patterns. These techniques include the following:

Geographic Information System (GIS): GIS integrates various spatial data, such as remote sensing imagery, soil sampling points, land use/land cover data, and contaminant concentration measurements. GIS enables the creation of contamination maps, identification of hotspots, and spatial analysis of relationships between contaminants and environmental variables.

Geostatistics: Geostatistical methods, such as kriging, provide a framework for spatial interpolation and estimation of contaminant concentrations at unobserved locations based on sampled data. Geostatistics can account for spatial autocorrelation and variability, enhancing the accuracy of contamination mapping.

Machine Learning and Data Mining: Machine learning algorithms and data mining techniques can be applied to large datasets to identify patterns, classify contaminated areas, and predict contaminant concentrations based on a combination of remote sensing, soil, and environmental variables.

10.4 Applications of Remote Sensing and Spatial Techniques in Mapping and Modelling Soil Contamination

Geostatistical Spatial Interpolation Techniques for Soil Contamination Mapping

By utilizing spatial interpolation techniques and geostatistical methods, it is possible to generate soil contamination maps at the grid cell level. These maps facilitate the examination of spatial variations in heavy metal pollution. They provide visual representations that help distinguish between natural background levels and areas significantly enriched due to anthropogenic activities. Consequently, these maps aid in identifying regions with contaminated topsoil, guiding the implementation of necessary remedial measures. Previous studies have utilized geostatistical spatial interpolation techniques to map contamination and determine its sources. For example, Nakayama et al. (2011) assessed metal concentrations in roadside soils near a Pb–Zn mine in Kabwe, Zambia, and Lusaka using mapping and spatial interpolation to identify mining and smelting activities as the source of metal pollution. Dong et al. (2011) modelled the distribution of heavy metals in reclaimed agricultural lands using geostatistical analyses and evaluated the ecological safety of these lands. Khalil et al. (2013) assessed soil contamination around an abandoned mine using geochemistry and simple kriging. A combination of GIS and stochastic simulation techniques was employed to estimate the spatial distribution of lead (Pb) within a mine in Portugal and classify soil quality (Reis et al., 2005). Other studies (Acosta et al., 2011; Kim et al., 2017; Yan et al., 2015; Bangroo et al., 2020; Suh et al., 2016) have also utilized geospatial techniques to investigate and map heavy metal contamination in various contexts. In the agricultural landscape of district Kulgam, Kashmir, geostatistical spatial interpolation techniques were utilized to map various soil properties. These properties, including pH, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), available phosphorus (P), and available potassium (K), were analysed and subjected to Box–Cox transformation for data normalization (Table 10.2) (Bangroo et al., 2023). Ordinary kriging (OK) and universal kriging (UK) were used to interpolate the soil parameters and generate respective maps (Figs. 10.1, 10.2, and 10.3). The study also assessed spatial autocorrelation using experimental variograms and cross-validation techniques, demonstrating moderate to strong spatial dependency (Table 10.3). The analysis showed that UK performed better than OK in predicting soil parameters, except for pH (Table 10.4). The spatial structure of soil chemical properties was analysed using the Global Moran's I Index, indicating random distribution patterns for the selected soil parameters (Table 10.5).

Overall, the use of geostatistical spatial interpolation and geospatial techniques enables the mapping and examination of soil properties, facilitating more efficient management decisions and ensuring productivity and sustainability in soil resource management, particularly in ecologically fragile regions such as the Kashmir Himalayas.

Table 10.2 Statistical overview of selected soil chemical properties within the study area

Parameter	Min	Median	Mean	Max	Kolmogorov test	Skewness	Kurtosis	CV	SD
pH (1:2.5)	5.73	6.52	6.52	7.42	0.0630	1.282	2.49	6.05	0.39
EC (dS m^{-1})	0.10	0.53	0.54	0.98	0.0710	1.285	2.56	38.18	0.21
OC (%)	0.43	1.78	1.63	3.03	0.0630	1.159	2.07	42.47	0.69
N (kg ha^{-1})	169.4	324.5	331.4	556.2	0.0059	0.259	1.96	27.28	90.4
P (kg ha^{-1})	2.66	17.71	20.56	56.10	0.0708	1.516	5.04	51.52	10.5
K (kg ha^{-1})	123.8	247.9	269.1	528.2	0.0020	0.654	1.51	38.25	10.9

Min minimum, *Max* maximum, *CV* coefficient of variation, *SD* standard deviation

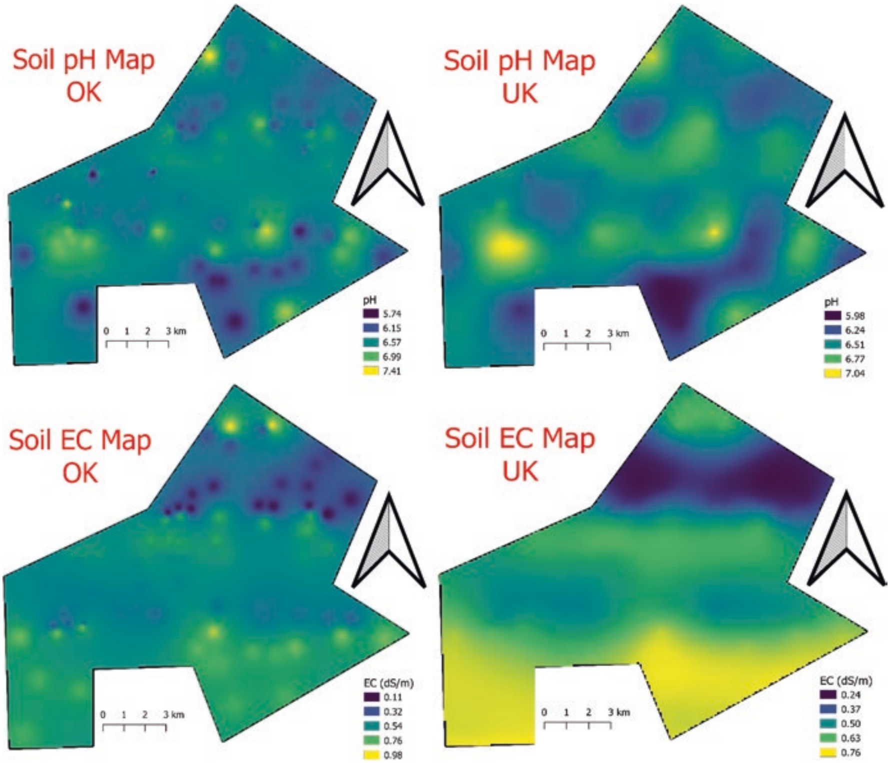

Fig. 10.1 Soil spatial variability of chemical properties by OK and UK (pH and EC) (Source: Bangroo et al., 2023)

Pollutant Transport Modelling Based on Hydrological Analysis

Local hydrological characteristics play a significant role in the movement of pollutants within the soil. The spatial disparities in heavy metal enrichment can be attributed to natural dispersion mechanisms such as leaching through rainwater infiltration or mechanical transportation via runoff. Several studies have dedicated their efforts to hydrological analyses to understand the distribution patterns of pollution within catchment areas. GIS tools were employed to evaluate pollution levels at an abandoned coal mine site. This assessment involved analysing the spatial distribution of pollutant concentrations in relation to surface runoff pathways and potential sources of contamination, including open pits, coal storage areas, and dump sites, and the spatial distribution of pollutant concentrations in relation to surface runoff pathways and potential contamination sources, such as open pits, coal storage areas, and dump sites (Yenilmez et al., 2011). The findings demonstrated that regions closer to contamination sources and along surface runoff pathways exhibited higher pollutant concentrations. GIS proved to be a valuable tool in accurately identifying areas with elevated pollutant levels, preventing the oversight of highly contaminated locations

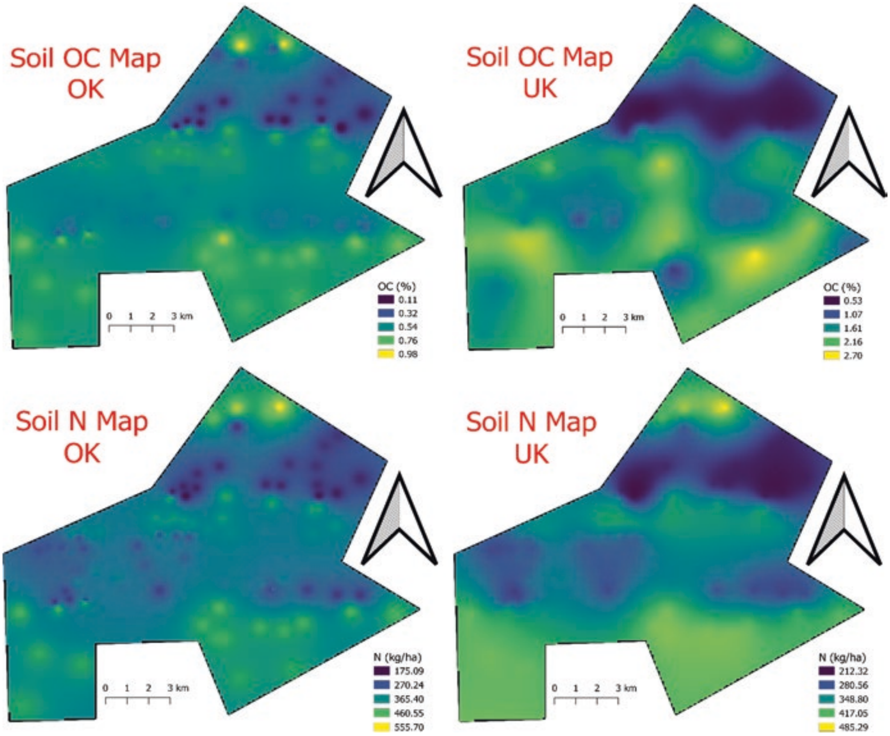

Fig. 10.2 Soil spatial variability of chemical properties by OK and UK (OC and N) (Source: Bangroo et al., 2023)

situated far from pollution sources. Moreover, by focusing on areas near surface runoff pathways, fewer samples were needed, resulting in reduced sampling costs. Investigating areas far from contamination sources became unnecessary. Suh et al. (2016) conducted a study that utilized hydrological analysis based on digital elevation models (DEMs) to assess the impact of the single-flow direction of surface runoff on the dispersion of copper (Cu). The study examined the flow direction of rainwater throughout the entire study area, considering local topographic relief, and compared it with the distribution of Cu concentration at sampling points. The findings revealed that the dispersion pattern of soil contaminants was influenced by the single-flow direction of rainwater, despite the inability to identify specific high-level pollution sources within the study area. This discovery can assist in the selection of additional sampling points for further investigation or validation purposes.

Overall, hydrological analysis plays a significant role in understanding the movement and distribution of pollutants in soil, particularly regarding the influence of runoff and dispersion processes. Incorporating GIS tools and DEM-based assessments provides valuable insights for identifying contamination sources, determining sampling locations, and optimizing resources in pollution investigation and monitoring.

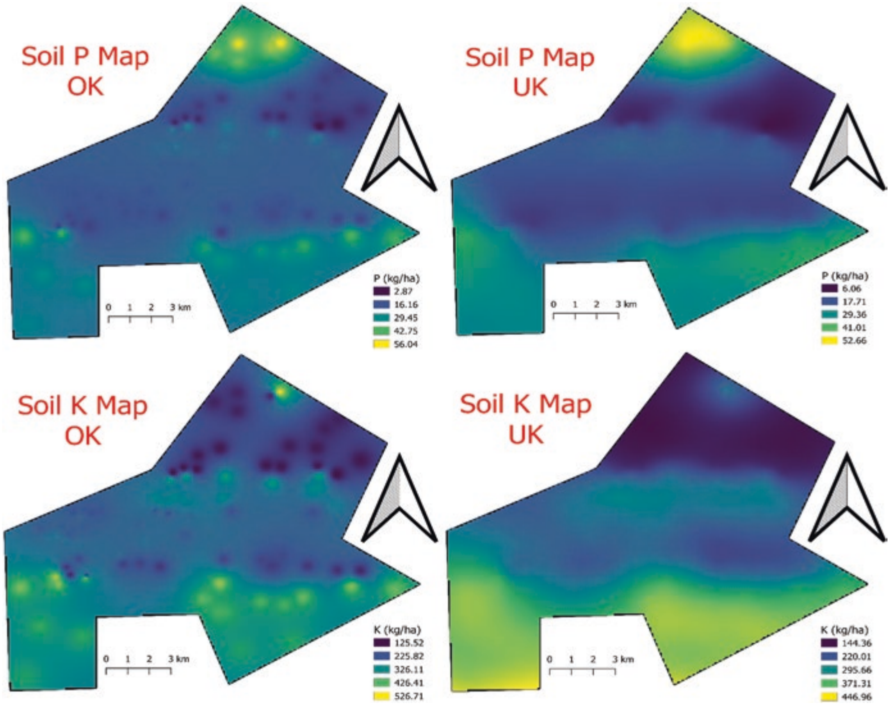

Fig. 10.3 Soil spatial variability of chemical properties by OK and UK (P and K) (Source: Bangroo et al., 2023)

Soil Erosion and Sediment Yield

Soil is a crucial ecosystem that sustains human life and prosperity, and ensuring its sustainability is vital for human well-being and global food security (Fei et al., 2019; Fei et al., 2020; He et al., 2019). The issue of soil pollution, especially contamination and deposition of heavy metals, has become a significant environmental concern, attracting widespread attention due to its societal implications (Azizi et al., 2022; Huang et al., 1997; Karimi et al., 2017; Mushtaq & Lala, 2017; Yang et al., 2018). Various geospatial modelling approaches have proven effective in quantifying erosion and sediment yield. The combination of geographic information systems (GIS) with the universal soil loss equation (USLE) and Revised Universal soil loss equation (RUSLE) model allows for the estimation of soil erosion from mine tailing dumps in specific mining regions (Wischmeier et al., 1971). The ArcMine waste erosion tool, a GIS extension developed by Kim et al. (2012), facilitates the efficient evaluation of erosion in abandoned mining regions. This software utilizes USLE (Universal Soil Loss Equation) factors to calculate and provide estimates of soil erosion throughout the designated area. Soil-related concerns in mining areas are typically divided into three primary aspects: pollutant transport analysis based

Table 10.3 Ordinary kriging and universal kriging semivariance analysis of spatial structure in soil chemical properties

Property	Ordinary kriging					Universal kriging				
	Model	Range	Nugget (N)	Sill (S)	Nugget/sill (N/S) (%)	Model	Range	Nugget (N)	Sill (S)	Nugget/sill (N/S) (%)
pH (1:2.5)	Sph	3229.6	0.085	0.217	39.17	Sph	3235.1	0.085	0.218	38.99
EC (dS m^{-1})	Exp	7237.4	0.014	0.050	28.00	Sph	5102.6	0.014	0.030	46.66
OC (%)	Exp	1834.9	0.071	0.507	14.00	Sph	3262.1	0.092	0.431	21.34
Available N (kg ha^{-1})	Exp	1830.6	0.167	0.796	20.97	Exp	1728.2	0.174	0.755	23.04
Available P (kg ha^{-1})	Exp	6186.1	0.063	0.640	09.84	Exp	5547.1	0.061	0.596	10.23
Available K (kg ha^{-1})	Sph	4613.8	0.113	0.272	41.54	Sph	4336.6	0.116	0.237	48.94

Sph spherical, *Exp* exponential model

Table 10.4 Prediction accuracy comparison between ordinary kriging and universal kriging

Property	Ordinary kriging							
	ME	MAE	RMSE	MSDR	ME	MAE	RMSE	MSDR
pH (1:2.5)	−0.010	0.331	0.435	1.165	−0.009	0.345	0.452	1.233
EC (dS m^{-1})	−0.005	0.123	0.171	1.325	0.001	0.106	0.156	1.091
OC (%)	0.011	0.403	0.543	1.143	−0.008	0.395	0.532	1.102
N (kg ha^{-1})	0.046	0.559	0.713	1.117	0.003	0.535	0.693	1.076
P (kg ha^{-1})	0.032	0.312	0.510	1.632	0.012	0.294	0.479	1.486
K (kg ha^{-1})	0.002	0.354	0.473	1.197	−0.003	0.330	0.462	1.188

ME mean error, *MAE* mean absolute error, *RMSE* root mean square error, *MSDR* mean squared deviation ratio

on hydrological assessment, geostatistical spatial interpolation for soil contamination mapping, and assessment of sediment yield originating from mine tailing dumps.

Heavy Metal Contamination

Heavy metals pose a significant threat to soil contamination, leading to detrimental health effects on living organisms. Geospatial technology offers a valuable approach to monitor and assess heavy metal contamination in soil, providing a comprehensive

Table 10.5 Test of significance of pattern analysis for selected soil chemical properties

Property	Moran's index	Variance	*z* score	*p* value
pH (1:2.5)	0.290	0.003	5.234	0.0000
EC (dS m^{-1})	0.094	0.003	1.816	0.0692
OC (%)	0.198	0.003	3.633	0.0002
Available N (kg ha^{-1})	0.161	0.003	2.988	0.0028
Available P (kg ha^{-1})	0.239	0.003	4.409	0.0000
Available K (kg ha^{-1})	0.094	0.003	1.817	0.0691

overview of the extent of contamination and identifying areas with high concentrations, known as hotspots (Su et al., 2022a, b; Zhang et al., 2018a, b). By employing geographic information systems (GIS), it becomes possible to analyse and map heavy metal contamination in soil, enabling more targeted and effective remediation strategies. Various techniques, including GIS-based interpolation methods, positive matrix factorization (PMF), and principal component analysis (PCA), are utilized to investigate the distribution patterns and sources of metal contamination in soils. Standard procedures such as PCA and PMF, along with contamination indices (González-Macías et al., 2014; Li et al., 2022; Xu et al., 2021; Wang et al., 2022; Yu et al., 2021) and ecological risk factors, are commonly employed to identify source contributions and estimate the risk associated with metal contamination in soils (Li et al., 2021; Proshad et al., 2022; Shi et al., 2022; Wang et al., 2020). Moreover, systematic utilization of contamination indices, including the geo-accumulation index (Igeo), contamination factor (Cf), pollution load index (PLI), and degree of contamination (Cd), is employed to assess heavy metal contamination in soils. Furthermore, human health risk assessment analysis is conducted to comprehensively evaluate the potential risks associated with such contamination (Maurya & Kumari, 2021; Qi et al., 2020; Saha et al., 2022). It is essential to distinguish between natural and anthropogenic sources of metal contamination to safeguard the soil ecosystem (Agyeman et al., 2021; Ayoubi et al., 2014; Ma et al., 2021; Luo et al., 2021a, b; Wu et al., 2020). Receptor models that incorporate multivariate analysis techniques, including partition computing-based positive matrix factorization (PC-PMF), absolute principal component score-multiple linear regression (APCS-MLR), GeogDetector models, and multivariate curve resolution-weighted alternating least squares (MCR-WALS), are commonly employed for source identification of metal contamination in soils (Chen et al., 2016; Fei et al., 2020; Kim et al., 2004; Ma et al., 2018; Schaefer & Einax, 2016; Wu et al., 2020). However, receptor models may not always fulfil certain key assumptions and may have limitations in accurately identifying contamination sources (Adgate et al., 1998; Ahmed et al., 2016; Jorquera & Barraza, 2013; Lv & Liu, 2019; Su et al., 2022a, b). The positive matrix factorization (PMF) model, despite being widely used, is an empirical approach that assumes a linear contaminant spread (Feng et al., 2020; Lv & Liu, 2019), potentially disregarding important spatial correlation information between soil samples and introducing uncertainties in source apportionment results (Chai et al., 2021).

Organic Compound Loading

Organic compounds, including polycyclic aromatic hydrocarbons (PAHs) and polychlorinated biphenyls (PCBs), are a significant source of soil contamination. The geospatial technology approach, which combines remote sensing and chemical analysis, is commonly used to monitor the presence of organic compound contamination in soil. Remote sensing data enable a comprehensive view of soil contamination on a large scale, identifying hotspots where concentrations of organic compounds are high. On the other hand, chemical analysis of soil samples provides more detailed information about the specific types and concentrations of organic compounds present in the soil. In a study conducted by Bangroo et al. (2021) in the apple orchards of Kashmir, the authors investigated the spatial distribution of different soil properties using classical and ordinary kriging techniques. They collected soil samples based on topography and land management zones and analysed properties such as pH, electrical conductivity (EC), organic carbon (OC), and available nutrients. The research findings unveiled notable variations in soil properties, as indicated by different coefficients of variation (CV) spanning from 9.0% for pH to 30.0% for organic carbon (OC). Furthermore, the study determined the average values of soil properties, including organic carbon (OC), nitrogen (N), available phosphorus (P), potassium (K), calcium (Ca), and magnesium (Mg). By utilizing semivariogram analysis and ordinary kriging (OK) based on different models, they plotted the spatial distribution of soil parameters, highlighting the degree of spatial dependence and variations in different regions. Similarly, Sánchez-Nilda et al. (2019) used remote sensing and chemical analysis to assess the distribution of PAHs in soil near a landfill in Costa Rica. Their findings indicated higher concentrations of PAHs in soil samples collected in proximity to the landfill compared to those collected farther away. This information can guide remediation efforts and help mitigate exposure to PAH-contaminated soil. In addition, Farooq et al. (2022) utilized digital soil mapping (DSM) techniques to forecast and assess the spatial patterns of soil organic carbon stock (SOCS) in the Himalayan region of Jammu and Kashmir, India. The results and related data are presented in Table 10.6. Geostatistical

Table 10.6 Soil organic carbon stocks under different land uses

Land use		SOCS (Mg/ha)
	Mean	46.26
Horticulture	95% C.I.	26.69–62.83
	Mean	13.12
Maize	95% C.I.	4.80–21.45
	Mean	30.23
Forest	95% C.I.	26.83–33.60
	Mean	5.48
Wasteland	95% C.I.	2.84–8.12
	Mean	33.01
	95% C.I.	23.12–42.90

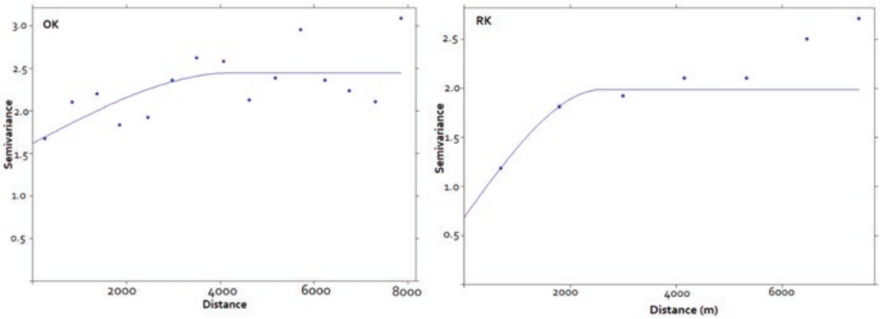

Fig. 10.4 Semivariogram of SOCS by ordinary krigingKriging (OK) and regression krigingKriging (RK) (Source: Farooq et al., 2022)

techniques, including ordinary kriging (OK) and regression kriging (RK), along with a machine learning algorithm called random forest (RF), were employed by Farooq et al. (2022) to analyse the spatial variations in soil organic carbon stock (SOCS). This assessment involved incorporating auxiliary variables derived from satellite data (as depicted in Fig. 10.4). The study found that RF performed better in terms of prediction performance and accuracy compared to OK and RK. However, the accuracy of RK predictions could be improved with further selection and choice of auxiliary variables and increased soil sampling density. Overall, geospatial technology, in conjunction with chemical analysis, plays a crucial role in monitoring and understanding the spatial distribution of organic compound contamination and soil properties, thereby aiding in the implementation of appropriate management practices for sustainable land use and remediation efforts.

Radioactive Contamination

Soil contamination by radioactive substances, such as radium and uranium, poses significant health risks. The application of geospatial technology allows the monitoring of radioactive substance contamination in soil through the utilization of remote sensing and gamma-ray spectrometry. Remote sensing data provide a comprehensive overview of the extent of soil contamination, enabling the identification of hotspots with high concentrations of radioactive substances. Meanwhile, gamma-ray spectrometry is employed to quantify the levels of radioactive substances in soil samples. For instance, Pourghasemi et al. (2017) conducted a study utilizing geospatial technology to monitor the distribution of radium in soil surrounding a uranium mine in Iran. The approach involved the integration of remote sensing data and gamma-ray spectrometry to assess the contamination levels. The study revealed that soil samples collected in close proximity to the mine exhibited elevated radium levels compared to samples collected at greater distances. These findings played a crucial role in remediation efforts aimed at reducing exposure to radium-contaminated soil. In summary, geospatial technology, combined with remote sensing and gamma-ray spectrometry, offers an effective means of monitoring and evaluating radioactive substance contamination in soil. By accurately identifying areas of contamination, remediation measures can be implemented to minimize the risks associated with exposure to radioactive substances in the soil.

10.5 Conclusion

In this chapter, the significant role of geospatial technology in assessing and monitoring soil contaminants using remote sensing and spatial technology is emphasized. The combination of remote sensing and geospatial technology provides a powerful tool for monitoring and mapping soil contamination. Various studies have showcased successful applications of remote sensing and geospatial technology in identifying hotspots of heavy metal and organic compound contamination. Additionally, gamma-ray spectrometry has been employed to measure the levels of radioactive substances. The integration of remote sensing, GIS, GPS, and geostatistical techniques with traditional soil sampling and laboratory analysis methods has yielded promising results in enhancing the spatial resolution and accuracy of contaminant mapping. However, certain challenges, such as limitations in accuracy, considerations of cost, and issues related to data integration, must be addressed for wider adoption and improved risk assessment. To ensure effective management of soil contamination, future research should focus on advancing geospatial techniques, integrating emerging technologies, and improving decision-making processes. This will facilitate more precise and comprehensive approaches to addressing soil contamination issues.

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Chapter 11
Noise Pollution Modelling Using GIS Techniques in Srinagar City

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Abstract Due to swift urbanization and shifts in lifestyle, loud noise has permeated every aspect of our lives, becoming an inescapable element. Extensive research has demonstrated that both indoor and outdoor environmental noise pollution pose significant health risks, particularly impacting the well-being of fetuses, infants, children, adolescents, and adults. The detrimental effects of noise pollution encompass not only noise-induced hearing loss but also a wide range of nonauditory health issues. The diagnosis of these adverse effects, attributable to noise pollution, is steadily rising across all age groups. This chapter presents a comprehensive approach utilized for evaluating and delineating the levels of noise pollution in Srinagar city. The assessment and mapping processes were carried out utilizing geospatial techniques. At each selected location, noise measurements were conducted using a sound level meter for 5 days at the same location for morning, afternoon, evening, and nighttime. The resulting noise map was constructed based on the average calculated values using the interpolation technique, which showed that the noise levels in the morning ranged from 44.23 to 78.00 dB, with the outskirts having the lowest values and the city center, Pantha Chowk, and Hazratbal registering the highest levels. Afternoon noise increases from 53.00 to 80.15 dB, and most of the city falls into the medium to high range. In the evening, noise decreases (36.00–79.75 dB), while during the night, levels vary from 36.00 to 60.96 dB, with higher levels in Lal Chowk, Rajbagh, Pantha Chowk, and Khonmoh due to vehicle movements. The findings of this study serve as valuable references and guidelines for future urban planning endeavors and the formulation of noise regulations in areas similar to Srinagar city. These results offer crucial insights into establishing appropriate noise limits to be implemented for the betterment of urban environments.

Keywords Geospatial techniques · Inverse distance interpolation · Noise mapping · Noise pollution · Srinagar city

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11.1 Introduction

Noise, which is characterized as sound caused by undesired human activities, is widely recognized as an environmental stressor and a source of annoyance (Stansfeld & Matheson, 2003). The rapid urbanization of numerous regions has led to the emergence of noise pollution as a prominent environmental concern (Oyedepo, 2013). Noise pollution poses a genuine problem in all developed and developing countries and plays a significant role in deteriorating the overall health of the population, acting as a catalyst for various stress-related ailments (Vladimir & Madalina, 2019). It has been noted that prolonged exposure to high-intensity sound waves has adverse effects on human health (Gupta et al., 2018; Mehdi et al., 2018). The expansion of transportation networks, increasing number of motor vehicles, widespread mechanization, and inadequate protection of densely populated residential areas from noise due to unplanned rapid urbanization contribute to numerous challenges concerning public health (Esmeray & Eren, 2021). Numerous studies have demonstrated that both short-term and long-term exposure to noise not only diminishes human hearing capabilities but also raises the risk of conditions such as high blood pressure, cardiovascular disease, anxiety, and insomnia (Jariwala et al., 2017; Münzel et al., 2021).

Despite noise pollution being a silent and gradual threat to human well-being, there has been a notable lack of concerted efforts to mitigate this issue (Singh & Davar, 2004). Elevated levels of environmental noise have a detrimental impact on quality of life, necessitating the need to address this issue. However, before taking action, it is crucial to analyze the problem, which involves measuring the levels of noise pollution (Arokoyu et al., 2016). Environmental noise monitoring faces the challenge of achieving comprehensive measurements that encompass both temporal and spatial domains (Maijala et al., 2018). A single-point noise measurement is seldom indicative of an entire neighborhood, necessitating multiple sensor locations.

However, due to the expenses involved in equipment and human resources, the reliability, validity, and representativeness of environmental data often fall short of satisfactory standards. Therefore, the utilization of geographic information systems (GIS) holds significant value in methodological and scientific pursuits, as it enhances workflow efficiency and automates specific calculations, thereby streamlining the user's tasks (Fig. 11.1) (Bilaşco et al., 2017; Garg et al., 2021). The effectiveness of geographic information systems lies in their ability to enable the acquisition, management, analysis, modeling, and precise mapping of results (Sheng & Tang, 2011). One of the notable advantages is the capability to populate the georeferenced database with attributes, allowing for the inclusion of noise sources. Additionally, the utilization of spatial analysis is another significant benefit offered by geographic information systems (Garg & Maji, 2014; Haq et al., 2012).

The current research endeavors to utilize geospatial techniques to map and identify the areas most susceptible to noise pollution. The study aims to emphasize both high sound intensity zones and quiet areas within Srinagar city, where traffic and its associated environmental noise are steadily escalating. Moreover, through GIS

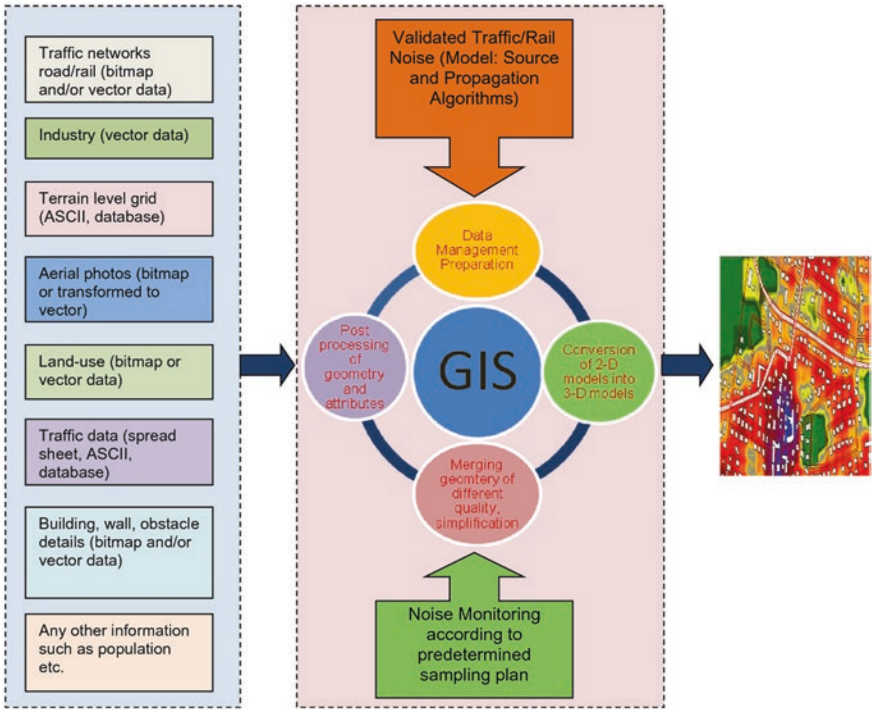


Fig. 11.1 Integrating GIS in noise mapping. (Source: Garg et al., 2021)

analysis, the study elucidates the variations in noise pollution across different representative time periods. In addition, the outcomes of the study can be utilized by local authorities in formulating policies to enhance public awareness regarding the risks associated with noise pollution and to contribute to the scientific literature by proposing potential measures to mitigate noise pollution.

11.2 Study Area

Srinagar, the summer capital of the Union Territory of Jammu and Kashmir, is situated at an elevation of 5200 feet above sea level, within the latitudinal range of 34°00′–34°14′ N and the longitudinal range of 74°43′–74°52′ E (Fig. 11.2). Extending along the Jhelum River, the city spans approximately 29 km in length and has an average width of approximately 6 km on both sides. Excluding the cantonment area dedicated to defense purposes, the current total area of Srinagar city is 278.1 km^2. As of 2023, the estimated population of Srinagar city is 1,627,000, while the Srinagar metro population is estimated at 1,742,000. With a population of over one million, Srinagar is undergoing rapid development. However, this growth has

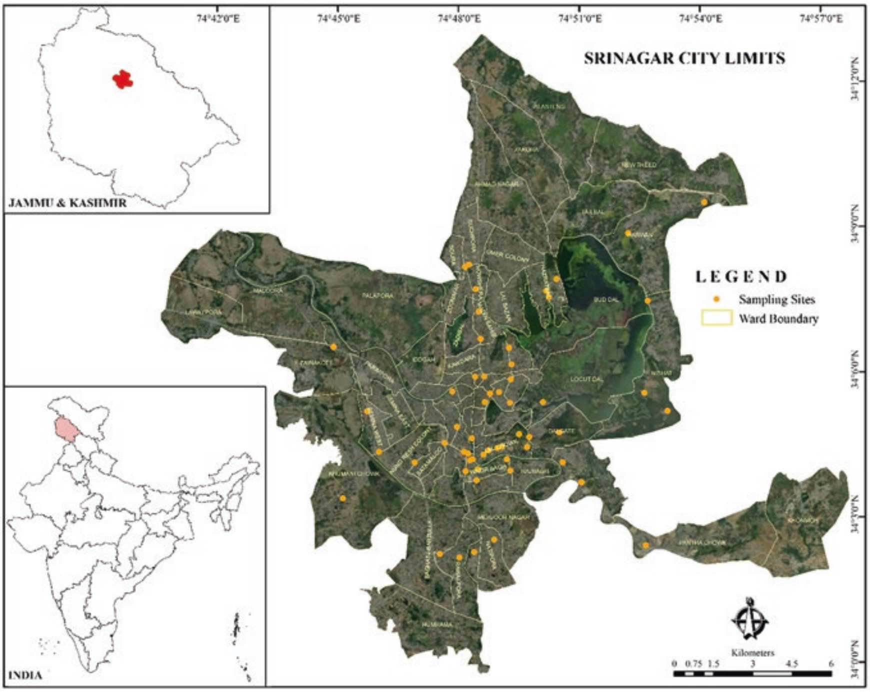


Fig. 11.2 Location map of Srinagar city with ward boundary

led to an escalation in noise pollution, adversely affecting the health and well-being of its residents.

11.3 Materials and Methods

Noise pollution modeling has been carried out for Srinagar city using the methodological framework presented in various studies (Esmeray & Eren, 2021; Farooq et al., 2017; Oguntunde et al., 2019). The noise level measurements were carried out during rush hours of the morning, afternoon, evening, and nighttime. Noise levels were assessed in four distinct categories of zones, namely, residential, commercial, industrial, and silence zones.

To achieve a comprehensive representation of all area types, a survey sampling strategy is implemented by dividing the city into multiple grid areas. This grid-based division facilitates a systematic assessment of noise levels across various regions of the city, ensuring the inclusion of all categories of areas in the evaluation process. An SLM 100 Type II sound meter was used to measure the noise levels, and a Trimble hand-held GPS device was used to obtain the exact coordinates of each location where noise level readings were recorded. The monitoring was carried out consistently for a duration of 5 consecutive days during 2019–2020, maintaining the same locations throughout the entire monitoring period.

The collected data from the sampling sites underwent further processing to enable its utilization within a GIS environment for the creation of noise level maps across different zones within Srinagar city. This was accomplished by employing the inverse distance weighting (IDW) interpolation technique, which predicts unknown noise values for specific geographic points based on surrounding data points. The acquired data were superimposed onto the Srinagar ward boundary and road layer, resulting in the creation of noise pollution maps. Through a comparison of the calculated noise levels with the noise standards set by the Central Pollution Control Board (CPCB), it becomes feasible to assess the level of compliance with the established guidelines (Table 11.1).

11.4 Results and Discussion

Monitored Noise Levels

Industrial Area The industrial zone comprises Sanatnagar, Baghi-Alimardan, and Shalteng. In the Sanatnagar industrial estate, the average noise levels were measured at 68 dB in the morning, 71.6 dB in the afternoon, and 68.8 dB in the evening (Table 11.2). The overall average noise level for the entire day was recorded as 69.67 dB, which was reduced to 39.5 dB during the night hours. In the Baghi-Alimardan industrial estate, noise levels ranged from 60 dB in the morning of December 28 to 76 dB in the afternoon of the same day. The average noise levels throughout the monitoring period were 69.25 dB in the morning, 73.2 dB in the afternoon, and 67 dB in the evening. The overall daily average noise level was

Table 11.1 Ambient air quality standards with respect to noise

Area code	Category of area/zone	Day time limits in dB (A)	Night time limits in dB (A)
(A)	Industrial area	75	70
(B)	Commercial area	65	55
(C)	Residential area	55	45
(D)	Silence zone	50	40

Table 11.2 Five-day average noise levels for selected industrial locations

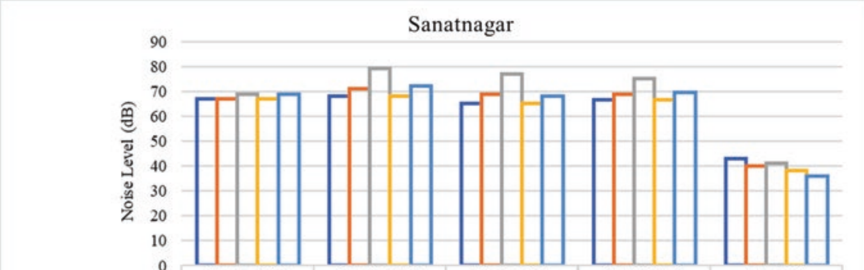
Five-day average	Morning (dB)	Afternoon (dB)	Evening (dB)	Daily average (dB)	Night hours (dB)
Sanatnagar	68	71.6	68.8	69.67	39.5
Baghi-Alimardan	69.25	73.2	67	71.00	37.75
Shalteng	66	70	66.2	66.00	40.5

71.00 dB, which decreased to 37.75 dB during the night hours. Similarly, in the Shalteng industrial estate, noise levels varied from 62 dB in the morning to 77 dB in the afternoon during the monitoring period. The average noise levels were 66 dB in the morning, 70 dB in the afternoon, and 66.2 dB in the evening. The overall average noise level for the day was 66.00 dB, with a slight increase to 40.5 dB during the night hours.

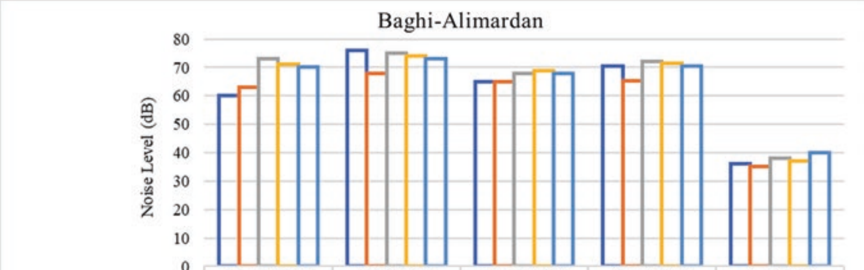
In the Sanatnagar industrial estate, the highest noise level of 79 dB occurred during the afternoon of December 30, 2019, while the lowest recorded noise level of 65 dB was observed in the evening of December 28, 2019, indicating a relatively quieter period at that time (Fig. 11.3). Similarly, in the Baghi-Alimardan industrial estate, the highest noise level of 76 dB was observed in the afternoon of December 28, 2019, while the lowest recorded noise level of 60 dB occurred in the morning of the same day, implying a quieter start to the day in terms of noise levels. The Shalteng industrial estate experienced its highest noise level of 77 dB during the afternoon of December 30, 2019, suggesting a significant presence of noise sources or activities during that specific time. Conversely, the lowest recorded noise level of 62 dB was observed in the morning of December 28, 2019.

Commercial Area The commercial zone, which includes Rajbagh, Batamaloo, Bemina Crossing, Hawal Chowk, Jahangir Chowk, Exchange Road, Ghantaghar Lal Chowk, T.R. C, Batwara Chowk, and Lasjan exhibited noise levels higher than the ambient air quality standards with respect to noise, which was 65 dB during the daytime (Fig. 11.4). The average noise levels recorded during morning hours were found to be higher for all the sites: 70.25 dB (Rajbagh), 76.25 dB (Batamaloo), 75.5 dB (Bemina Crossing), 72.25 dB (Hawal Chowk), 77 dB (Jahangir Chowk), 75.75 dB (Ghantaghar Lal Chowk), 75.75 dB (T.R. C), and 67.75 dB (Batwara Chowk) (Table 11.3). Among all the sites, the noise level during morning hours was found to be within limits for Exchange Road (59.5 dB) and Lasjan (64 dB). During the afternoon hours, the average noise recorded for Rajbagh, Batamaloo, Bemina Crossing, Hawal Chowk, Jahangir Chowk, Exchange Road, Ghantaghar Lal Chowk, T.R. C, and Batwara Chowk were recorded on the higher side except for Lasjan at 74.4 dB, 80.2 dB, 79.6 dB, 74.8 dB, 78.8 dB, 76.2 dB, 73.4 dB, 75.8 dB, 72 dB, and 58.8 dB, respectively. The highest recorded noise levels were observed during afternoon hours and were 77 dB (Rajbagh), 85 dB (Batamaloo), 86 dB (Bemina Crossing), 76 dB (Hawal Chowk), 86 dB (Jahangir Chowk), 79 dB (Exchange Road), 81 dB (Ghantaghar Lal Chowk), 91 dB (T.R. C), 78 dB (Batwara Chowk), and 76 dB (Lasjan).

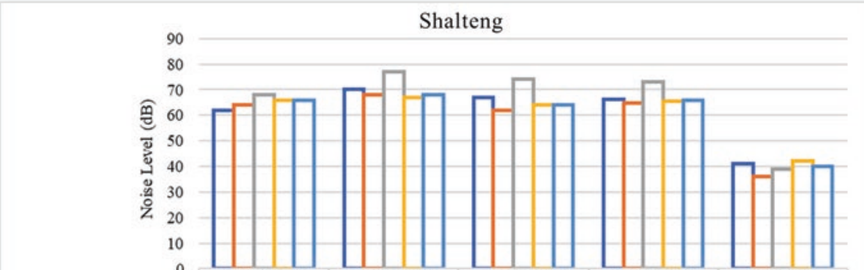
Residential Area For residential areas, the locations selected for the record of noise level are those that experience the highest footfall in Srinagar city, that is, Jawahar Nagar, Mehjoor Nagar, Chanapora, Hyderpora, Dalgate, Habbakadal, and Tankipora (Fig. 11.5). Among these areas, the highest average noise level was recorded for Chanapora and Dalgate at 64 dB and 62 dB, respectively, during morning hours. This is followed by Jawahar Nagar (59 dB) and Mehjoor Nagar (58 dB). During morning hours on average, the lowest noise was recorded for Habbakadal (43.5 dB)



	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	67	68	65	66.5	43
Afternoon (dB)	67	71	69	69	40
Evening (dB)	69	79	77	75	41
Daily Average (dB)	67	68	65	66.67	38
Night Hours (dB)	69	72	68	69.67	36



	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	60	76	65	70.5	36
Afternoon (dB)	63	68	65	65.33	35
Evening (dB)	73	75	68	72	38
Daily Average (dB)	71	74	69	71.33	37
Night Hours (dB)	70	73	68	70.33	40



	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	62	70	67	66.33	41
Afternoon (dB)	64	68	62	64.67	36
Evening (dB)	68	77	74	73	39
Daily Average (dB)	66	67	64	65.67	42
Night Hours (dB)	66	68	64	66	40

Fig. 11.3 Noise levels recorded for selected industrial locations

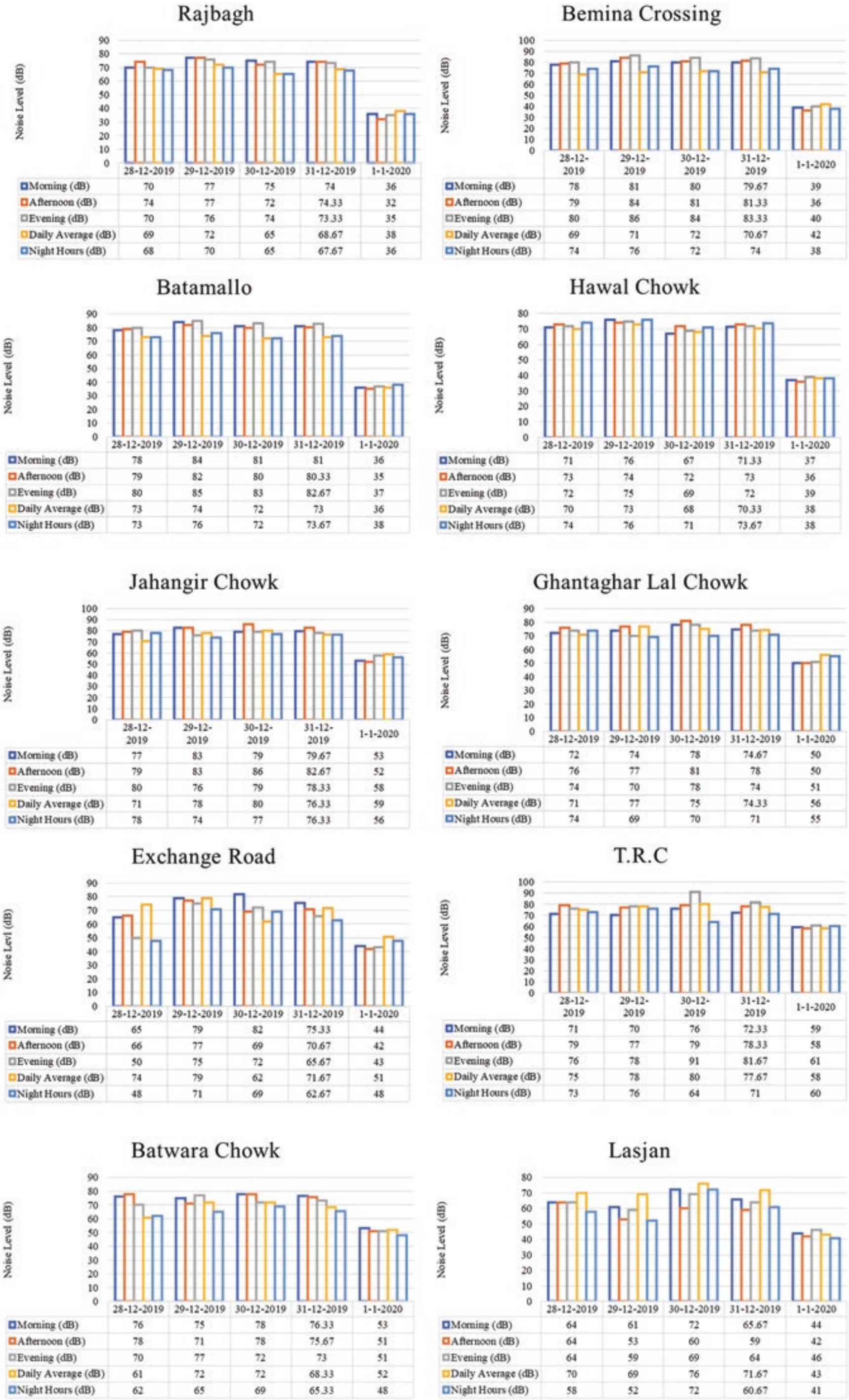


Fig. 11.4 Noise levels recorded for selected commercial locations

Table 11.3 Five-day average noise levels for selected commercial locations

Five-day average	Morning (dB)	Afternoon (dB)	Evening (dB)	Daily average (dB)	Night hours (dB)
Rajbagh	70.25	74.4	70.2	70	36.25
Batamaloo	76.25	80.2	77.6	75	36.75
Bemina Crossing	75.5	79.6	77.8	74	39.75
Hawal Chowk	72.25	74.8	69.4	72	38
Jahangir Chowk	77	78.8	80.2	78	56.5
Exchange Road	59.5	76.2	70.8	74	46.5
Ghantaghar Lal Chowk	75.75	73.4	76.4	73	53
T.R.C	75.75	75.8	78	70	59.5
Batwara Chowk	67.75	72	73.8	63	51
Lasjan	64	58.8	69.8	65	43.5

and Tankipora (46 dB), which is within the limits of the standards for residential areas (Table 11.4). During nighttime, the noise levels for all seven locations were found to be under limits. On a daily average basis, it exceeds 62 dB for Chanapora and 60 dB for Jawahar Nagar, Mehjoor Nagar and Dalgate.

The growing body of research emphasizes the significant influence of interactions with nature on people's physical health and psychological well-being, both directly and by moderating various processes. To create health-promoting urban environments, residential areas should be carefully planned to provide easy access to nearby green spaces, offering relief from environmental stress and opportunities for rest and relaxation, while also striving for lower sound levels from road traffic. In their study, Gidlöf-Gunnarsson and Öhrström (2007) investigated the impact of the perceived availability of nearby green areas on well-being among groups living in different noise conditions. The results revealed that improved accessibility to green spaces positively affected the well-being and daily behavior of both groups, leading to reduced long-term noise annoyances and a lower prevalence of stress-related psychosocial symptoms, along with increased outdoor space utilization.

Silence Zone Silence zones are areas encompassing a distance of no less than 100 m around hospitals, educational institutions, and courts (Sahlathasneem & Deswal, 2023). Within these zones, the permissible noise level should not surpass 50 dB during the day and 40 dB at night. For silence zones, fourteen educational institutes were selected for recording the noise level, which includes lower and high courts as well (Table 11.5). In addition, the noise level was recorded at eight major hospitals in Srinagar City. It was observed that the noise level exceeded the permissible limit of 50 dB during the day for all educational institutes. The daily average was recorded for Gandhi Memorial College, Presentation Convent School, Higher Secondary School Amira Kadal, Amar Singh College, and Govt. Girls Higher Secondary School Khanyar were 54.96 dB, 71.53 dB, 71.87 dB, 73.668 dB, and 72.36 dB, respectively (Fig. 11.6). During the afternoon, the Higher Secondary

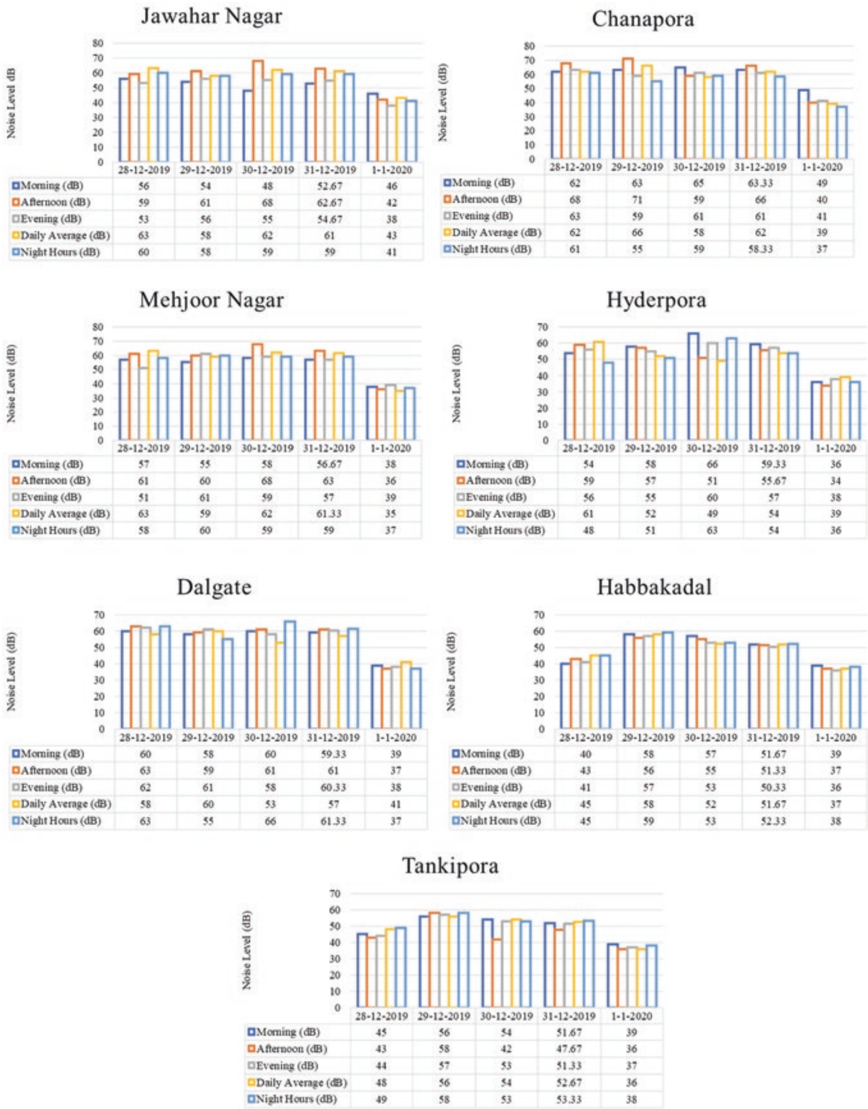


Fig. 11.5 Noise levels recorded for selected residential locations

School Amira Kadal and Amar Singh College recorded the highest noise level, reaching 84 dB. These locations stood out as having louder environments compared to others. The higher noise levels around educational institutes make children vulnerable in regard to the nonauditory health effects of noise. Due to their limited cognitive capacity to comprehend and cope with stressors, they are more susceptible to its impacts (Stansfeld & Matheson, 2003). Additionally, as children are still in the developmental stage, exposure to environmental stressors such as noise could

Table 11.4 Five-day average noise levels for selected residential locations

Five-day average	Morning (dB)	Afternoon (dB)	Evening (dB)	Daily average (dB)	Night hours (dB)
Jawahar Nagar	59	57	58	60	42
Mehjoor Nagar	58	59	61	60	37.25
Chanapora	64	63	60	62	41.5
Hyderpora	56	54	58	57	37.25
Dalgate	62	59	60	60	38.75
Habbakadal	43.5	57.6	54	51	37.5
Tankipora	46	57	51.2	50	37.5

potentially lead to irreversible negative consequences for their physical and cognitive well-being (Stansfeld & Clark, 2015).

Conversely, Gandhi Memorial College displayed the lowest noise level of 50 dB in both the morning and evening, indicating relatively quieter surroundings during those time periods. In addition, the Higher Secondary School Amira Kadal surpassed the average noise levels during nighttime to 46.75 dB. Likewise, the noise levels at major hospitals in Srinagar City exceed the permissible limit during the whole day (Fig. 11.7). During the morning hours, the JLNM Rainawari registered the highest recorded noise level, reaching 75.5 dB, followed by L. hospital (74.5 dB), SKIMS Soura, and JVC (72 dB). The situation is even more concerning during nighttime, as noise levels surpass the permissible limits of 40 dB for all hospitals, except for Gousia Hospital Khanyar and the Institute of Mental Health and Neuro Sciences.

Noise pollution in and around hospitals poses a serious health hazard, as recognized by Khaiwal et al. (2016). The World Health Organization (WHO) recommends maintaining continuous background noise levels in hospital rooms below 35 dB, with nighttime peaks inward not exceeding 40 dB (Berglund et al., 1999). High noise levels in hospitals can lead to issues concerning patient safety and recovery. Jue and Nathan-Roberts (2019) found that exposure to elevated noise levels significantly affects various aspects, including patients' sleep quality, speech processing, and various physiological functions. Additionally, it may also contribute to stress and burnout among hospital workers. Grumet (1993) reported a significant correlation between increasing noise levels and extended length of hospital stay, emphasizing the importance of noise control in healthcare settings as a high priority.

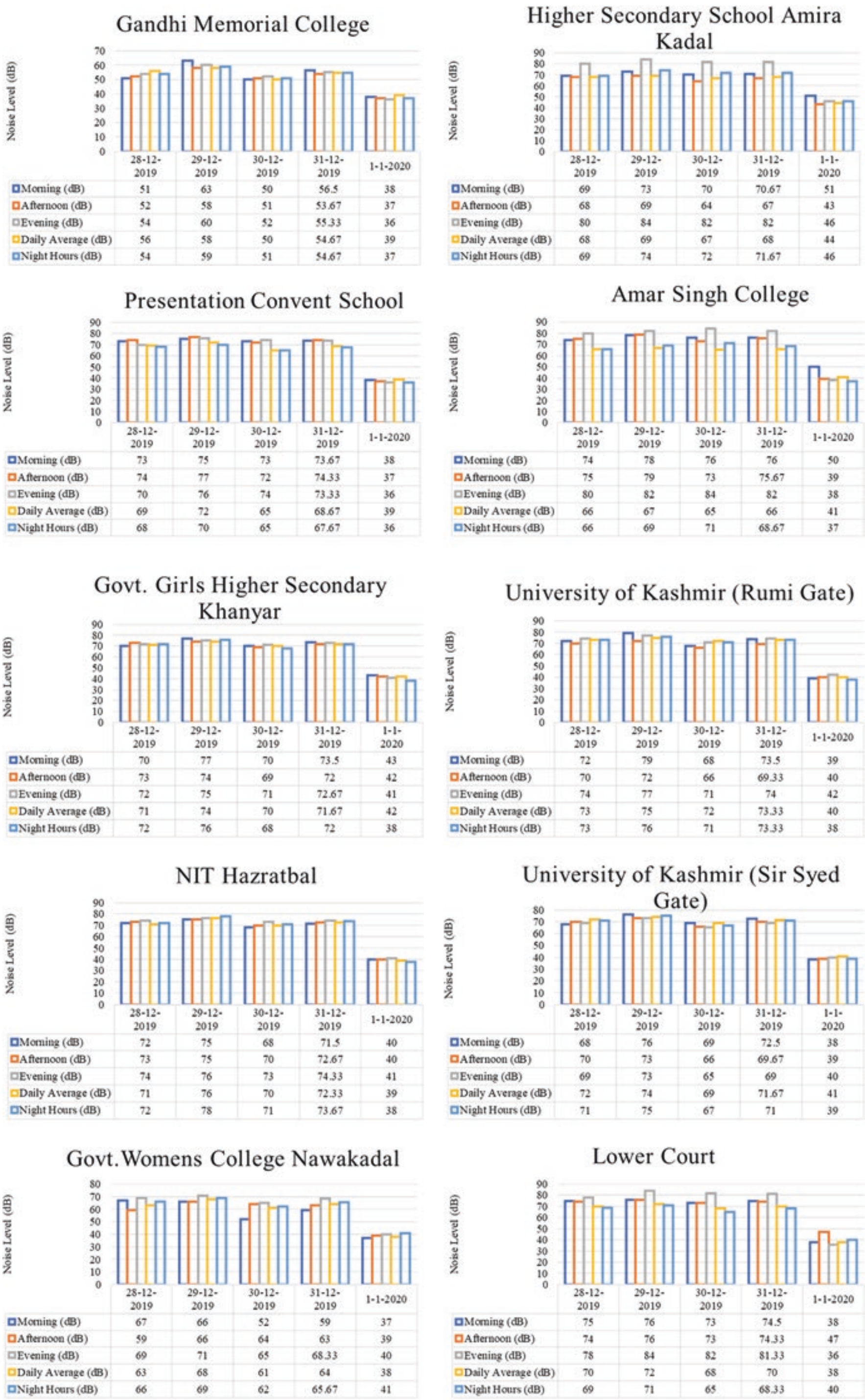
Spatial Distribution of Noise Pollution in Srinagar City

Figure 11.8 (a–d) displays noise pollution maps generated using the inverse distance weighting (IDW) technique in ArcGIS. These maps represent the average noise levels during morning, afternoon, evening, and nighttime. Focusing on the interpolated map for morning hours, it becomes evident that the noise levels range

Table 11.5 Five-day average noise levels for selected silence zones (educational institutes and hospitals)

Five-day average	Morning (dB)	Afternoon (dB)	Evening (dB)	Daily average (dB)	Night hours (dB)
Educational institutes					
Gandhi Memorial College	54	59.6	50.8	54.96	37.5
Presentation convent school	70.25	74	69.8	71.53	37.25
Higher Secondary school Amira kadal	71.25	73.8	71	71.87	46.75
Amar Singh College	71.75	75	73.8	73.668	41.5
Govt. Girls Higher Secondary Khanyar	72	75.2	69.6	72.36	41
NIT Hazratbal	72.5	76	70.4	72.9	39.5
University of Kashmir Hazratbal (Rumi Gate)	72.5	75.8	69.6	72.69	39.75
University of Kashmir Hazratbal (Sir Syed Gate)	70.5	74.2	67.2	70.76	39.5
Govt Women's College Nawakadal	64.25	68	68.8	64	39
High court	73.75	76.6	74.4	75.3	37.5
Lower Court	72.75	75.8	72.2	73.69	38
Govt. Women's College M.A Road	56	70	66.4	65.36	52.75
S.P. College	60	73.6	74.6	71.36	52.5
Delhi Public School Pantha Chowk	77.5	76	75.6	76.33	49.5
Hospitals					
Gousia Hospital Khanyar	68.25	73.2	67.4	69.4	40.5
JLNM Rainawari	75.5	77.6	73.8	75.6	41.25
Institute of Mental Health and Neuro Sciences	59	60.2	55.8	58.27	38.25
L.D Hospital	74.5	75.6	72.8	74.27	42.5
SKIMS Soura	72	76.8	70.2	73.03	41.25
JVC	72	75.4	71.6	72.26	37.5
G.B. Panth Hospital	70.5	75.2	72.4	72.67	61
Chest Disease Hospital	67	73.2	70.8	71.07	51

from 44.23 to 78.00 dB. On the outskirts of the city, particularly toward the northeast and northwest, the average noise levels are observed to be the lowest. This may be attributed to the positive impact of green spaces on mitigating traffic noise pollution at the local scale; however, their effects on a broader urban level remain unexplored (Margaritis & Kang, 2017). Conversely, the highest noise values are concentrated in the main city center, with Pantha Chowk toward the east and Hazratbal located in the middle experiencing notably high noise pollution, exceeding the permissible limits. The remaining areas generally exhibit low to medium noise values.



Gandhi Memorial College

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	51	63	50	56.5	38
Afternoon (dB)	52	58	51	53.67	37
Evening (dB)	54	60	52	55.33	36
Daily Average (dB)	56	58	50	54.67	39
Night Hours (dB)	54	59	51	54.67	37

Higher Secondary School Amira Kadal

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	69	73	70	70.67	51
Afternoon (dB)	68	69	64	67	43
Evening (dB)	80	84	82	82	46
Daily Average (dB)	68	69	67	68	44
Night Hours (dB)	69	74	72	71.67	46

Presentation Convent School

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	73	75	73	73.67	38
Afternoon (dB)	74	77	72	74.33	37
Evening (dB)	70	76	74	73.33	36
Daily Average (dB)	69	72	65	68.67	39
Night Hours (dB)	68	70	65	67.67	36

Amar Singh College

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	74	78	76	76	50
Afternoon (dB)	75	79	73	75.67	39
Evening (dB)	80	82	84	82	38
Daily Average (dB)	66	67	65	66	41
Night Hours (dB)	66	69	71	68.67	37

Govt. Girls Higher Secondary Khanyar

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	70	77	70	73.5	43
Afternoon (dB)	73	74	69	72	42
Evening (dB)	72	75	71	72.67	41
Daily Average (dB)	71	74	70	71.67	42
Night Hours (dB)	72	76	68	72	38

University of Kashmir (Rumi Gate)

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	72	79	68	73.5	39
Afternoon (dB)	70	72	66	69.33	40
Evening (dB)	74	77	71	74	42
Daily Average (dB)	73	75	72	73.33	40
Night Hours (dB)	73	76	71	73.33	38

NIT Hazratbal

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	72	75	68	71.5	40
Afternoon (dB)	73	75	70	72.67	40
Evening (dB)	74	76	73	74.33	41
Daily Average (dB)	71	76	70	72.33	39
Night Hours (dB)	72	78	71	73.67	38

University of Kashmir (Sir Syed Gate)

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	68	76	69	72.5	38
Afternoon (dB)	70	73	66	69.67	39
Evening (dB)	69	73	65	69	40
Daily Average (dB)	72	74	69	71.67	41
Night Hours (dB)	71	75	67	71	39

Govt.Womens College Nawakadal

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	67	66	52	59	37
Afternoon (dB)	59	66	64	63	39
Evening (dB)	69	71	65	68.33	40
Daily Average (dB)	63	68	61	64	38
Night Hours (dB)	66	69	62	65.67	41

Lower Court

	28-12-2019	29-12-2019	30-12-2019	31-12-2019	1-1-2020
Morning (dB)	75	76	73	74.5	38
Afternoon (dB)	74	76	73	74.33	47
Evening (dB)	78	84	82	81.33	36
Daily Average (dB)	70	72	68	70	38
Night Hours (dB)	69	71	65	68.33	40

Fig. 11.6 Noise levels recorded for selected silence zones (educational institutes)

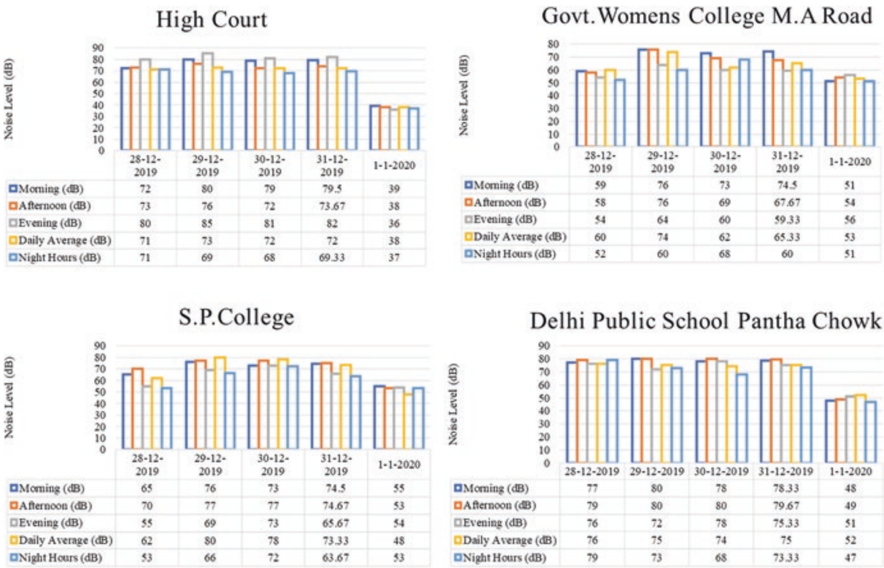


Fig. 11.6 (continued)

During the afternoon, there was a noticeable increase in the average noise level compared to the morning hours, ranging from 53.00 to 80.15 dB. The lowest value of 53.00 dB was limited to specific locations such as Nishat, Dalgate, Nowshera, and Baghat-I-Barzulla. However, the majority of the city experienced medium to high noise levels during this time. Similar to the morning hours, the highest noise pollution during the afternoon was observed in Lal Chowk and its adjacent areas, which serve as the primary commercial zones and major hubs of the city. The commercial areas are exceeding the noise levels as per the standards. On the other hand, areas situated in the north and north-western outskirts of the city had noise levels mostly falling within the medium range.

During the evening, the average noise level map indicates a reduction in noise compared to the afternoon hours, ranging from 36.00 to 79.75 dB. Despite this decrease, the noise levels in commercial areas remain on the higher side, even as day activities wind down. Similar to the morning and afternoon, the main city center continues to exhibit the highest noise values during the evening. Interestingly, Pantha Chowk, which had the highest noise level in the morning, experienced a decrease during the afternoon but showed a surge again in the evening hours. This could be attributed to the traffic flow transitioning from the main city to other districts. Overall, while there is a slight reduction in noise during the evening, it is still important to consider and adhere to the established noise limits, especially in commercial zones, to mitigate potential disturbances during this time.

Throughout the night, the average noise level displayed variations ranging from 36.00 to 60.96 dB. The majority of the city areas maintained noise levels within permissible limits, registering lower values. However, specific areas such as Lal

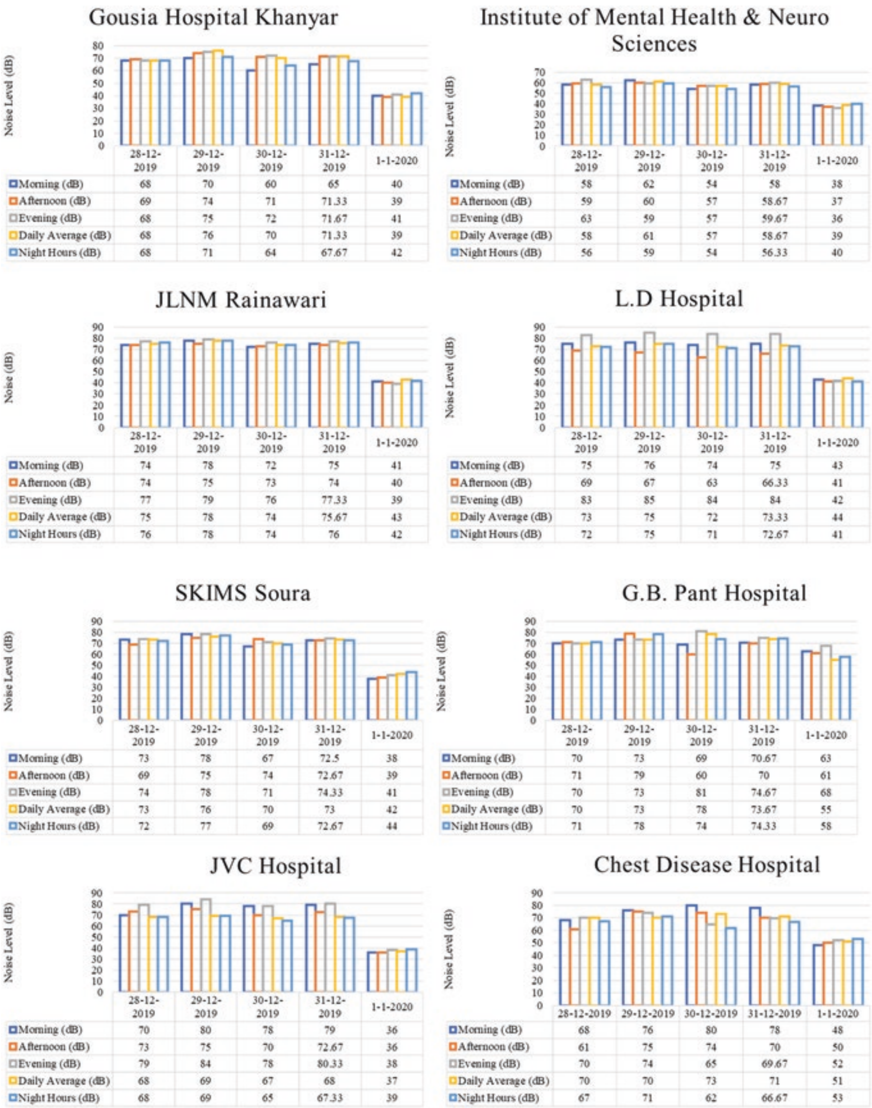


Fig. 11.7 Noise levels recorded for selected silence zones (hospitals)

Chowk, Rajbagh, and their connecting regions, along with Pantha Chowk and Khonmoh, recorded higher noise levels, reaching 60.96 dB during the night. This increase in noise can be attributed to the movement of vehicles, particularly heavy ones, using routes that pass through Pantha Chowk and Khonmoh, leading to the Jammu highway. In their study, Banerjee et al. (2009) also observed a similar pattern of significantly elevated noise levels during nighttime, which was attributed to the movement of heavy trucks. Despite these localized higher noise levels, the

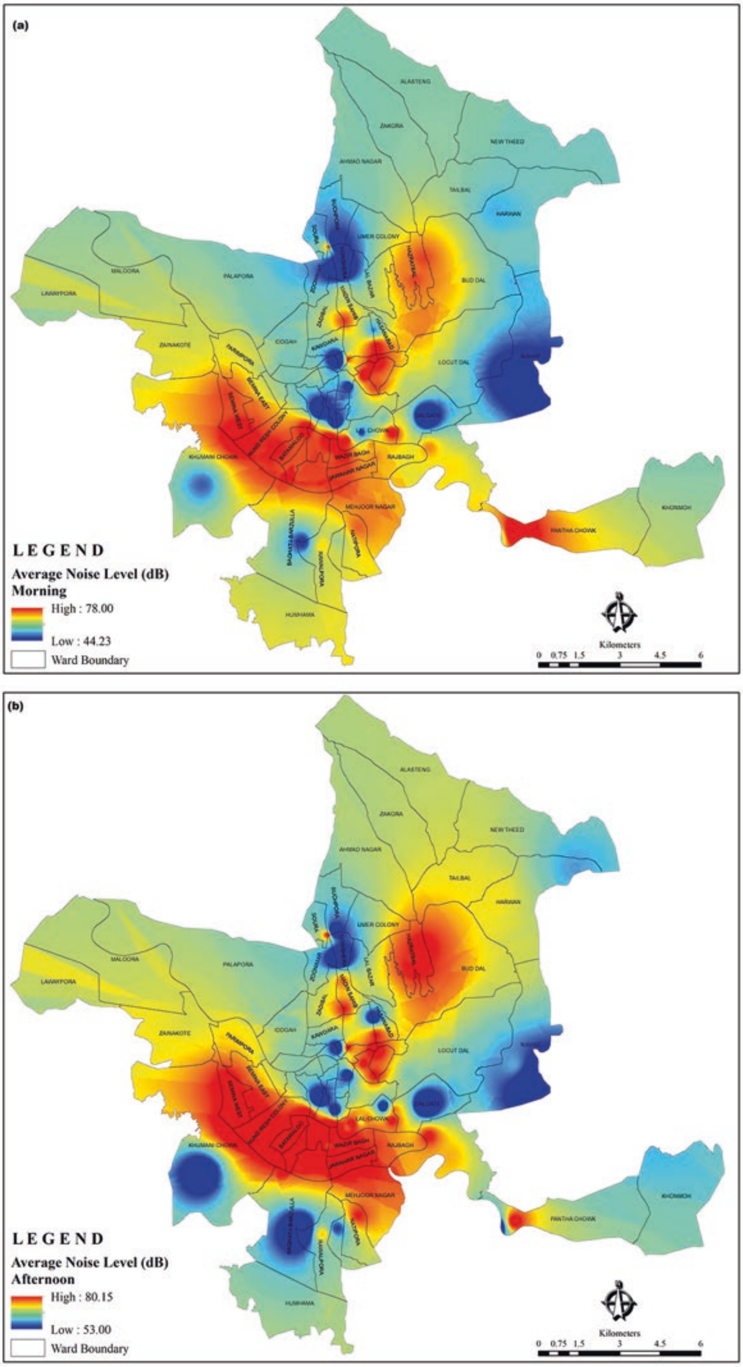


Fig. 11.8 Spatial distribution of noise level in Srinagar city developed using IDW

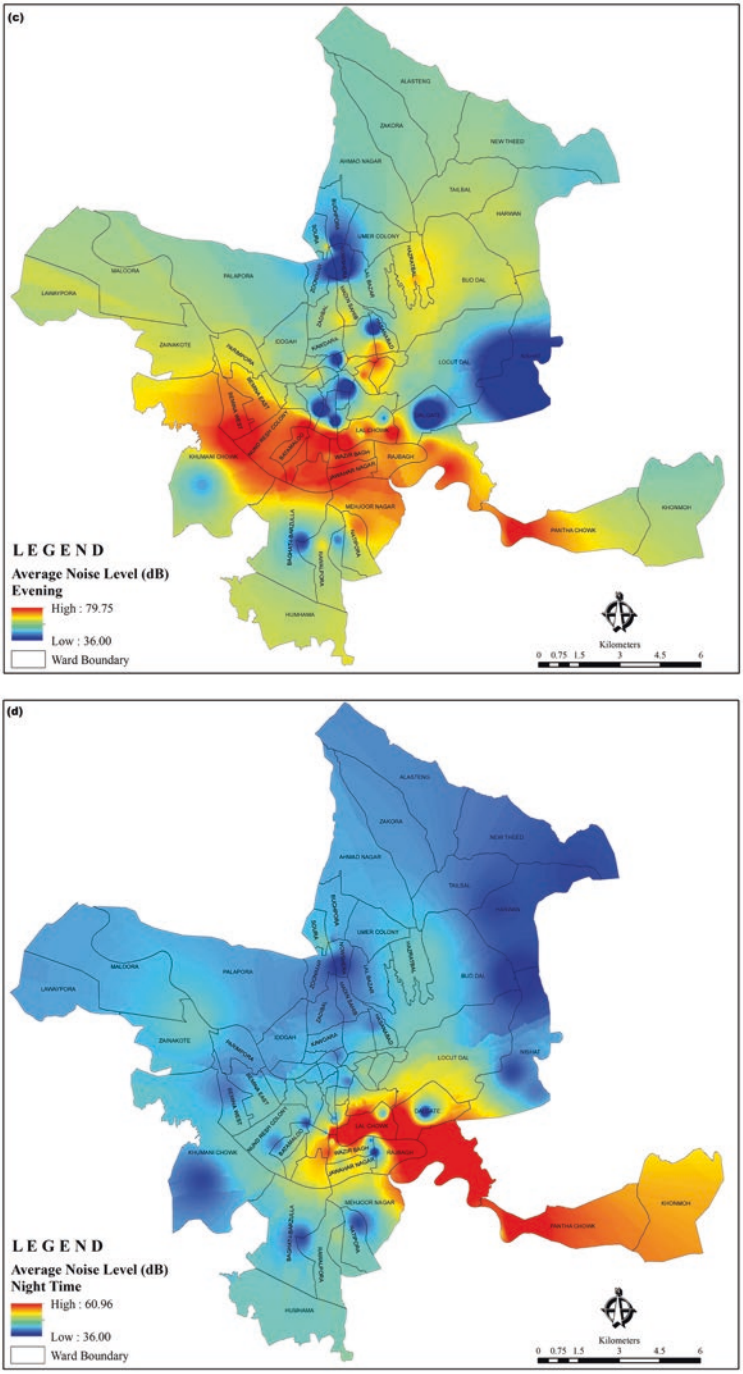


Fig. 11.8 (continued)

overall noise situation in the city during the night remained generally within acceptable limits, contributing to a quieter and more peaceful environment during nighttime hours.

11.5 Conclusion

In conclusion, the noise pollution maps derived using the IDW technique in ArcGIS provide valuable insights into the spatial distribution of average noise levels across the city during different time periods. The noise level findings indicate that the acoustic environment in our study area is generally classified as medium to high. This suggests that prolonged exposure to these noise levels could potentially impact human health and overall quality of life. Noise levels vary throughout the day in the city, with mornings ranging from 44.23 to 78.00 dB and higher levels in the city center. Afternoons see an increase from 53.00 to 80.15 dB, while evenings show a reduction from 36.00 to 79.75 dB, and nights vary from 36.00 to 60.96 dB, with higher levels in specific areas due to vehicle movements. This study's findings highlight the presence of moderate to high noise zones, with significant variations based on both location and time of day. The primary factors contributing to these variations are related to traffic characteristics, such as traffic volume, vehicle horns, vehicle-mounted speakers, and the presence of unmuffled vehicles at road junctions, major roads, and commercial centers. Monitoring selected residential and commercial areas consistently revealed noise levels exceeding acceptable thresholds. Overall, the noise pollution analysis indicates that the city's outskirts generally enjoy quieter environments, while noise levels tend to be higher in the city center and major commercial zones. To maintain a healthier and more sustainable soundscape, it is crucial for urban planners and policymakers to address noise hotspots and implement suitable mitigation measures, especially in areas with consistently high noise levels. Such efforts can contribute to a more pleasant living environment for the city's residents and promote overall well-being and quality of life.

11.6 Recommendations

The installation of smart sensors in cities for noise monitoring is highly recommended. These advanced sensors can provide real-time data on noise levels across different areas, helping authorities identify noise hotspots and patterns (Fig. 11.9). With this information, effective noise mitigation strategies can be developed to improve the overall acoustic environment, enhance public health, and ensure a better quality of life for residents. Smart sensors offer a cost-effective and efficient way to monitor and manage noise pollution in urban areas, making them an essential tool for modern urban planning and environmental management.

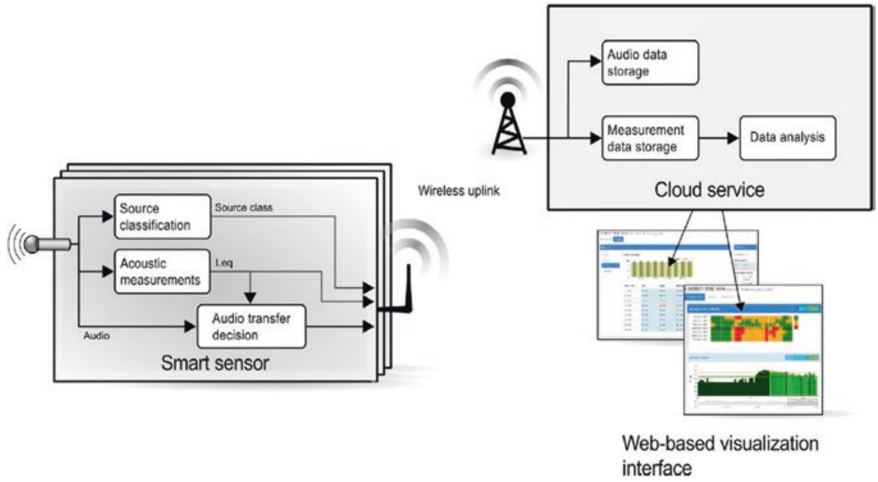


Fig. 11.9 Schematics showing the working flow of smart sensors for noise monitoring along with a web-based visualization interface. (Source: Maijala et al., 2018)

Furthermore, integrating a web-based interface for data visualization would significantly enhance the accessibility and usability of the noise monitoring system. By offering a user-friendly web platform, the general public, researchers, and policymakers can easily access and interpret noise data, fostering greater awareness and engagement in noise pollution management efforts. This interactive visualization plays a crucial role in empowering communities to actively participate in creating a quieter and more sustainable urban environment.

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Chapter 12
Geostatistics Interceded Groundwater Quality Study with Emphasis on Kriging Across the Andhra Pradesh State of India

Jagadish Kumar Mogaraju

Abstract This work aims to use geostatistical tools to understand the spread of groundwater quality variables across the state. Ordinary kriging, simple kriging, and universal kriging techniques were used in this study with root mean square error (RMSE), mean square error (MSE), root mean square standardized error (RMSSE), and averaged standard error (ASE) metrics. Groundwater quality variables such as bicarbonate, chloride, electrical conductivity, fluoride, potassium, magnesium, sodium, nitrate, pH, SAR, and sulfate were tested in this study over a GIS workspace. A correlation map was generated to show the strong correlation between the variables. Principal component analysis was performed to extract principal components from the dataset. Cluster analysis was performed, and 9 clusters were obtained. The size of the first cluster is 904, with an explained proportion of within-cluster heterogeneity of 0.979 and a silhouette score of 0.629. The total sum of squares for all the clusters is 13,740, and the sum of squares value is 3697.

Keywords Clustering · Geostatistics · GIS · Groundwater · Interpolation · Kriging

12.1 Introduction

Geospatial products have always helped in our understanding of our natural resources, leading to the improvement of our lives (McCall & Minang, 2005). The breadth of geospatial applications is always being extended across diverse areas of our society, seldom with limited drawbacks (Karan & Irizarry, 2015). The conventional methods of mapping and interpretation have been laborious and expensive processes that lead to coarse errors in some cases (Langford & Bell, 1997). The errors presented by GIS products are always in the form of a puzzle hidden in plain sight (Audet & Abegg, 1996). The advancement of computer-aided processing in cartography and allied disciplines has limited the ingress of faults or errors in the

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interpretation process (Golz et al., 2015). The fundamental concepts of mathematics, geography, physics, and computer programming, along with various areas of geo-intelligence, were combined to obtain the best results on several occasions (Kune et al., 2016). The main idea of surveying in the GIS sense is to portray the objects or living entities integrated with factors presented by nature onto the computer interface so that we can perform certain operations to ease our daily activities (Zhong et al., 2012). The role played by geospatial tools in the mapping of water resources can be considered a capstone achievement we have witnessed for three decades (Vadjunec et al., 2022). Starting from investigating the quality of surface waters to groundwater, GIS has always aided researchers across domains. Kriging and other geostatistical tools can be used in various GIS operations (Goyal et al., 2021). This method aids us in estimation and is based on a non-discrete model of spatial variation that is random. It also considers the value variations across space via a variogram model (Cressie, 1990). In a simple sense, we can say that the kriged estimate is a weighted average of the attribute values or a linear sum of the data in the vicinity (Kleijnen, 2009). Kriging has been used to solve complicated problems in fields that are not limited to public health and pollution (Oliver & Webster, 1990). We consider linear combinations (weighted) of the estimates in linear kriging. These weights are assigned to the data samples in the vicinity. We can minimize the variance and bias in the kriging method. This technique relies on LS methods or least-squares methods for spatial prediction. Ordinary kriging (OK) can be performed using a single variable, and it can be categorized as a robust method due to its far and wide applications (Wackernagel, 2003). As we might not know the mean of the simple kriging (SK) method, its application is limited (Webster & McBratney, 1987). We can use this method in alternative forms, such as disjunctive and indicator kriging. This is possible, as the data will be transformed to yield means. Log-normal kriging is a variant of ordinary kriging in which we can use the logarithms of measured values (Ro & Yoo, 2022). This method can be used on data that are positively skewed (excess). Universal kriging (UK) is also called kriging with drift (Zimmerman et al., 1999). It detects random constituents and deterministic components that are not stationary in a variable. It gives us trends and variograms based on the components that the data falls into. This method integrates both trends and variograms in making the prediction. We can expect an RML, or residual maximum likelihood, while using this method, which is an enhancement of the kriging process (Reyes et al., 2015). Kriging analysis is also called factorial kriging, and it can be employed if the variation observed is in nested form. The nested form means that there are more scales of variation. This method estimates the singular components of variation distinctly, and this will be included in a single analysis. Ordinary cokriging (OCK) can be classified as an extended variant of OK that considers more than one variable in the prediction process (Goovaerts, 1998). It is important to check whether there is a proportion of coregionalization that exists within the variables while using this method and yielding meaningful results. This method is used if some attribute is easily measured in the field with limited expense across many points and if there is a spatial correlation existing with the attribute measured at a few points with high expense. In this method, we can use the spatial information generated using the attribute values collected from several sites to estimate the attribute values that are sporadically collected due to budget constraints. Indicator kriging (IK) can be classified as a nonparametric and nonlinear method of kriging (Solow, 1986). In this method, continuous variables can be systematically changed into binary values or indicators. It can use any type of distribution, and we can compute the empirical cumulative distributions. This method also offers us confidence limits and is hence used across several applications. We can also integrate qualitative data to enhance prediction accuracy. Another extension of kriging is disjunctive kriging (DK), which can be classified as a nonlinear and parametric method (Matheron, 1976). We can use this method in decision-making protocols, which can be attributed to the probabilities defined by the user threshold. Probability kriging (PK) can use rank order for an attribute value and is often normalized to 1 (Sullivan, 1984). Bayesian kriging invariably shares some of the characteristics of SK and UK but is based on drift conditions (Pilz & Spöck, 2008). The main aim of the kriging process is to predict the value of the variable that is random at unsampled points. Kriging is often based on the assumption that we are blinded to know the mean.

Most of the equations used in kriging can be used to determine the weights. It assigns large weights to the points that are in the vicinity of the block or points that are to be kriged. We can assume that the closest points (4–5) can define 80% of the weight. These weights can be based on the sampling configurations. It is obvious that the points that are closer can have more weight than the points that are far away. We can investigate the relative proportions based on the positions of the points that can be visible on the variogram. If the nugget variance is large, the weights of the points that are closest to the block or target point can be small. The relative weights can be based on the size of the block. If there is an increase in the size of the block, then the weights of the points in the vicinity decrease. This also implies that the weights of the far-away or distance points increase relatively. This process continues or iterates until the weights are equal. The points that are clustered have minimal weights compared to the points that are in isolation. The nugget variance is proportional to the kriging variance, and it is important to define this as a minimum limit rather than a variance. The model should be fitted using various tools to obtain the best results. Our target lies in the fact that the nugget effect must be clearly reflected in the experiment and is always dependent on the nugget variance and kriging variances.

12.2 Study Area

Andhra Pradesh State, with a land area of 1,63,000 km^2, is the seventh-largest state in India. It is located between EL 76° 45′ and 84° 47′ and NL 12° 37′ and 19° 09′. The state borders Telangana, Chhattisgarh, and Orissa states to the north, Tamil Nadu and Karnataka to the south, Karnataka to the west, and the Bay of Bengal to the east (970 km) (Kamaraju et al., 1996). The historical groundwater level monitoring data help prepare the state's sustainable development plan as well as analyze changes in the groundwater regime across time and space. To examine seasonal and long-term variations, these stations are observed four times a year in May, August, November, and January. For a chemical examination, water samples are taken in May. Thirteen districts serve as administrative hubs for the 1.63 lakh sq. km. state of Andhra Pradesh. With a decadal growth rate of 9.2%, the state has a total population of 4.96 crore. The Godavari, Krishna, Pennar, Vamsadhara, Nagavalli, and Gundlakamma Rivers drain the state primarily. The majority of the state is covered by a gneissic complex, which has sedimentary formations as structural fill and metasedimentary formations and metasediments as basin fill. The task of groundwater management, development, augmentation, protection, and regime monitoring in terms of both quality and quantity in the state has been undertaken by the Central Groundwater Board. This is done to arrive at proper parametric indices of evaluation and prudent development of groundwater resources (Murthy, 2000).

Since 1969, a historical database on groundwater levels and water quality has been developed. The majority of the dug wells that tap unconfined aquifers are located inside the boundaries of a settlement and are utilized for domestic purposes. Some of these are public wells, while others are private wells. Four times a year, manual inspections are performed on the piezometers that the department installed to tap confined and unconfined aquifers as part of various projects and exploration programs. The state is administered by 670 revenue mandals with 17,398 revenue villages, and it is divided into 13 districts (Srikakulam, Vizianagaram, Vishakhapatnam, East Godavari, West Godavari, Krishna, Guntur, Prakasam, SPS Nellore, YSR Kadapa, Kurnool, Anantapur, and Chittoor). According to the 2011 census, the state has a total population of 4.96 crore (with a male-to-female ratio of 997), of which 90% live in rural areas and 10% in urban areas. Population density ranges from 188 people per km^2 in YSR Kadapa to 518 people per km^2 in Krishna district (average density: 304 people per km^2). According to the DES and the government of Andhra Pradesh (2015), the total population increased by 9.2% during the course of the decade (2001–2011 census) (Mutheneni et al., 2018).

The state of Andhra Pradesh can be split physiographically into three main zones: the coastal plains, the Eastern Ghats, and the western pediplains. The first two zones are located in a small strip that runs from northeast to southwest, and the third zone takes up the remaining space. It is between 0 and 600 m above mean sea level. The coastal plains are a small strip that widens in the middle along the Godavari-Krishna deltas, running from Kalingapatnam (Srikakulam district) in the north to Pulicat (Nellore district) in the south (up to 80 km^2). The sea level at the shore rises to 150–200 m AMSL in the western coastal lowlands. Due to the two deltas, the area has great agricultural land. The Eastern Ghats tightly encircle the Coastal Plains, except for the region between the Godavari and Krishna rivers. The hill ranges rise to an altitude of 600–1200 m AMSL and follow NE–SW and N–S directions in the north and south, respectively. The Southern Ghats are covered by the Rayalaseema region's Nallamala, Erramala, Seshachalam, Velikonda, and Palakonda hills (Etikala et al., 2019).

This category includes a significant portion of the state, which includes the Kurnool and Anantapur districts in the Rayalaseema area. The pediplains have tracts that are flat to undulating and have rolling topography. Except for a few locations where the elevation ranges from 600 to 900 m AMSL, this plateau in the state's heartland usually lies between heights of 150 and 600 m AMSL. The northern/central portions of the state are drained by the Godavari, Krishna, and their tributaries, while the southern portion is drained by the Pennar before it joins the Bay of Bengal. In the state, there are 11 medium river basins and three major basins. The three main river basins are the Godavari, Krishna, and Pennar, while the minor drainages between the Musi and Gundlakamma rivers are located in the medium basins of Vamsadhara, Nagavali, Sarada, Yeleru, Gundlakamma, Paleru (A), Manneru, and Uppateru. In the western peniplain, the drainage pattern is typically dendritic with large valleys. With steep and small valleys, the drainage of the Eastern Ghats is coarse and dendritic. The eastern coastal tract is marked by young streams and valleys and is cut through by an extensive network of feeder and distributary canals. Deltas and coastal plains are covered by the mature river courses of the Godavari, Krishna, and Pennar Rivers as they meander through the enormous expanses. River deltas are particularly large and distinguished by a significant thickness of alluvial material (Nageswara Rao et al., 2017).

Along with its tributaries, Chitravati, Papaghni, Kundu, Sagileru, and Cheyyeru, the River Penna traverses the southern portion of the state and drains a sizable portion of the Rayalaseema region and the Nellore district in the coastal region. The geography of the drainage basins is undulating and consists of a network of ridges and valleys accentuated by hill ranges. The northeastern region of the state, in the Srikakulam district, is drained by the Vamsadhara and Nagavalli rivers and their tributaries. Local rivulets such as Sarada are the main drainage systems for the Visakhapatnam district. Most of the East Godavari district is drained by the River Yeleru, whereas the West Godavari district is drained by Yerrakalava and Tammileru. The Pennar, Swarnamukhi, and Araniar rivers drain the district of Nellore. The state features a wide range of soil types, including saline, red, laterite, black cotton, and deltaic alluvium soils. Most of the coastal region's red clayey soils are found in the Srikakulam, Visakhapatnam, East Godavari, and West Godavari districts. In the districts of Guntur and Krishna, black cotton soil is typical. Both Prakasam and Nellore districts have laterite soils, together with red earths with loamy subsoil and red sandy loamy soil. A portion of the Kadapa, Kurnool, and Anantapur districts has black cotton soil, and a portion of the Chittoor and Kadapa districts has red loamy soil. In the district of Anantapur, red earths predominate (Govil et al., 2001).

The state's tropical climate is affected by geographical changes as well as maritime impacts. In comparison to the coastal zone, the Deccan Plateau maintains more temperate weather. During the southwestern monsoon, Vishakhapatnam and its surrounding area's Eastern Ghats, which function as a barrier to easterly winds in conjunction with depression from the Bay of Bengal, play a key role. Andhra Pradesh State is home to a vast range of geological formations, from the most recent alluvium to the oldest Archaean crystalline formations. The predominant rock types in the Rayalaseema region of the state are peninsular gneisses. Dharwars, which are composed of amphibolites, gneisses, schists, and quartzites, are found in the districts of Chittoor, Anantapur, Kurnool, Kadapa, Nellore, and Prakasam as small, isolated bands inside granites. The districts of Srikakulam, Vizianagaram, and Visakhapatnam, as well as the highland regions of the East Godavari and West Godavari districts, contain a substantial belt of Charnockites and Khondalites. In the districts of Krishna, Guntur, and Prakasam, the Charnockite bands can also be found as small patches next to coastal alluvium. The horizontally oriented lava flows known as Deccan traps are limited to small outcrops in Rajahmundry on each side of the Godavari River.

Individual flows can range in thickness from a few meters to 30 m. Near Rajahmundry, there are intertrappean beds made up of sandstones, cherts, and limestones that are between trap flows. The trap flows are supported by infra-trappean beds, which are composed of deposits of limestone and sandstone. From Pangidi in the West Godavari district to Kateru in the East Godavari district, a 6 km strip of land is exposed. Locally, this group's formation is referred to as the Rajahmundry formation. It is primarily made up of sandstones, which are found as isolated outcrops gradually sloping toward the shore from Eluru to Rajahmundry. Along the southern shore, sandstones of comparable age can be found in the districts of Chittoor, Prakasam, and Nellore. This category includes laterite soils, alluvium, and beach sands, among others. Except for the area close to Visakhapatnam, the coastline is covered in beds of clay, sand, gravel, and rocks. This distribution is not only restricted to deltas but even deep inside the interior, in isolated pockets along the Godavari, Krishna, Pennar, and Vamsadhara river systems. In the sloping East and West Godavari districts, the alluvial deposits reach a thickness of more than 600 m. The thickness varies up to 20 m in the districts of Srikakulam and Visakhapatnam (Banerji, 1990; Raju, 2007; Rao et al., 1998; Suresh et al., 2010).

A scientific surveillance system called groundwater level monitoring is used to identify both short-term and long-term changes in the groundwater regime. Information on changes in groundwater levels with progressive groundwater development by natural and artificial recharge/surface water irrigation systems is provided by water level data throughout time. The monthly information on the groundwater regime scenario in the various hydrogeological environments in the area is provided with a good amount of accuracy by the monitoring of a network of groundwater monitoring wells. These strata make up approximately 83% of the area and comprise basalt lava flows from the Deccan traps, metasedimentary rocks from Kadapa and Kurnool, and crystalline rocks from the Archaean era. These rocks typically do not have primary porosity, and secondary porosity develops as a result of weathering, fracture, the formation of solution channels and cavities, and vesicle connectivity. The depth of weathering in these rocks ranges from 5 to 10 m bgl (and, on rare occasions, up to 20 m), and the bulk of fractures are found within a depth of 100 m. Bore wells, dug wells, and dug cum bore wells are the most common abstraction structures in these rocks. The output of groundwater from these rocks ranges from 0.1 to 3 lps. The weathering depth in the Khondalite deposits ranges from 10 to 40 mbgl with yields of 0.5–2 lps. Consolidated metasedimentary strata, including the rocks of Kadapa and Kurnool, have undergone extensive compaction and metamorphism, which has reduced their initial porosity. Structural characteristics such as folds, faults, lineaments, fractures, fissures, solution cavities, and channels are the only places where groundwater may be found in these formations. These formations weather to a depth of 5–10 m bgl, with yields ranging from 0.01 to 19 lps (generally 1–5 lps). Compared to other Kadapas, the Kurnool group of rocks has a higher promise (general yield 5–10 lps). Sandstones from the Gondwana formations and Rajahmundry sandstones are examples of semiconsolidated formations. These structures' yields range from 10 to 70 lps. Coastal, deltaic, and inland river alluvium are examples of unconsolidated formations. Under high water tables and in limited spaces, groundwater occurs. Poor water quality can be found in deeper aquifers. Godavari deltas and Krishna and Pennar deltas have yields that range from 0.7 to 30 lps. In prehistoric channels, the quality of the groundwater is potable (Rajesh et al., 2012; Rao et al., 1997; Subba Rao, 2002; Sujatha & Reddy, 2003).

This work aims to determine the prediction capabilities of ordinary kriging and error propagation while using this process.

12.3 Materials and Methods

Data

The datasets needed for this study are collected from the Central Pollution Control Board, Government of India. The timeframe of the datasets is from 2000 to 2010. The state of Andhra Pradesh is chosen for this study. It is one of the southern states of India. The datasets contain groundwater quality variables such as carbonate (CO_3), calcium (Ca), chloride (Cl), electrical conductivity (EC), fluoride (F), bicarbonate (HCO_3), potassium (K), magnesium (Mg), nitrate (NO_3), SAR, sulfate (SO_4), and pH. Because hydrogen ions participate in the majority of chemical events that change the composition of water, hydrogen ion activity is a key variable in the groundwater system. The pH value in the majority of natural fluids depends on the balance between carbon dioxide, carbonate, and bicarbonate. The pH of a solution is equal to the −ve logarithm of the hydrogen ion concentration (H^+) in moles/liter. Pure water includes an equal amount of H^+ and OH^- (hydroxyl) ions at pH 7 (at 25 °C). When the H^+ ions outnumber the OH^- ions, the pH value is less than 7, and it is greater than 7 when the OH^- ions outnumber the H+ ions. An electrolyte's electrical conductance (EC), which is measured in microS/cm and is the reciprocal of the specific resistance. Electrical conductivity typically rises with flow and time (resident time) in the aquifer, and its measurement reveals the degree of groundwater mineralization. The EC value (microS/cm at 25 °C) in the research region ranges from 50 to 25,430. Kadapa district's Jammalamadugu has the highest EC. A portion of the Kurnool, Kadapa, Krishna, Guntur, East, and West Godavari districts have high ECs, which is indicative of an overall (85.3%) EC that is in the best range of 500–3000 microS/cm. The primary sources of dissolved CO_2 and HCO_3 ions in groundwater are raindrops. More CO_2 from the soil's organic matter that has decomposed is dissolved when this precipitation enters the soil. The solubility of CO_2 in groundwater is decreased by an increase in temperature or a drop in pressure. As water and carbon dioxide flow through soil, the carbonate minerals are dissolved, and bicarbonate is produced. The pH of groundwater has a significant impact on the presence of carbonates in it. In groundwater, carbonates are often present when the pH is over 8.3, and they are only in trace amounts or missing when the pH is below 8.3. Groundwater has a bicarbonate content that typically ranges from 100 to 800 mg/L. The levels of bicarbonate in the state's groundwater range from 9.2 to 2837 mg/L, with an average concentration of 467 mg/L and the maximum concentration found in Donkapallisatram in the Kadapa district. One of the main inorganic anions found in water and wastewater is chloride, which is represented by the symbol Cl^-. Groundwater contamination from sewage wastes and the cultivation of coconut plants may lead to an abnormal concentration of Cl^-. The primary sources of fluoride in groundwater include fluoride-bearing minerals found in rocks such as fluorite (CaF_2), apophyllite, fluorapatite, cryolite, and villumite. Locally high F concentrations in groundwater can be explained by ion exchange, evaporative concentration, and the dissolution of F-bearing minerals. Instead of the existence of fluoride-bearing minerals in bulk rocks or soils, the weathering of rocks and leachable fluoride in a region is more crucial in determining the presence of fluoride in groundwater. The weathering of silicate minerals such as orthoclase, microcline, nepheline, biotite, and leucite is a frequent source of K^+ in groundwater. Some of the sources of K^+ in the ground fluids are the dissolution of evaporites in sedimentary rocks that contain highly soluble sylvite and nitre. Other anthropogenic sources of K^+ in ground fluids include fertilizers, manure, human and animal waste, and the intrusion of salty waters as a result of over-pumping. The primary sources of magnesium (Mg^{2+}) in groundwater are the weathering of basic igneous rocks such as dunites and pyroxenites, volcanic rocks such as basalt, metamorphic rocks such as amphibolites, talc, and tremolite-schists, and sedimentary rocks such as dolomite and gypsum. The usage of surface water for irrigation is another source of Mg^{2+} in groundwater. The magnesium concentration in the state is substantially lower than the calcium concentration, as it is in most natural water. Rainwater and atmospheric nitrogen react to produce nitrate and ammonium ions. High levels of nitrate in groundwater have been reported as a result of anthropogenic pollution, particularly leaching from septic tanks and sewage systems. The content of sulfate (SO_4^{2-}), which ranges from a few to several thousand mg/L in natural waters, is widely dispersed in native ecosystems (APHA, 1998). Sulfide minerals found in sedimentary rocks, such as pyrite, gypsum, and anhydrite, are the principal sources of SO_4^{2-} in groundwater.

Methodology

Geostatistics A category of statistics called geostatistics is employed to examine and forecast the values connected to spatial or spatiotemporal occurrences. The analyses include the spatial (and, in some cases, temporal) coordinates of the data.

Initially designed as a useful way to characterize spatial patterns and extrapolate values for areas where samples were not gathered, many geostatistical tools were created. Since then, these instruments and techniques have been developed to offer not only interpolated values but also measurements of uncertainty for those values. For well-informed decision-making, uncertainty assessment is essential because it offers details on the potential outcomes (values) for each place rather than simply a single interpolated value. A (potentially sparse) primary variable of interest can now be supplemented by secondary datasets using mechanisms provided by geostatistical analysis, which has progressed from uni- to multivariate analysis and allows for the creation of more precise interpolation and uncertainty models. The dataset and the model, once fully described, can be used to provide interpolated values for all unsampled locations within a region of interest. Typically, a map displaying the values of the modeled variable serves as the output. At this point, the impact of outliers can be studied because they are likely to alter the interpolated map's interpolated parameter values (ESRI).

The same model can also be used to produce metrics of uncertainty for the interpolated values, depending on the interpolation technique. The data are subjected to ordinary kriging, simple kriging, and universal kriging. The prediction maps and prediction standard error (SE) maps were prepared. The models were optimized in this process. The evaluation metrics considered in this study are the root mean square error (RMSE), mean standardized error (MSE), root mean square standardized error (RMSSE), and average standard error (ASE). Correlation analysis was performed to determine the interrelationships among the variables. Although correlation cannot always mean causation, we prepared correlation plots to represent whether there are any variables that are positively or negatively correlated.

PCA The information in a dataset containing variables/observations described by numerous intercorrelated quantitative variables can be condensed and visualized using principal component analysis (PCA). It is possible to think of each variable as a different dimension. It could be exceedingly challenging to depict a multidimensional hyperspace if your datasets contain more than three variables. A multivariate data table's key information is extracted using principal component analysis and expressed as a set of a few new variables known as principal components. The originals and these extra variables are a linear combination. There are fewer or the same number of primary components as there were original variables. A given dataset's information reflects the entire variance it includes. Finding the principal components along which the data vary most is the aim of PCA. PCA minimizes information loss while reducing the dimensionality of multivariate data to two or three principal components that can be visually represented. When the variables in the dataset are highly connected, the PCA approach is especially helpful. The presence of correlation suggests that the data are redundant. Because of this duplication, PCA can be used to transform the original variables into fewer new variables that account for the majority of their variance.

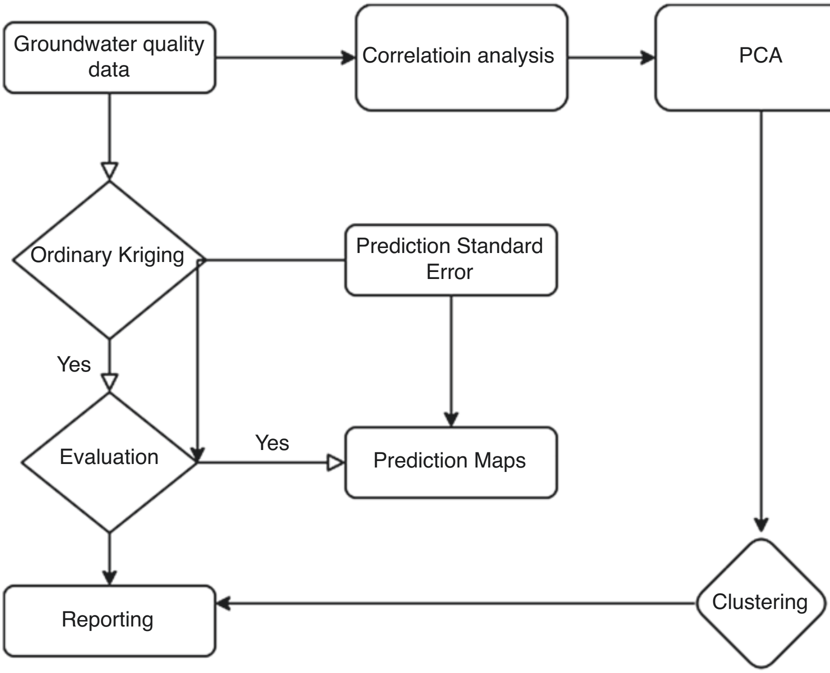

Fig. 12.1 Methodology

Cluster Analysis A key problem in partitioning clustering, such as k-means clustering, which needs the user to define the number of clusters k to be formed, is determining the best number of clusters in a dataset. In direct approaches, a criterion is optimized, such as the average silhouette or the within-cluster sums of squares. Elbow and silhouette methods are related techniques. The main goal of k-means clustering is to form clusters with the least amount of overall intra-cluster variation, also known as the overall within-cluster sum of squares (WSS). We need the total WSS, which quantifies how compact the clustering is, to be as minute as possible. The elbow technique examines the relationship between the total WSS and the number of clusters. To prevent the total WSS from being significantly improved by adding another cluster, one should select a number of clusters.

The detailed methodology is given in Fig. 12.1.

12.4 Results and Discussion

Statistics The summary statistics show that there are 917 valid observations with 65 missing observations (Table 12.1). The SO_4 variable had a high skewness of 10.482 and a kurtosis of 168.028.

Table 12.1 Summary statistics

	Valid	Missing	Mean	Std. deviation	Maximum	Skewness	Kurtosis
CO3	917	65	7.506	14.697	168	3.563	21.283
Ca	917	65	40.62	47.781	384.333	1.786	5.577
Cl	917	65	198.656	335.579	4231.6	5.488	48.82
Ec	917	65	1201.276	1641.723	20,870	4.331	35.31
F	917	65	0.509	0.705	7.294	3.208	18.74
HCO3	917	65	205.596	211.578	1299	0.781	0.225
K	917	65	23.98	63.699	640	5.213	33.721
Mg	917	65	33.185	44.047	469.465	2.997	17.035
NO3	917	65	61.103	108.534	1732.5	5.909	68.642
Na	917	65	144.585	265.674	4120.5	6.341	67.856
SAR	917	65	3.087	4.468	42.255	3.256	17.597
SO4	917	65	75.591	183.071	3620	10.482	168.028
TH	917	65	235.051	275.985	2385	2.265	10.541
TA	917	65	164.445	179.089	1064.8	0.815	0.076
pH	917	65	5.058	3.929	9.445	−0.504	−1.732

Kriging Ordinary kriging (OK), simple kriging (SK), and universal kriging (UK) were conducted on the datasets, and the following information was obtained:

(i) For bicarbonate, an RMSE of 207.10, an MSE of 0.006, an RMSSE of 1.02, and an ASE of 201.2 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.2.

(ii) For calcium, an RMSE of 46, an MSE of −0.005, an RMSSE of 1.04, and an ASE of 43.9 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.3.

(iii) For chloride, an RMSE of 321, an MSE of −0.002, an RMSSE of 0.96, and an ASE of 336 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.4.

(iv) For electrical conductivity, an RMSE of 1601, an MSE of 0.007, an RMSSE of 0.968, and an ASE of 1658 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.5.

(v) For fluoride, an RMSE of 0.63, an MSE of 0.004, an RMSSE of 1.15, and an ASE of 0.5 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.6.

(vi) For potassium, an RMSE of 61, an MSE of −0.001, an RMSSE of 1.115, and an ASE of 54.8 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.7.

(vii) For magnesium, an RMSE of 43, an MSE of −0.001, an RMSSE of 1, and an ASE of 42.8 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.8.

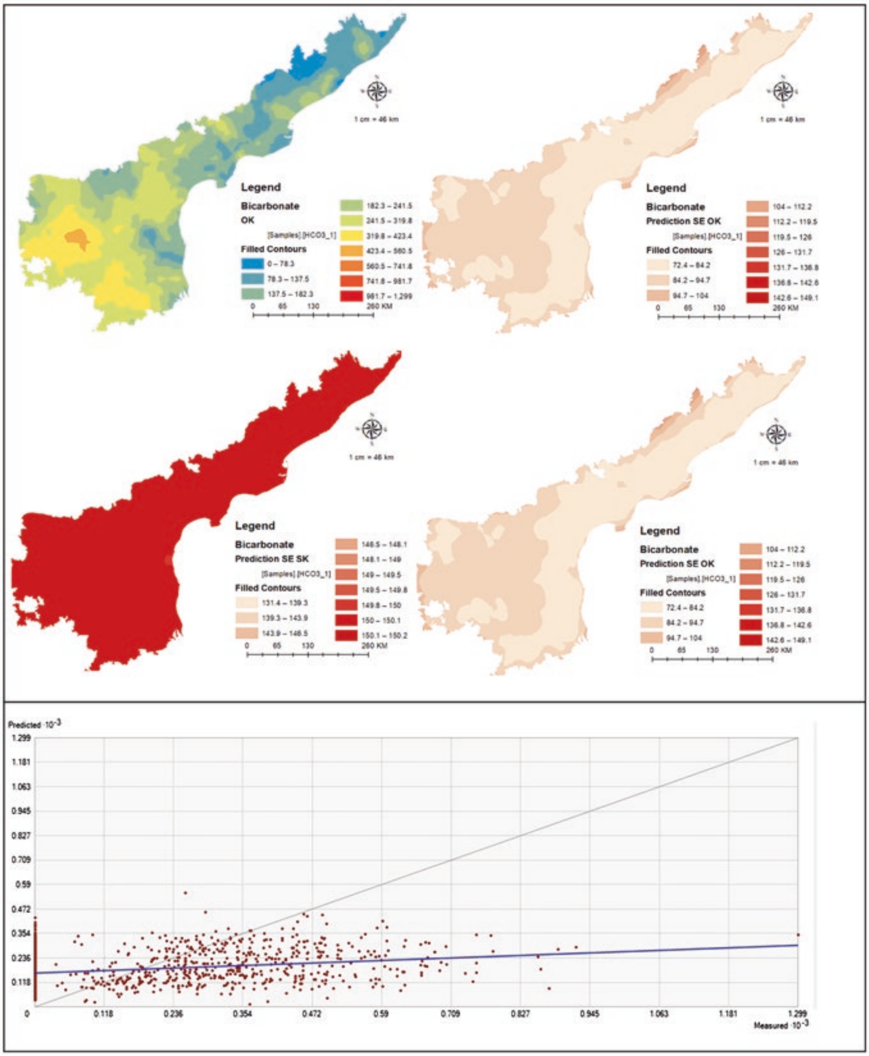

Fig. 12.2 Bicarbonate-OK, SK, and UK maps and plots (***RMSE: 207.10, MSE: 0.006, RMSSE: 1.02, ASE: 201.2***)

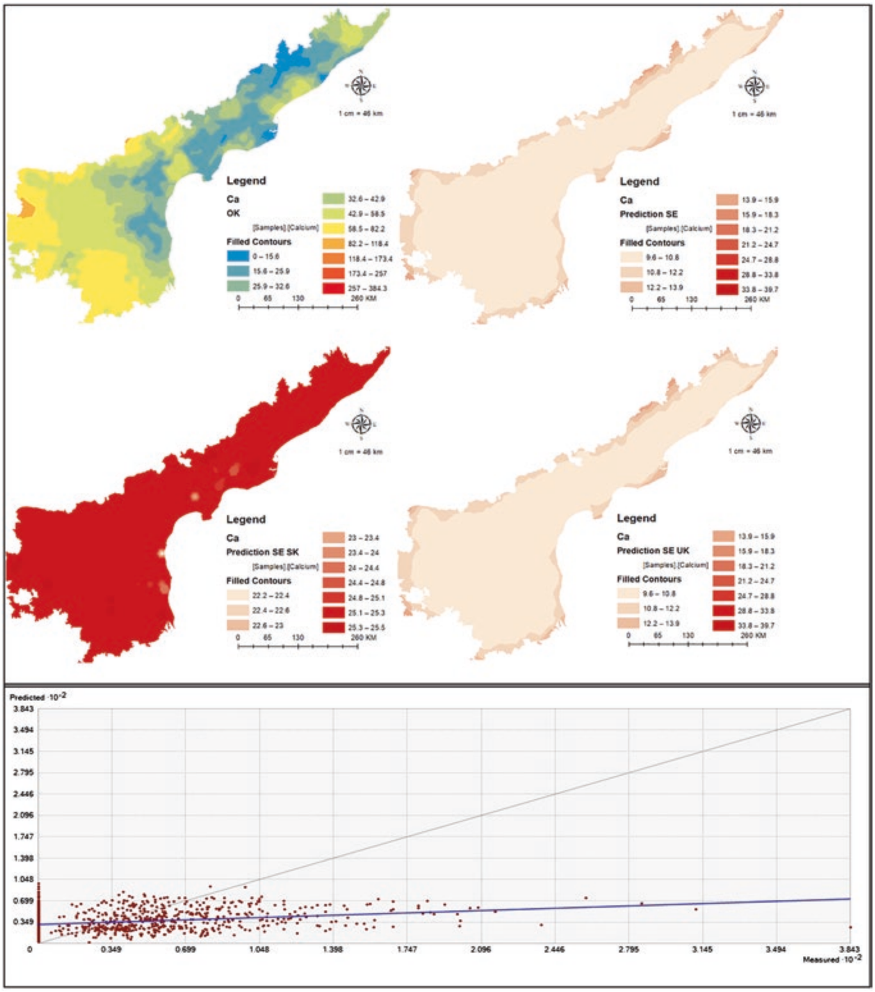

Fig. 12.3 Calcium-OK, SK, and UK maps and plots (***RMSE: 46, MSE: −0.005, RMSSE: 1.04, ASE: 43.9***)

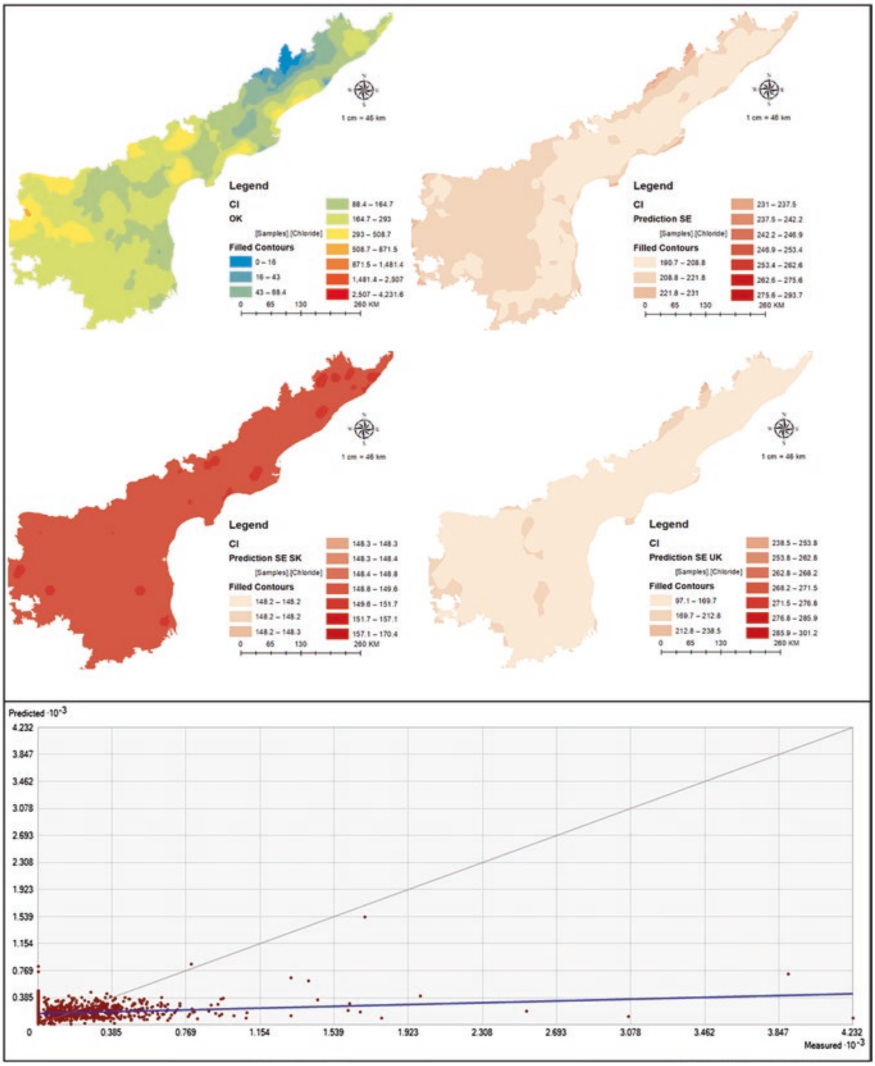

Fig. 12.4 Chloride-OK, SK, and UK maps and plots (***RMSE: 321, MSE: −0.002, RMSSE: 0.96, ASE: 336***)

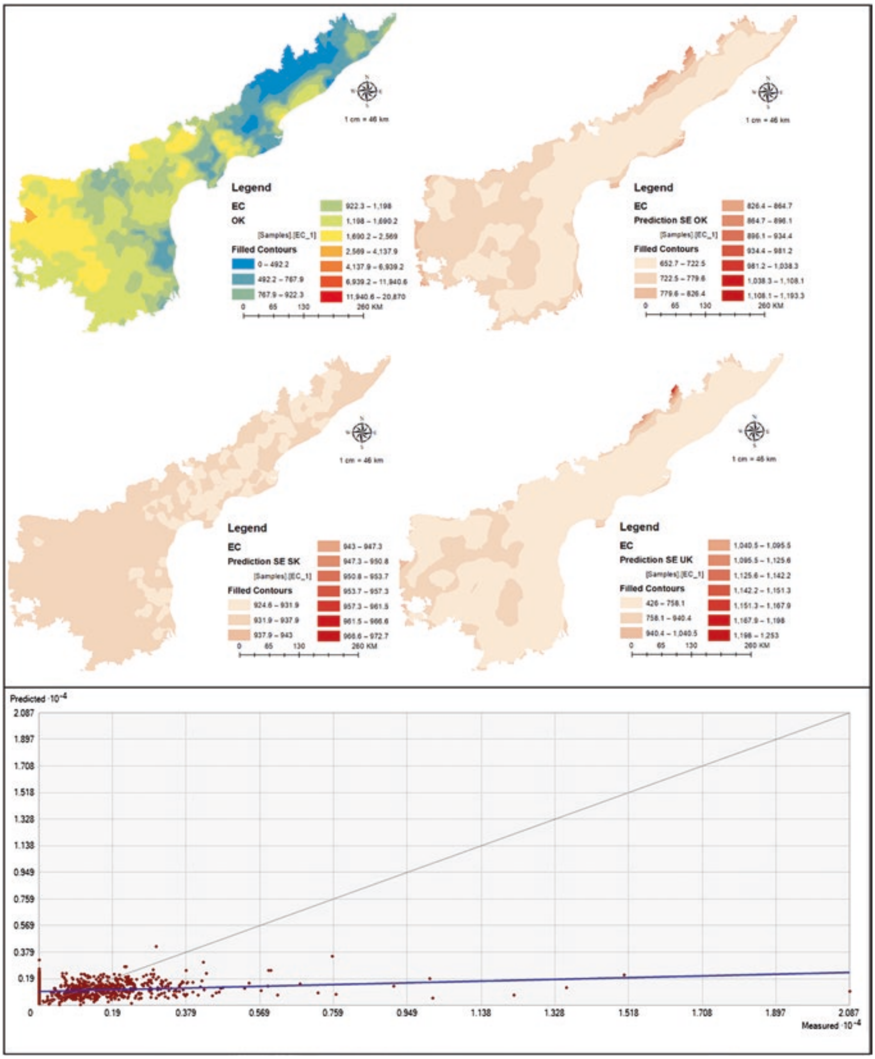

Fig. 12.5 Electrical conductivity-OK, SK, and UK maps and plots (***RMSE: 1601, MSE: 0.007, RMSSE: 0.968, ASE: 1658***)

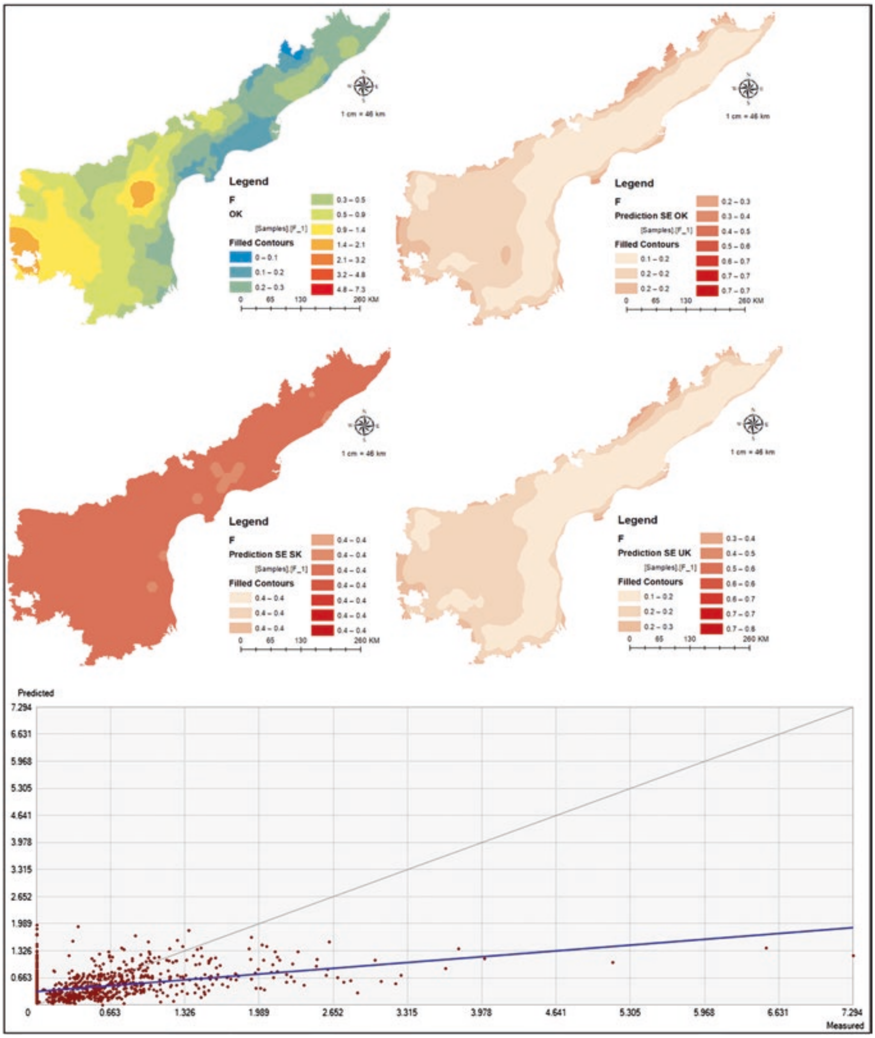

Fig. 12.6 Fluoride-OK, SK, and UK maps and plots (***RMSE: 0.63, MSE: 0.004, RMSSE: 1.15, ASE: 0.5***)

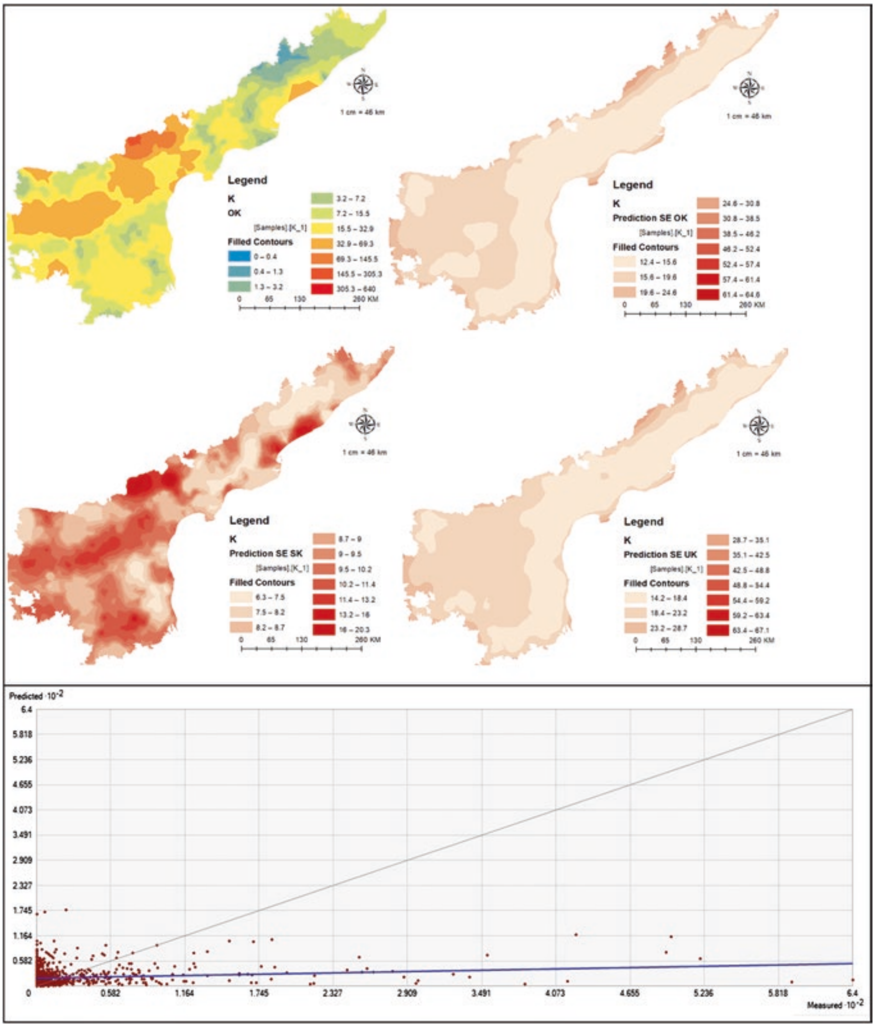

Fig. 12.7 Potassium-OK, SK, and UK maps and plots (***RMSE: 61, MSE: −0.001, RMSSE: 1.115, ASE: 54.8***)

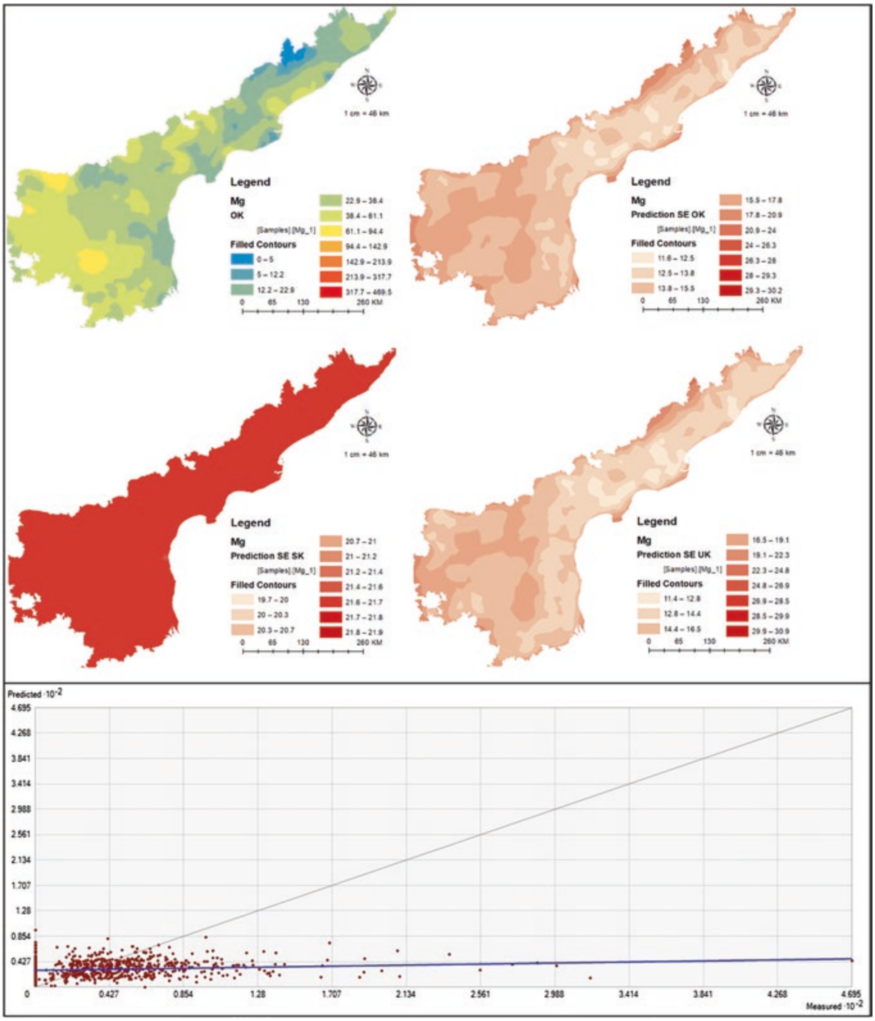

Fig. 12.8 Magnesium-OK, SK, and UK maps and plots (***RMSE: 43, MSE: −0.001, RMSSE: 1.008, ASE: 42.8***)

(viii) For sodium, an RMSE of 256, an MSE of −0.002, an RMSSE of 0.99, and an ASE of 260.2 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.9.

(ix) For nitrate, an RMSE of 99.6, an MSE of −0.005, an RMSSE of 1.179, and an ASE of 83.7 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.10.

(x) For pH, an RMSE of 3.96, an MSE of 0.003, an RMSSE of 0.974, and an ASE of 4.06 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.11.

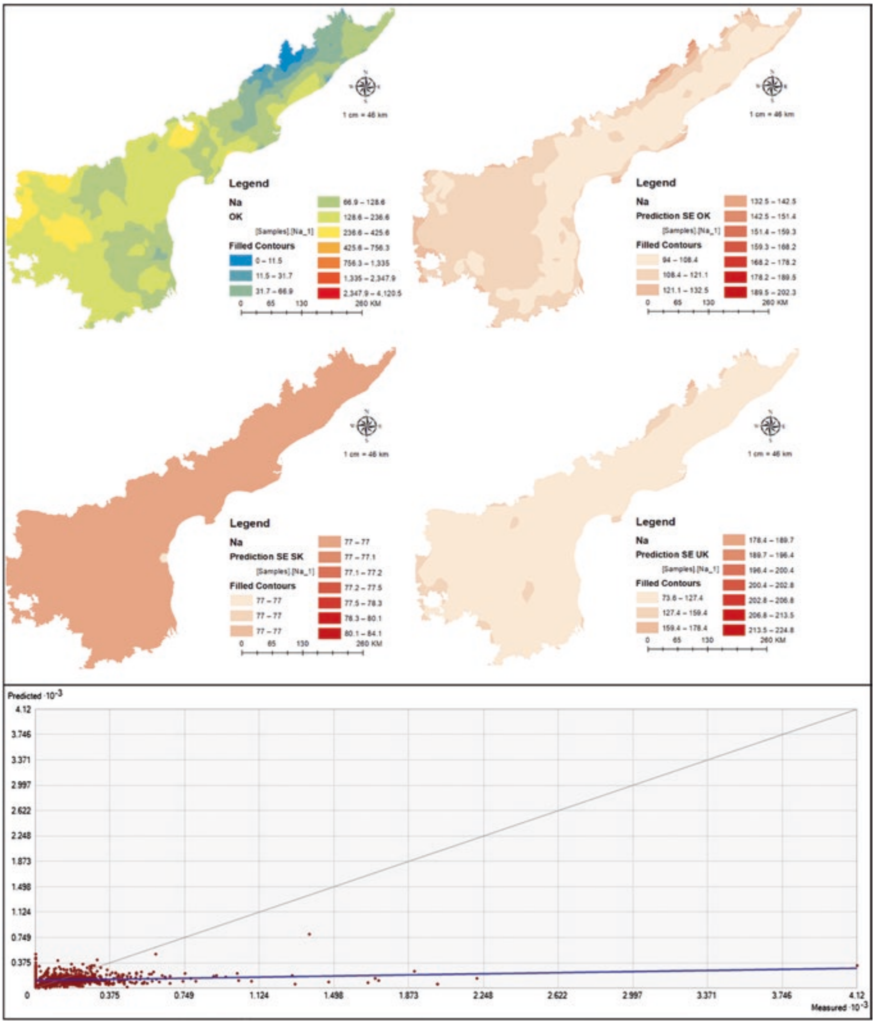

Fig. 12.9 Sodium-OK, SK, and UK maps and plots (***RMSE: 256, MSE: −0.002, RMSSE: 0.99, ASE: 260.2***)

(xi) For SAR, an RMSE of 4.39, an MSE of 0.0020, an RMSSE of 1.03, and an ASE of 4.24 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.12.

(xii) For sulfate, an RMSE of 174, an MSE of −0.0008, an RMSSE of 1.006, and an ASE of 174.16 were obtained using ordinary kriging. The prediction standard error (PSE) maps and OK maps are given in Fig. 12.13.

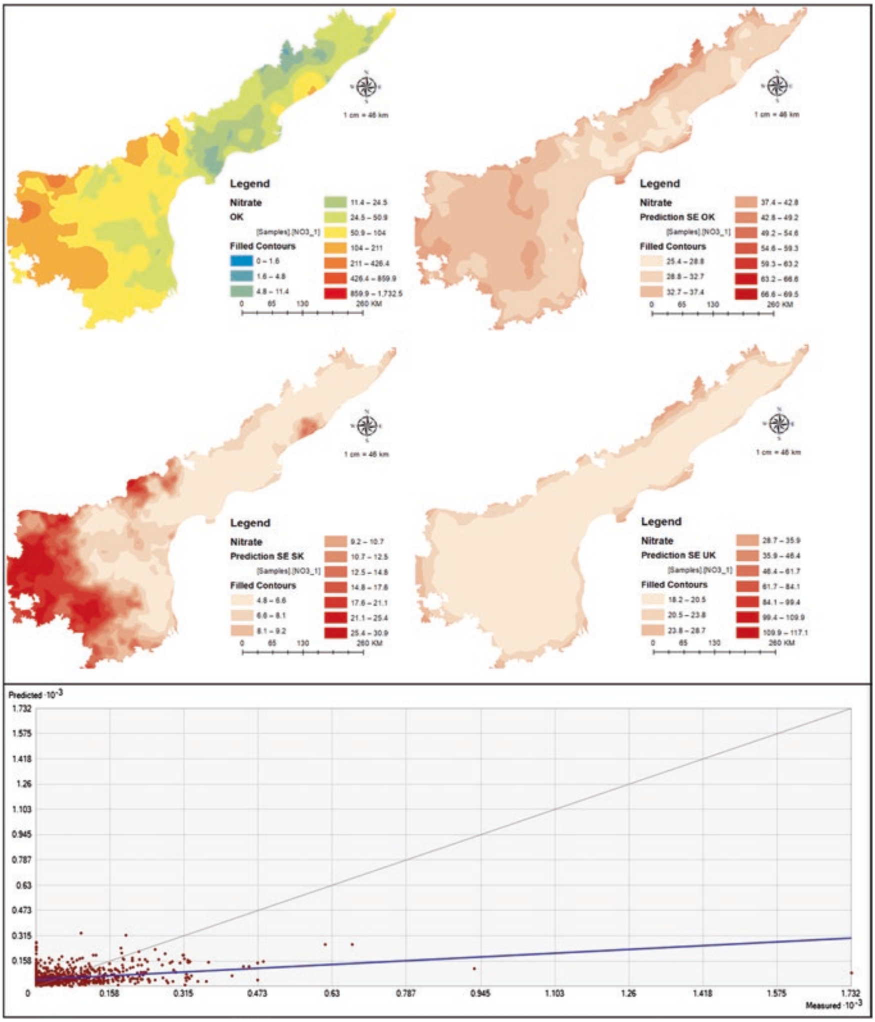

Fig. 12.10 Nitrate-OK, SK, and UK maps and plots (***RMSE: 99.6, MSE: −0.005, RMSSE: 1.179, ASE: 83.7***)

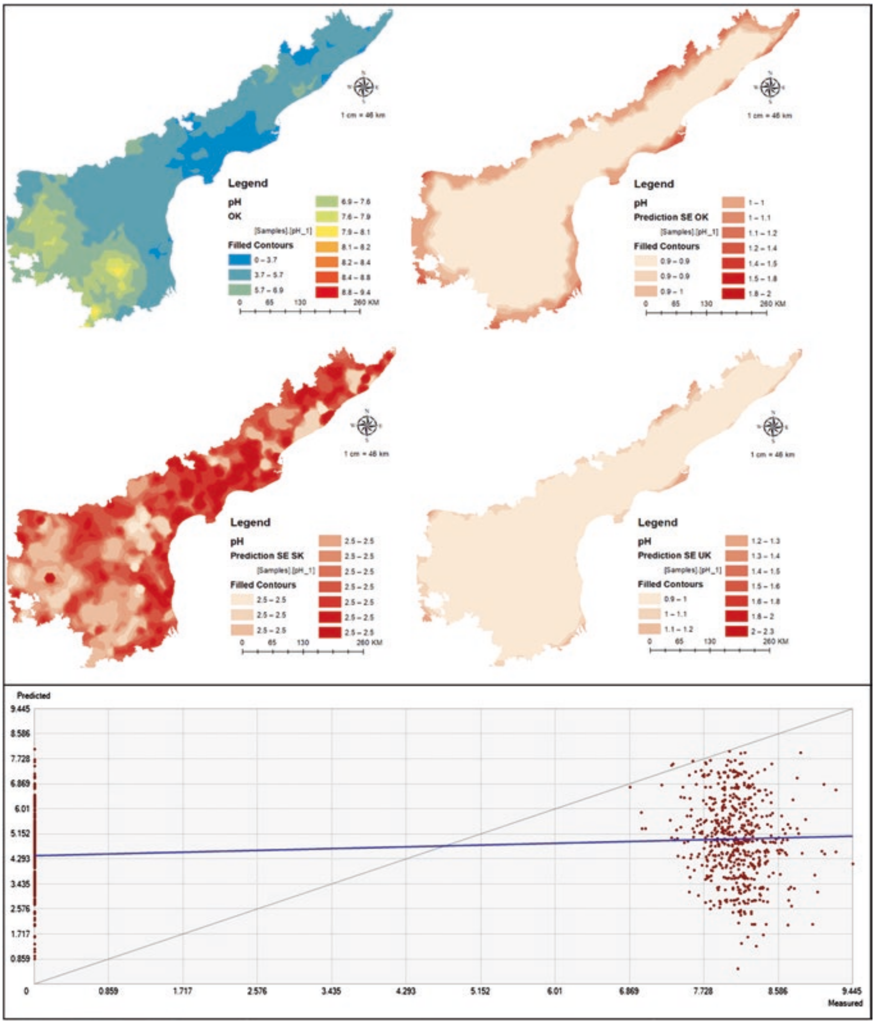

Fig. 12.11 pH-OK, SK, and UK maps and plots (***RMSE: 3.96, MSE: 0.003, RMSSE: 0.974, ASE: 4.06***)

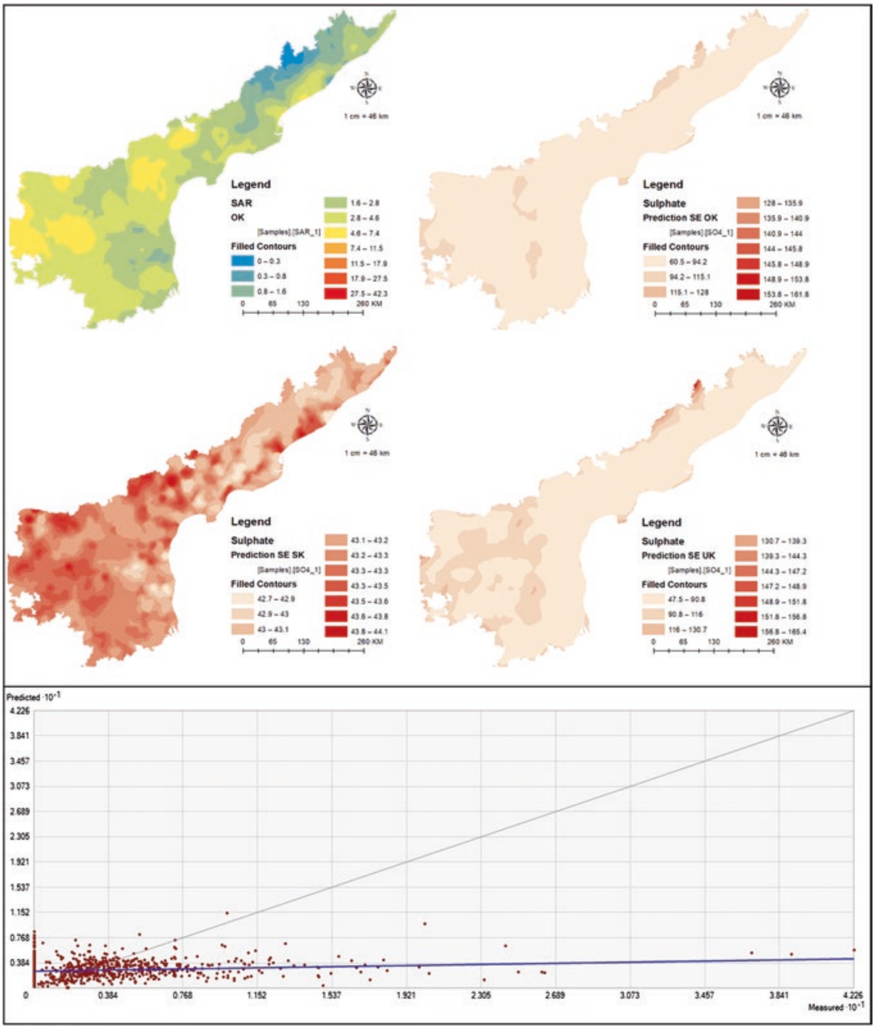

Fig. 12.12 SAR-OK, SK, and UK maps and plots (***RMSE: 4.39, MSE: 0.0020, RMSSE: 1.03, ASE: 4.24***)

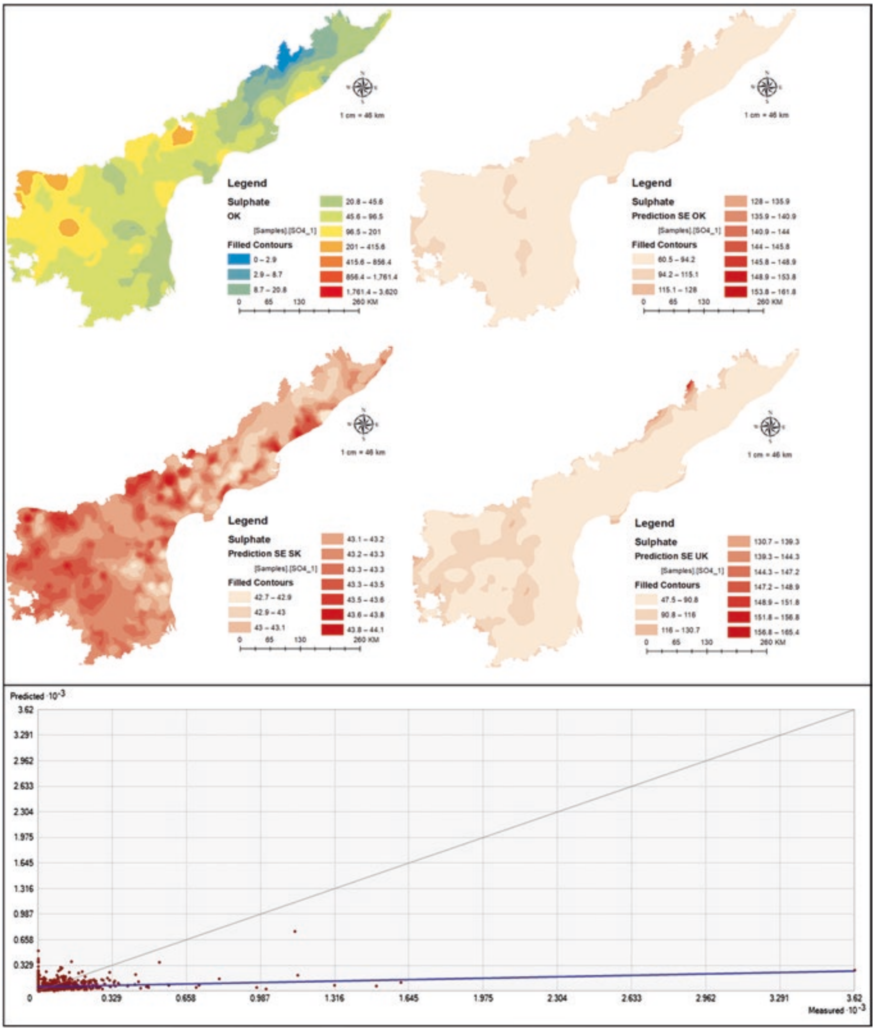

Fig. 12.13 Sulfate-OK, SK, and UK maps and plots (***RMSE: 174, MSE: −0.0008, RMSSE: 1.006, ASE: 174.16***)

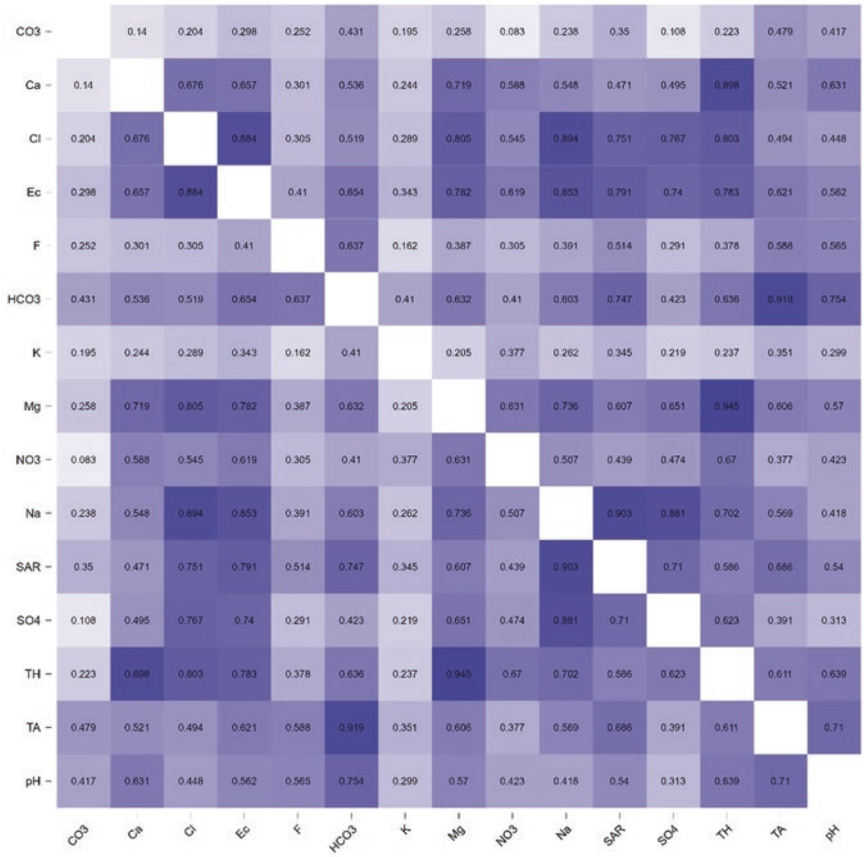

Fig. 12.14 Correlation heatmap

Correlation Analysis pH is strongly correlated with bicarbonate (0.754) and total alkalinity (0.71). Total alkalinity is strongly correlated with bicarbonate (0.91) and pH (0.71). Total hardness is strongly correlated with Ca, Cl, EC, Mg, and Na. The other strong correlations (thick blue) can be observed in the correlation heatmap given in Fig. 12.14.

PCA The principal components were extracted from the dataset. We obtained three principal components with Na, sulfate, and chloride dominating PC1, bicarbonate, total alkalinity, and pH dominating PC2, and TH and Mg dominating PC3. Sodium exhibited low uniqueness and hence high commonality, with F having high uniqueness with low commonality. The varimax rotation method was applied (Table 12.2).

Clustering Analysis Cluster analysis was performed with the dataset, and nine clusters were obtained. The size of the first cluster is 904, with an explained proportion of within-cluster heterogeneity of 0.979 and a silhouette score of 0.629.

Table 12.2 Component loadings

	PC1	PC2	PC3	Uniqueness
Na	0.902			0.025
SO4	0.87			0.156
Cl	0.784		0.496	0.108
SAR	0.763	0.539		0.102
Ec	0.712		0.486	0.132
Mg	0.51		0.702	0.165
TH	0.426		0.829	0.054
HCO3		0.824		0.118
TA		0.819		0.158
pH		0.717	0.529	0.203
CO3		0.687		0.51
F		0.686		0.476
Ca			0.852	0.159
NO3			0.719	0.378
K				0.801

Note. Applied rotation method is varimax

Table 12.3 Clusters

Cluster information									
Cluster	1	2	3	4	5	6	7	8	9
Size	904	5	1	2	1	1	1	1	1
Explained proportion within-cluster heterogeneity	0.979	0.015	0	0.005	0	0	0	0	0
Within sum of squares	9836.031	154.151	0	52.033	0	0	0	0	0
Silhouette score	0.629	0.275	0	0.161	0	0	0	0	0

Note. The between sum of squares of the 9 cluster model is 3697.79
Note. The total sum of squares of the 9 cluster model is 13,740

Table 12.4 Evaluation metrics

Evaluation metrics	
	Value
Maximum diameter	14.647
Minimum separation	4.643
Pearson's γ	0.618
Dunn index	0.317
Entropy	0.1
Calinski–Harabasz index	41.793

Clusters 1, 2, and 4 have values that can be considered. The total sum of squares of all the clusters is 13,740, and the sum of squares value is 3697 (Table 12.3). The evaluation metrics and hierarchical clustering are shown in Tables 12.4 and 12.5. The number of clusters with the lowest BIC, WSS, and AIC is given in Fig. 12.15.

Table 12.5 Hierarchical clustering

Hierarchical clustering					
Clusters	*N*	R^2	AIC	BIC	Silhouette
9	917	0.269	10312.21	10963.06	0.62

Note. The model is optimized with respect to the BIC value

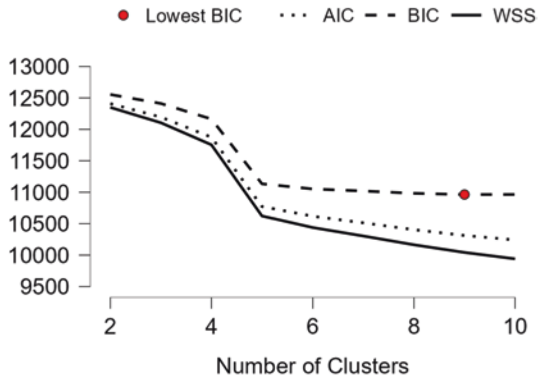

Fig. 12.15 Representation of clusters

12.5 Challenges and Solutions

The availability of datasets across all time frames is not possible with groundwater surveys, as they are very expensive. The appropriate solution is to apply geostatistical tools such as kriging and perform cross-validation at random points to keep the expenditures as low as possible. There is a need to share data among the borewell companies and groundwater agencies belonging to the private and public sectors so that the cost of digging sampling wells can be reduced and the quality and quantity of groundwater can be updated frequently.

12.6 Conclusions

This study illustrates the need for geostatistical tools such as kriging to obtain important insights into the spread of groundwater quality in the region or state of Andhra Pradesh. This can be a valuable tool in groundwater studies where the funds for surveying are limited.

12.7 Limitations of This Study

The limitation of this study is the data availability, and there was no continuous update of the data across the state earlier.

12.8 Recommendations

The following recommendations are proposed:

(i) Geostatistical tools should be widely used in groundwater studies to obtain appropriate insights.
(ii) Cross-validation in the field is to be conducted regularly to optimize the model.
(iii) Excess dependence on geostatistical tools with no accurate data from the field should be avoided.
(iv) Data sharing among bore well companies and government departments must be made mandatory.
(v) The groundwater samples should be collected by the bore well companies and deposited with the local authorities regularly.

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Conflict of Interest The authors declare no conflict of interest.

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Chapter 13
Air Quality and Human Health

Janhavi Singh, Swagata Payra, and Sunita Verma

Abstract Air quality is a measurement that describes how good or poor air is present within the atmosphere. Good air contains a barely low amount of solid particles and chemical pollutants. Poor air consists of a high concentration of solid suspended particles along with gaseous pollutants, resulting in low visibility and damage to living organisms as well as the environment. Air pollutants, such as particulate matter and chemical pollutants (primarily ozone), disturb the energy balance of the planet, which directly influences or impacts climate in the worst ways. From an extremely local to the global level, the problem of degrading air quality has managed to leave its footprints all over the earth. As new epidemiological research became available, the consequences of air quality on human health became recognizable and rose to the top of the priority list by 2000. In 2019, the degradation of global air quality caused massive destruction over East Asia, Europe, and North America, taking away the lives of seven million people, extensive damage to crops, and a rapid reduction in biodiversity. Therefore, strong technical solutions and policies are needed to reduce the adverse effects of climate change. Policies developed for sustainable development of the environment globally as well as regionally can improve the condition of human health, vegetation quality and agriculture yield, which is degrading due to exposure to harmful pollutants. Recently, the clean air events at COP-27 also addressed the crucial role of air quality in climate change and human health and focused on the urgency of tackling air pollution in a global

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partnership. For all of these efforts to work, the enlightenment of the general public regarding degrading air quality and its impact is necessary.

Keywords Air pollution · Air quality index · Airborne particulate matter · $PM_{2.5}$ · PM_{10} · Human health · Lung cancer

13.1 Introduction

Currently, one of the major health drivers is air quality over the region of interest, and its accurate assessment and forecasting are important in densely populated urban spaces (Bohnenstengel et al., 2015). With the growth in the human population, the upgradation in the standard of living and the necessity to provide for such a lifestyle resulted in rapid urbanization and industrialization. Furthermore, these two necessary evils gave rise to a broad spectrum of problems, out of which the dominant one is degraded air quality across the globe. It became apparent with the first-ever reporting of higher concentrations of carbon monoxide (CO) over South America, Africa, and Asia measured via Measurement of Air Pollution from Satellite (MAPS) onboard *Columbia* in 1981 that the issue of air pollution is a matter of international concern (Marsh et al., 1988). Additionally, satellite-borne observations of tropospheric air pollutants such as NO_2, SO_2, and HCHO by TROPspheric Ozone Monitoring Instrument (TROPOMI), Ozone Monitoring Instrument (OMI), Scanning Imaging Absorption Spetro-Meter for Atmospheric ChartographY (SCHIAMACHY), and Global Ozone Monitoring Experiment (GOME), CO by TROPspheric Ozone Monitoring Instrument (TROPOMI) and Measurement of Pollution in the Troposphere (MOPITT), and Aerosol Optical Depth (AOD) by TROPspheric Ozone Monitoring Instrument (TROPOMI), Ozone Monitoring Instrument (OMI), and Moderate Resolution Imaging Spectrometer (MODIS) have revealed air pollution on global to national scales (Akimoto, 2003; Vellalassery et al., 2021).

Ambient air quality is generally governed by atmospheric gaseous constituents (e.g., carbon monoxide, ozone, and nitrogen dioxide), particulate matter (primarily PM_{10} and $PM_{2.5}$), chemical species such as volatile organic compounds (VOCs) and biological particles (Cincinelli & Martellini, 2017). Additionally, the sources and processes leading to high concentrations of these major pollutants in complex urban areas are not fully understood, thereby limiting our ability to accurately assess and forecast air quality (Baklanov et al., 2016). Degrading air quality on a global scale is a problem that can be attributed to air pollutants having a longer lifetime (typically on the order of 1 week), as they will either resist atmospheric dissociation processes or at least be translocated to another continent (Akimoto, 2003). The intercontinental translocation of pollutants made it inevitable for the human population residing in underdeveloped and rapidly industrializing developing countries to remain unaffected by air pollution generated elsewhere (Akimoto, 2003). Another important aspect of degrading global air quality is the impact of aerosol or particulate matter (terms that are used synonymously by the scientific community but have slightly different meanings). Among all the pollutants, atmospheric particulate matter (particles of variable but very small diameter) is found to be the culprit of a wide range of detrimental effects from their direct and indirect effects on climatic systems and radiative forcing to their hazardous impacts on human health (Satheesh & Ramanathan, 2000; Wang et al., 2014). These particles are spread across the globe but exhibit spatiotemporal variability and strong regional imbalance, which makes it difficult for the scientific community to accurately quantify their ambient concentration and the related impacts (Ramanathan et al., 2001).

Degrading air quality impacts all spheres negatively from climate to biodiversity, but its impact on public and individual health has gained much attention due to increased morbidity and mortality (Mangia et al., 2011). Exposure to higher concentrations of air pollutants damages the health of all the species living in the surroundings. Keeping the aspect of damage to health, one of the major groups exposed to and affected by degrading air quality is the human population residing in urban environments. This human population is unavoidably exposed to stressful environmental circumstances, such as pollutant emissions from local and nonlocal sources (Mayer, 1999). There are numerous air pollutants that play a negative role in damaging human health. One such example is PM, which is capable of infiltrating the human respiratory system through inhalation, central nervous and reproductive system dysfunctions, cardiovascular and respiratory diseases and cancer (Gao et al., 2014; Zhou et al., 2014). It is made very clear from all the aforementioned facts that degrading air quality poses a major threat to both the climatic system of the earth and human beings. The evolution of air pollution as a global threat to the climatic system and human health is summarized in Fig. 13.1. The only way to tackle this

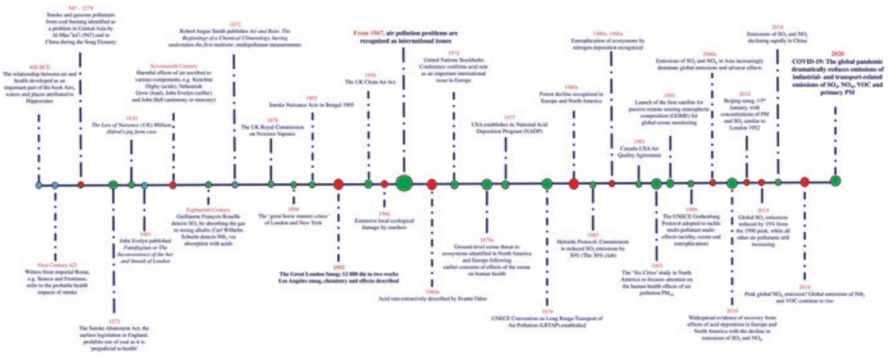

Fig. 13.1 Important milestones in the evolutionary history of air pollution. (Data adopted from: Fowler et al., 2020)

problem is through a multidisciplinary approach by scientific experts coupled with public awareness programs. Finally, international and national organizations and governing agencies must address the emergence and seriousness of this issue and propose sustainable solutions.

Fundamental Elements and Scales of the Air Pollution Problem

A complex mixture of particulate matter and harmful gases with variations in their source and composition both spatially and temporally is termed air pollution (Seinfeld & Pandis, 2016), an emerging global health threat. For example, vehicular and industrial emissions along with construction activities are the major cause of air pollution in urban and suburban areas, contributing to particulate matter and ambient smoke. The increased concentration of these pollutants results in the formation of smog, haze, and dense fog throughout the winter season, resulting in bad weather and less visibility, which is a hazard to human health (Prakash et al., 2013; Sharma et al., 2014). These negative impacts of air pollution, particularly on human health, make it a serious threat in need of urgent attention.

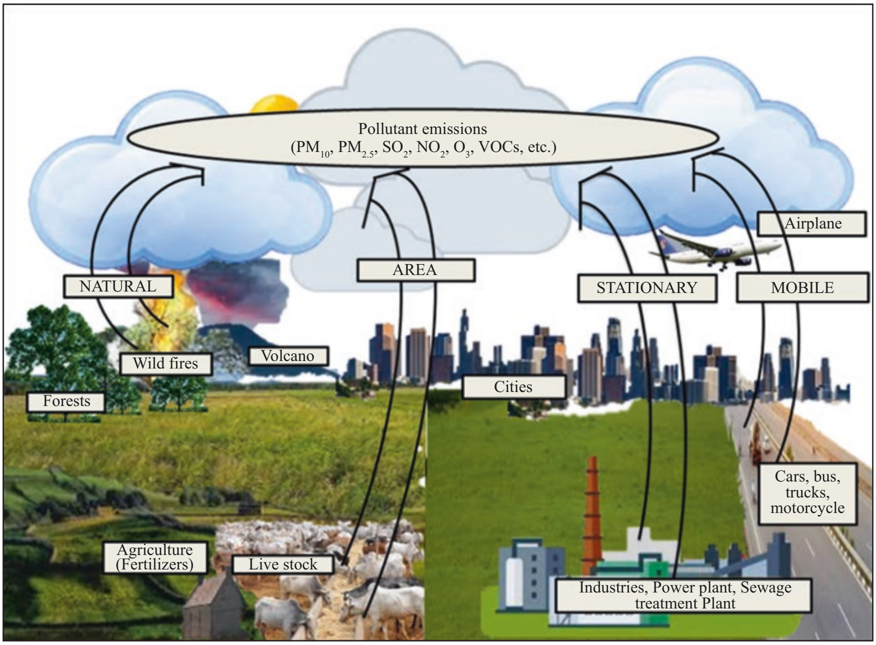

Fig. 13.2 Various sources of air pollution

13.2 Sources of Air Pollutants

The sources of air pollution are numerous. One could classify the source of air pollution as natural, implying that such pollutants were present before the term itself came into existence. Natural forms of air pollution can be defined as pollution caused by natural phenomena. Major sources of air pollution are presented in Fig. 13.2. Few classifications of sources of air pollutants that are generally used while studying air pollution are addressed below.

Based on the source of origin or of the precursors, there are two sources of air pollution (Kaushik & Kaushik, 2014):
Natural sources: Air pollution via forest fires, biological decay, pollen grains of flowers, spores, volcanic eruptions, sea salt sprays, naturally occurring radioactive minerals present in the earth, photochemical oxidation of terpenes, marshes, etc., are all natural sources.

Anthropogenic sources: The anthropogenic sources are agricultural activities, vehicular emissions, industrial units, thermal power plants, and fossil fuel burning.

Based on processes involved in the formation of pollutants:
Primary sources: Air pollutants that are injected directly into the atmosphere from an identifiable source are classified as primary pollutants. A few examples of primary air pollutants are radioactive substances, carbon monoxide (CO), oxides of sulfur (SO_x), and oxides of nitrogen (NO_x), hydrocarbons.

Secondary sources: When pollutants are manifested in the atmosphere via microphysical processes or chemical reactions among already existing atmospheric constituents, they are categorized as secondary pollutants. Peroxyacetyl nitrate (PAN), tropospheric ozone (O_3), and photochemical smog are a few examples of secondary air pollutants.

Based on the mobility of the sources emitting pollutants:
Stationary sources: Sources that are immovable are classified as stationary sources of air pollution. These are further subdivided into two categories:

Point sources: A single facility or specific place, producing a significant amount of pollutants and often characterized by the presence of smoke stalk, is classified as a point source. A few examples are industrial units, municipal incinerators, and petroleum storage.

Area sources: Area sources can be defined as numerous small stationary sources emitting pollutants when combined to form a significant source of pollution. For example, stationary sources when fuel combustion takes place—wood-burning furnaces, fireplaces, waste management activities, and crop burning.

Mobile sources: Sources that are movable are classified as mobile sources of air pollution. Emissions from these sources are the major cause of air pollution in urban areas. These are subdivided into two categories:

(i) On-road sources—(also called Highway sources) include automobiles fueled with diesel fuel, petrol, gasoline, or other alternative fuels.

(ii) Nonroad sources—(also called off-road sources) include emissions from equipment utilized in agricultural and construction activities, recreation, and many other purposes.

13.3 Major Air Pollutants

Key air pollutants include carbon monoxide (CO), particulate matter (PM_{10} and $PM_{2.5}$), oxides of sulfur (SO_x), oxides of nitrogen (NO_x), ozone (O_3), ammonia (NH_3), lead (Pb) and several oxidized volatile organic compounds (VOCs). Of these, eight pollutants (PM_{10}, $PM_{2.5}$, NO_2, SO_2, CO, O_3 NH_3, and Pb) are used to calculate the air quality index (AQI) over the Indian region. Additionally, short-term (up to 24 h) National Ambient Air Quality Standards are prescribed for this set of pollutants.

Particulate Matter (PM) Small solid particles and liquid droplets are collectively termed particulates. These are present in the atmosphere in fairly large numbers and pose a serious threat to ambient air quality. These particles have a diameter ranging from 0.0002 μ to 500 μ and atmospheric lifetimes varying from a few seconds to several months. Airborne particulates are broadly classified into two categories:

(i) Coarse particulate matter
(ii) Fine particulate matter

There are numerous processes through which particulate matter is continuously injected into the atmosphere. Of all the sources, physical processes, including agricultural tilling, fugitive dust emissions from industrial sectors, vehicular abrasion (i.e., brake and tire wear), and road dust resuspension are dominant contributors to coarse particulate matter (aerodynamic diameters between 2.5 μm and 10 μm). On the other hand, fine particulate matter (aerodynamic diameters less than 2.5 μm) is primarily manifested in the atmosphere via secondary formation.

Carbon Monoxide Carbon monoxide is a colorless, tasteless, and odorless gas that is insoluble in water and 96.5% as heavy as air. The formation of this gas is largely attributed to the poor mixing of combustion fuel and combustion air. In urban regions, major sources contributing to outdoor concentrations of CO are biomass-burning activities, industrial processes, on-road transportation (diesel-powered engines and gasoline-powered engines), off-road engines, and agricultural burning in the surrounding suburban and rural areas. Likewise, forest fires, volcanic eruptions, marsh gas production, natural gas emissions, and controlled burns of vegetation are significant sources of CO.

Sulfur Dioxide Sulfur dioxide is a pungent and colorless gas produced primarily from the combustion of sulfur-containing materials. Sources of sulfur dioxide include volcanic eruptions, fuel combustion (mostly coal), coal-fired industrial plants and transportation facilities. However, the dominant effect of natural sources or anthropogenic sources will be largely influenced by the region of interest.

Nitrogen Oxides Nitric oxide (NO) and nitrogen dioxide (NO_2) are the two nitrogen oxides that are primarily involved in air pollution. On the global scale, dominant sources emitting NO_x are lighting and oxidation of N_2O in the stratosphere, biomass burning, microbial activity in the lithosphere and combustion of fossil fuel. Of these, gasoline and diesel engines and stationary power plants are significant sources in urban spaces. The most damaging effect of NO_x is that it aids in the formation of surface-level ozone and other photochemical oxidants while being converted from NO to NO_2 via a photochemical chain of reactions.

Ground-Level Ozone Ground-level ozone is a "secondary pollutant," as it is produced in the atmosphere via photochemical reactions between volatile organic compounds (VOCs) and nitrogen oxides (NO_x). This particular pollutant is known to have significant effects on human health, including a range of morbidity health endpoints, such as hospital admissions, asthma symptom days and premature mortality. In addition, ozone is also known to significantly decrease the yield of certain crops, damage vegetation, and even affect non-living materials, such as synthetic materials, acetate, nylon, cotton, polyester, and other textiles.

Ammonia With a peculiar pungent odor, ammonia is a colorless gas that can be easily dissolved in water and is corrosive in nature. It is a naturally occurring constituent in the Earth's atmosphere and falls back on the surfaces of water, land, and plants via dry and wet deposition processes. Popular as a primary air pollutant, ammonia also acts as a precursor in secondary particle formation processes. Chemically reacting with nitric and sulfuric acids in the atmosphere, ammonia gives rise to ammonium salts—a damaging type of particulate matter.

Although the sources of lead emissions change when we shift from one location to another, some of the major sources emitting lead into the atmosphere are metal and ore processing industries, leaded aviation fuels, lead-acid battery manufacturers, and waste incinerators. The highest ambient concentration of lead is reported in the close vicinity of lead smelters (Xing et al., 2020). Airborne lead exhibits a wide range of detrimental effects on ecosystems and human health.

13.4 Scales of the Air Pollution Problem

From an extremely local to the global level, the problem of air pollution has managed to leave its footprints all over the earth. This particular section addresses five different levels of air pollution that are studied in general. These levels are local (up to approximately 5 km), urban (extending up to an order of 50 km), regional (ranging from 50 to 500 km), continental (extending 500 km to several thousand kilometers) and global (extending worldwide).

Local-Level Air Pollution Usually, characterized by numerous small emitters or a few large emitters, local air pollution has a greater potential impact for a given release as the height of release of pollutants from sources is lower. Under stable atmospheric conditions, these pollutants remain entrapped near the Earth's surface, resulting in a dome of air pollutants just above the point of release. Sources that are major contributors to the local-level problem of air pollution include vehicular emissions, industrial units and power plants. An example of local air pollution is carbon monoxide (CO) from automobiles, which will allow higher concentrations of CO to exist near roadways and ultimately be brought to the earth's surface.

Urban-Level Air Pollution The problem of air pollution over urban regions can be further classified into two subcategories. The first is the emission of 1 pollutants (directly released from the source), while the second is the formation of 2 pollutants (formed via chemical reactions between atmospheric precursors) in the atmosphere above. Urban-scale air pollution problems can result from sources emitting at the same scale as well as those emitting at the local level. Nonetheless, the problem of urban levels of air pollution is primarily a manifestation of secondary pollutant formation (Boubel et al., 2013). Pollutants that are relatively nonreactive or slightly reactive will result in higher concentrations, impart their detrimental effects and ultimately either become dispersed or deposited. In contrast, secondary formations of pollutants such as ozone will not only aggravate air pollution but will also have much more hazardous effects than their chemical precursors.

Regional-Level Air Pollution There are three specific scenarios that contribute to the problem of air pollution at the regional scale. The first is the production of oxidants at the urban scale. These atmospheric oxidants are further carried over and impact air quality at a regional level. This type of condition develops when a major metropolitan region exists in close vicinity, containing secondary pollutants in its immediate atmosphere. Pollutants from these regions are transported to the surrounding area, thereby increasing the level of air pollution over a large region. The second scenario develops as a result of the transportation of relatively slow-reacting primary air pollutants that are capable of undergoing chemical transformations over long-range transportation. Provided favorable meteorological conditions, these pollutants impart their detrimental effects not only on the emission region but also on part of the world where they get carried away and hence contribute to regional-level air pollution. The final category of difficulty is the reduced visibility at a regional scale attributable to the formation of fine nitrate and sulfate particles. This problem negatively impacts the aesthetic value of a region.

Continental-Level Air Pollution The continental scale of air pollution is indistinguishable from that of the regional scale for relatively smaller continents such as Australia or Europe. The separation in both scales becomes clearer with respect to the national policies of one country that will significantly impact the neighboring estates. Perhaps this is one of the greatest concerns in regard to the problem of air pollution at the continental level.

Global-Level Air Pollution Global air quality is usually affected by air pollutants having a relatively longer atmospheric lifetime, air pollutants that are resistant to tropospheric decomposition processes and pollutants that are involved in the tropospheric-stratospheric exchange processes. Understanding the global scale of air pollution requires a much clearer knowledge of the exchange processes between the stratosphere and troposphere and the hemispherical transport phenomenon.

13.5 Air Quality Indexing System

The U.S. Environmental Protection Agency (EPA) was the first to set standards for national air quality in 1971. It would be an incomplete assessment of regional air quality if only the tonnage of pollutants is taken into consideration. The relative toxicity of a pollutant, although qualitative, is an essential parameter for the assessment of how clean the atmosphere of a certain region is. Therefore, several units for expressing air pollutants and air quality parameters are as follows (De, 2010):

- Gases and vapors, $\mu g/m^3$ (also ppm by volume)
- Weight of particulate matter, $\mu g/m^3$
- Particulate matter count, no. per cubic meter
- Visibility, km
- Emission and sampling rates, m^3/min
- Pressure, mm of Hg
- Temperature, °C

The problem arises while conveying and explaining these parameters and their related datasets to the non-scientific community. A huge database created from the aforementioned parameters, which in general is incapable of delivering the status of air quality to the decision makers, government officials and particularly to the commoners. This gave birth to the need for a common index that can be easily perceived by the public, commonly known as the AQI. The air quality index (AQI) can be defined as an effective tool that combines and transforms complex air quality data of various pollutants into a single nomenclature, number (index value), and color. It is generally used by government organizations to communicate the present or predicted air quality to the general public.

Basic Criteria for an Air Quality Index An ideal air quality index must be capable of reflecting the measured air quality over a region for a given time period in a publicly perceivable way. In pursuit of achieving these desired characteristics, air quality indexing systems often aim to standardize and synthesize air constituent concentration datasets that allow quick comparisons (Kanchan et al., 2015). To design, select, or formulate an air quality index, the following points should be taken into consideration (Kanchan et al., 2015):

(i) Should be able to convey a correct and readily understandable estimate of air pollution level to the public.
(ii) Should be inclusive of the primary criteria pollutants and their synergistic effects.
(iii) The formula should be so designed that it can include or disregard other pollutant datasets and the averaging time, if needed.
(iv) Must be related to the National Ambient Air Quality Standards of the respective country or estate.
(v) Should be able to negate ambiguity (occurs when the index gives false alarm of poor air quality over a region) and eclipsing (occurs when the index fails to indicate deteriorating air quality over a region).
(vi) Should be based on a reliable dataset of air pollutants obtained from monitoring stations that can effectively provide an appropriate representative for the region of interest.

Air Quality Indices and Related Standards Around the World

AQI System in the USA The U.S. Environment Protection Agency has established AQIs for five primary criteria air pollutants (ground-level ozone (O_3), particulate matter (including both $PM_{2.5}$ and PM_{10}), CO, SO_2 and NO_2). The agency mandates the reporting of AQI for at least 5 days in a week for all metropolitan statistical areas (MSAs) with a human population of more than 320,000. The AQI under this system is determined from individual pollutant concentrations after appropriate selection (the highest concentration among all the monitors within each reporting area) and truncation. The breakpoints and the AQI corresponding to the selected concentration are noted in Table 13.1 and designed by the agency. The individual pollutant index is calculated from Eq. 13.1 by incorporating the pollutant concentration data and the corresponding information from Table 13.1. Finally, after rounding off the index to the nearest integer, the individual pollutant index having the highest value represents the AQI for the given region:

$$I_{\mathrm{p}} = \frac{\left(I_{HI} - I_{LO}\right)}{BP_{HI} - BP_{LO}}\left(C_{\mathrm{P}} - BP_{LO}\right) + I_{LO} \tag{13.1}$$

where

I_{P} = Index for pollutant P
C_{P} = Rounded concentration of pollutant P

Table 13.1 Air pollutant concentration breakpoints and their corresponding AQI value and categories as per U.S. EPA

Concentration breakpoints								
O_3 (ppm) 8 h	O_3 (ppm) 1 h[a]	$PM_{2.5}$ (μg/m³) 24 h	PM_{10} (μg/m³) 24 h	CO (ppm) 8 h	SO_2 (ppb) 1 h	NO_2 (ppb) 1 h	AQI value	Air quality category
0.000–0.054	–	0.0–12.0	0–54	0.0–4.4	0–35	0–53	0–50	Good
0.055–0.070	–	12.1–35.4	55–154	4.5–9.4	36–75	54–100	51–100	Moderate
0.071–0.085	0.125–0.164	35.5–55.4	155–254	9.5–12.4	76–185	101–360	101–150	Unhealthy for sensitive groups
0.086–0.105	0.165–0.204	(55.5–150.4)[b]	255–354	12.5–15.4	(186–304)[c]	361–649	151–200	Unhealthy
0.106–0.200	0.205–0.404	(150.5–250.4)[b]	355–424	15.5–30.4	(305–604)[c]	650–1249	201–300	Very unhealthy
([d])	0.405–0.504	(250.5–350.4)[b]	425–504	30.5–40.4	(605–804)[c]	1250–1649	301–400	Hazardous
([d])	0.505–0.604	(350.5–500.4)[b]	505–604	40.5–50.4	(805–1004)[c]	1650–2049	401–500	Hazardous

Source: (Kanchan et al., 2015)

[a]Areas are generally required to report the AQI based on 8-h ozone values. However, there are a small number of areas where an AQI based on 1 h ozone values would be more precautionary. In these cases, in addition to calculating the 8 h ozone index value, the 1-h ozone value may be calculated, and the maximum of the two values reported

[b]If a different SHL for $PM_{2.5}$ is promulgated, these numbers will change accordingly

[c]1 h SO_2 values do not define higher AQI values (≥200). AQI values of 200 or greater are calculated with 24-h SO_2 concentrations

[d]8-h O_3 values do not define higher AQI values (≥301). AQI values of 301 or higher are calculated with 1-h O_3 concentrations

BP_{HI} = Break point that is greater than or equal to C_P.
BP_{LO} = Break point that is less than or equal to C_P
I_{HI} = AQI value corresponding to BP_{HI}
I_{LO} = AQI value corresponding to BP_{LO}

A revised EPA air quality index (RAQI) was introduced later by Cheng et al., 2004. In this, an extra term for entropy has been added to the AQI formula (Kanchan et al., 2015). The determination of RAQI is achieved by Eq. 13.2:

$$\mathrm{RAQI} = \max\left(I_1, I_2 \ldots I_n\right) * \frac{Avg_{\mathrm{daily}\,\sum_{j=1}^{n} I_j}}{Avg_{\mathrm{annual}}\left[Avg_{\mathrm{daily}\,\sum_{j=1}^{n} I_j}\right]} * \frac{Avg_{\mathrm{annual}}\left\{\mathrm{Entropy}_{\mathrm{daily}} * \max\left[I_1, I_2 \ldots . I_n\right]\right\}}{\mathrm{Entropy}_{\mathrm{daily}} * \max\left[I_1, I_2 \ldots . I_n\right]} \tag{13.2}$$

AQI System in European Cities The Common Air Quality Index (CAQI) is used to present the ambient air quality in the cities of Europe developed under the project *Citeair* (revised under *Citeair II*). By integrating and transforming all comprehensive measurements into a singular relative figure, the CAQI offers a readily understandable way to represent air quality in European cities. Additionally, this indexing system differentiates between traffic and city background conditions. To provide a comparative perspective between the cities, three indices with different time scales are made available: an hourly index, a daily index and an annual index. The CAQI is calculated by linear interpolation between the class borders, presented in the grid system (Table 13.2). Ranging from 0 (very low) to >100 (very high), there are in total five levels in which the air quality can be presented. The selection of the classes for indexing is influenced by EU legislation; nonetheless, the final CAQI is the maximum value of the subindices for each pollutant.

AQI System in Russia By normalizing the pollutant concentrations to MPC (Maximum Permissible Concentrations—established for over 400 pollutants), the subindex of individual pollutants can be calculated, which is then added to give the Integral Air Pollution Index (IAPI). This method was suggested for representing air quality over Russian cities by Bezuglaya et al. (1993). The subindices of individual pollutants in the IAPI can be determined by the following Eq. 13.3:

$$I_{li} = \frac{X_i}{MPC_i} \tag{13.3}$$

where

X_i = Concentration of *i*th pollutant

Table 13.2 Pollutant grid for calculating CAQI hourly and daily grids as per EU legislation

		Traffic						City background							
		Core pollutants			Pollutants			Core pollutants				Pollutants			
			PM_{10}		$PM_{2.5}$					PM_{10}		$PM_{2.5}$			
Index class	Grid	NO_2	1-h	24-h	1-h	24-h	CO	NO_2	O_3	1-h	24-h	1-h	24-h	CO	SO_2
Very low	0 25	0 50	0 25	0 15	0 15	0 10	0 5000	0 50	0 60	0 25	0 15	0 15	0 10	0 5000	0 50
Low	25 50	50 100	25 50	15 30	15 30	10 20	5000 7500	50 100	60 120	26 50	15 30	15 30	10 20	5000 7500	50 100
Medium	50 75	100 200	50 90	30 50	30 55	20 30	7500 10,000	100 200	120 180	50 90	30 50	30 55	20 30	7500 10,000	100 350
High	75 100	200 400	90 180	50 100	55 110	30 60	10,000 200,000	200 400	180 240	90 180	50 100	55 110	30 60	10,000 20,000	350 500
Very high[a]	>100	>400	>180	>100	>110	>60	>200,000	>400	>240	>180	>100	>110	>60	>200,000	>500

Source: (CITEAIR, 2021)
NO_2, O_3, SO_2: hourly value/maximum hourly value in μg/m^3
CO: 8 h moving average/maximum 8 h moving average in μg/m^3
PM_{10}: hourly value/daily value in μg/m^3
[a]An index value above 100 is not calculated but reported as "> 100"

I_i = Subindex of ith pollutant
c_i = Degree of exponent
MPC_i = Maximum permissible concentration of ith pollutant

Furthermore, the degree of pollutant caused by an air pollutant can be expressed by comparing it with that of sulfur dioxide (Eq. 13.4):

$$I_{2i} = \left(\frac{X_i}{MPC_i} \right)^{C_i} \tag{13.4}$$

Swamee and Tyagi (1999) criticized this method, suggesting ambiguity in the nature of the subindices, which might lead to a false alarm situation. They further proposed a non-linear aggregation of the subindices.

API System in South Africa In the Dynamic Air Pollution Prediction System (DAPPS) project led by four South African partners, an Air Pollution Index (API) system was developed (Cairncross et al., 2007). Inclusive of PM_{10}, $PM_{2.5}$, O_3, CO, SO_2, and NO_2, this API system is based on the relative risk of excess daily mortality linked with short-term exposure to air pollutants. Exposure levels corresponding to the same relative risk are allotted the same subindex value, and the incremental risk values for every pollutant are considered to be constant. The final API is calculated using Eq. 13.5:

$$API = \sum PSI_i = \sum a \cdot C \tag{13.5}$$

This proposed system was tested using a pollutant concentration dataset collected in Cape Town, and a scale of 0–10 was utilized for assessment.

Table 13.3 Pollutant concentration range and their corresponding AQI value and categories as per NAAQS, India

AQI category	AQI	Concentration range[a]							
		PM_{10}	$PM_{2.5}$	NO_2	O_3	CO	SO_2	NH_3	Pb
Good	0–50	0–50	0–30	0–40	0–50	0–1.0	0–40	0–200	0–0.5
Satisfactory	51–100	51–100	31–60	41–80	51–100	1.1–2.0	41–80	201–400	0.5–1.0
Moderately polluted	101–200	101–250	61–90	81–180	101–168	2.1–10	81–380	401–800	1.1–2.0
Poor	201–300	251–350	91–120	181–280	169–208	10–17	381–800	801–1200	2.1–3.0
Very poor	301–400	351–430	121–250	281–400	209–748[a]	17–34	801–1600	1200–1800	3.1–3.5
Severe	401–500	430 +	250 +	400 +	748 +[a]	34 +	1600 +	1800 +	3.5 +

Source: (CPCB, 2021)
[a]CO in mg/m^3 and other pollutants in μg/m^3; 2 h-hourly average values for PM_{10}, $PM_{2.5}$, NO_2, SO_2, NH_3, and Pb, and 8-h values for CO and O_3

API System in China The Chinese Air Pollution Indexing System follows a similar method for the calculation of AQI with the exception being that the health definition parallel to each class of AQI is different. The State Pollution Control Board of China is the regulatory body responsible for monitoring air pollution levels across the entire province. The API is based on five criteria pollutants: PM_{10}, NO_2^-, SO_2, CO, and ground-level ozone (O_3).

AQI System in India The Indian AQI system has six categories (good, satisfactory, moderately polluted, poor, very poor and severe) and a scale ranging from 0 to 500. Based on the ambient concentration of pollutants, the subindex is calculated, which is developed and evolved for eight pollutants, namely, $PM_{2.5}$, PM_{10}, CO, O_3, NO_2, SO_2, NH_3, and Pb. The final Indian Air Quality Index can be calculated using Eq. 13.7 (Report, 2022):

$$AQI = \max\left(I_1, I_2, \ldots\ldots.. I_n\right) \tag{13.6}$$

where

I = Subindex for individual pollutant.

Additionally, health breakpoints are also available along with the AQI categories (Table 13.3 taken from CPCB (2021)). Finally, the worst subindex determines the overall AQI of a particular region.

Fuzzy Air Quality Index (FAQI) Based on fuzzy aggregation, a method for predicting AQI was developed by Mandal et al. (2012). When the output values of AQI were compared with those calculated via traditional methods, it was revealed that using a fuzzy inference system improves tolerance for impression data. The mathematical relation between the output parameter (FAQI) and air pollutants is given in Eq. 13.7:

$$\mathrm{FAQI} = f\left(SPM, RPM, \mathrm{SO_2}, \mathrm{NO_x}\right) \tag{13.7}$$

Later, a fuzzy pattern recognition model for AQI computation was developed considering five atmospheric pollutants (PM_{10}, CO, O_3, NO_2, and SO_2) for the assessment of air quality in Agra, India (Gorai et al., 2014). Using the analytical hierarchical process (AHP), weights were assigned to each pollutant based on the degree of health impacts. These weights were also considered during AQI determination. The AQI ranged from 1 to 6, and although the calculation is complex in nature, it can be easily programmed. The methodologies for air quality indexing developed all around the world are presented in Fig. 13.3.

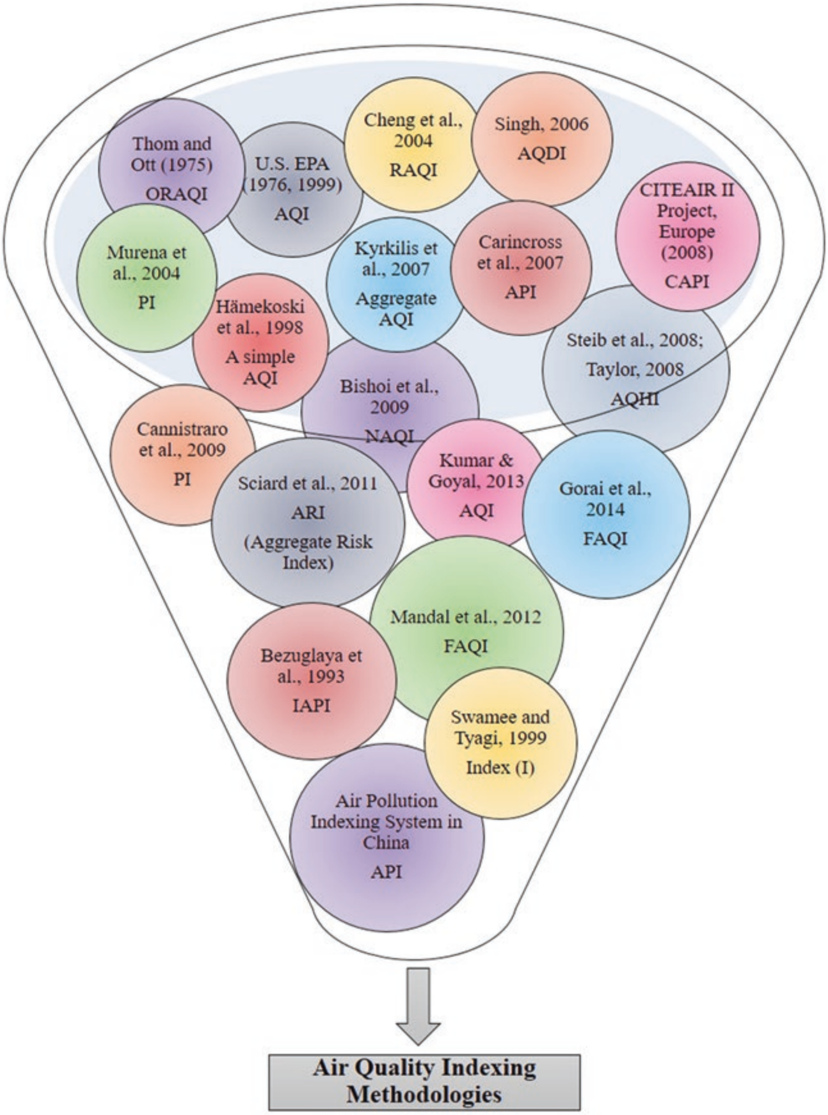

Fig. 13.3 Different air quality indexing methods around the world. (Data adopted from: Kanchan et al., 2015)

13.6 Status of AQI

Since the time of Hippocrates in approximately 400 BC, air pollution has been recognized as a threat to human health. Throughout the next two millennia, successively written accounts of air pollution appearing in various countries can be found until measurements, beginning in the eighteenth century, reveal the growing scale of poor air quality in urban centers and close to industry, as well as the chemical characteristics of the gases and particulate matter. As severely polluted cities became the defining issue, the industrial revolution boosted both the amount of primary pollutant emissions and the geographical spread of contributing countries, culminating in the Great Smog of London in 1952. Until the latter decades of the twentieth century, when transboundary issues such as acid rain, forest decline, and ground-level ozone were the principal environmental and political air quality challenges, Europe and North America dominated emissions and suffered the majority of harmful consequences. As curbs on sulfur and nitrogen oxide (SO_2 and NO_x) emissions began to take effect in Europe and North America, emissions in East and South Asia expanded rapidly, and by the early years of the twenty-first century, these estates had surpassed global emissions. By 2000, fresh epidemiological evidence had pushed the consequences of air quality on human health back to the top of the priority list. Global measurements of both primary and secondary pollutants were available by this time, thanks to vast networks of surface measurements and satellite remote sensing, which rendered the assessment of air quality and related detrimental impacts a rather feasible task.

Air Quality over the Globe: The Complete Picture

With the subject area being vast, the focus here is on the chronology of human-caused air pollution, identifying the major challenges, their origins, and regional and worldwide trends. During the early stages of the industrial revolution, which began in the late eighteenth century in the United Kingdom and extended across Europe and North America, fast increases in coal burning in growing towns significantly boosted SO_2, NO_2, NH_3, and smoke emissions. During this time, the issue of air pollution was primarily concerned with human health. Domestic emissions from the rapidly rising urban population were also a source of additional pollution. It is also worth noting that NH_3 emissions from the large urban population of horses used for transportation would have added to the NH_3 emitted by coal combustion (Sutton et al., 2020). Due to a scarcity of observations and a focus on pollutants from combustion sources, little attention has been given to the combination of SO_2, NO_x, and NH_3 in the nineteenth-century urban chemical climate. However, significant NH_3 emissions would have favored the generation of particulate $(NH_4)_2SO_4$ and fast SO_2 deposition to terrestrial surfaces (Fowler et al., 2001). From 1750 to the twentieth century, air quality deteriorated mostly in metropolitan areas or around significant industrial point sources. The 1952 London haze, which resulted in the untimely deaths of approximately 12,000 people, shifted this viewpoint. The efforts to limit air pollution in the 1950s and 1960s were targeted at safeguarding human health, with a concentration on urban air quality, notwithstanding prior worries about ecological implications. There were rainfall analyses in the seventeenth century, presumably the first by Ole Borch in Denmark. Agriculturalists began to use them more frequently in the 1800s (Brimblecombe, 1987), and they are now widely used internationally (Miller, 1905), providing early evidence of intercountry pollution trade from observations of contaminated snowfall. By 1980, acid rain, or more accurately acid deposition, enabled the relevance of both wet depositon and dry deposition to the overall input to the ground (Fowler, 1984) to become a global issue, with all industrial countries doing research and many developing control measures.

A significant advance was the expansion of the ecological focus from freshwaters to forests, as well as the number of contaminants implicated in consequences. In the early 1970s, this proved the occurrence of ozone quantities that posed a threat to vegetation and human health over Europe (Derwent et al., 1978). Since preindustrial times, the background concentration of ozone in Europe has increased by a factor of 2 (Volz & Kley, 1988). Furthermore, the importance of nitrogen compounds expanded as our understanding of acid deposition grew, and ground-level ozone was identified as an additional regional-scale air pollution issue. At the turn of the twenty-first century, a study of the effects of pollutants on ecosystems revealed that 24% of the world's forests were subjected to phytotoxic ozone exposure (Fowler et al., 1999). In the Netherlands, the United Kingdom, North America, and China, negative impacts were discovered (Fowler et al., 2020). Studies exploring the impacts of pollutants on human health, based on comparable epidemiological methodologies, demonstrated the magnitude of the consequences on human health in both developed and developing countries. According to current estimates, outdoor $PM_{2.5}$ concentrations are responsible for 4.2 million premature deaths and 100 million disability-adjusted life-years lost globally each year (Cohen et al., 2017). These studies established air pollution as one of the leading causes of premature death worldwide, and they highlighted the human health impacts of contaminants at far lower concentrations than those implicated in the 1952 London haze.

PM is mentioned in the first descriptions of air pollution, although nomenclature has been uneven and often ill-defined, with names such as smoke, soot, fume, haze, and dust being used haphazardly across the literature. PM refers to the sum of all solid and liquid particles suspended in air and is a complex mixture of size spanning at least four orders of magnitude (1–10,000 nm) and a wide variety of chemical makeup (Harrison, 2020). By a wide margin, PM is the most significant contributor to human health consequences, and it is also the form in which the majority of sulfur and nitrogen-containing pollutants are transported across long distances. By absorption (e.g., black carbon) as well as dispersion and reflection of radiation, PM contributes to changes in the Earth's energy balance. Consequently, many of the linkages between air quality and climate change are attributable to interactions between PM and the radiative balance and thus climate (Von Schneidemesser et al., 2015). Smog contains both particle and gaseous components, although PM has the greatest impact on visibility. Many of the consequences of pollutants on ecosystems are caused by PM deposition, which occurs either directly on foliar surfaces or indirectly by occult or moist deposition (Stevens et al., 2020).

From the 1990s to the present, most primary pollutant emissions have fallen in Europe, North America, and Japan, with SO_2 emissions showing the most success,

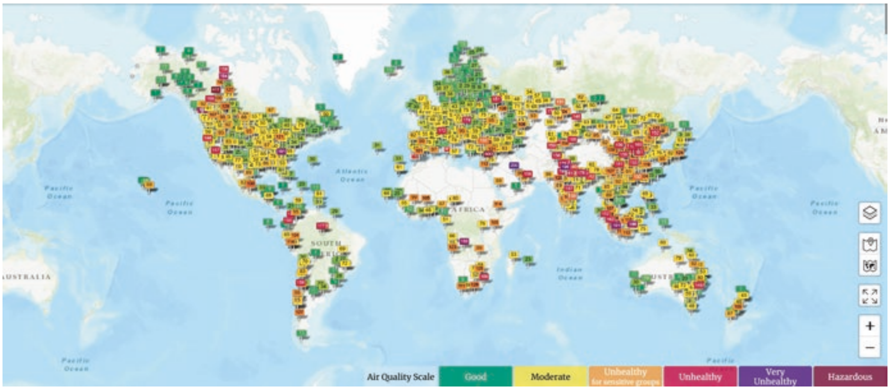

Fig. 13.4 World's air pollution: real-time air quality index (Accessed on: 30/12/2021). (Source: https://waqi.info/#/c/7.915/8.792/2.4)

while NO_2 and VOC emissions have also decreased by more than half in these regions. In contrast, emissions in East and South Asia, as well as elsewhere, grew from 1990 to 2010, resulting in moderate decreases in worldwide total emissions, even for SO_2, with a reduction of 15% from the peak in 1990 (Hoesly et al., 2018). The global total NO_x emissions have continued to rise, with all decreases in emissions in Europe, North America, and elsewhere being offset by increases elsewhere, primarily in Asia. The situation is similar for NH_3 and VOC to that of NO_x, with the global total constantly growing (Hoesly et al., 2018). Zheng et al., 2020 extensively reported and described the huge increases in emissions of all principal pollutants in South and East Asia. In Asian megacities, levels of PM, SO_2, and NO_2 are comparable to London's highly polluted environment during smog episodes in the 1950s, such as the Beijing 'haze' occurrences in January 2012. As a result, the worldwide load of air pollution has increased in the first two decades of the twenty-first century. The distribution of ambient $PM_{2.5}$ concentrations experienced by different regional populations shows that rather than the countries that were afflicted in the early phases of the Industrial Revolution, the current global air pollution health burden is borne disproportionately by countries in East and South Asia (Fowler et al., 2020). Despite this, the vast majority of the world's population lives in areas where ambient $PM_{2.5}$ levels exceed the WHO guideline limit. It is worth noting that this focus on human health diverts attention away from the fact that pollution effects on managed and natural ecosystems continue to exceed criteria (Emberson, 2020). Furthermore, satellite data found that emissions increased in Asia while decreasing in Europe and North America from 1996 to 2004 (Richter et al., 2005).

Sulfur emissions have decreased globally from their peak in 2000, with recent trends in China indicating a reduction of nearly 50% in emissions since 2012 (Fowler et al., 2020). Although surface ozone levels have continued to rise (Lu et al., 2020), China's NO_x emissions have decreased by approximately 25% in the last 8 years (Zheng et al., 2018). However, there are solid reasons to be cautious because ammonia emissions, which are a major contributor to PM and

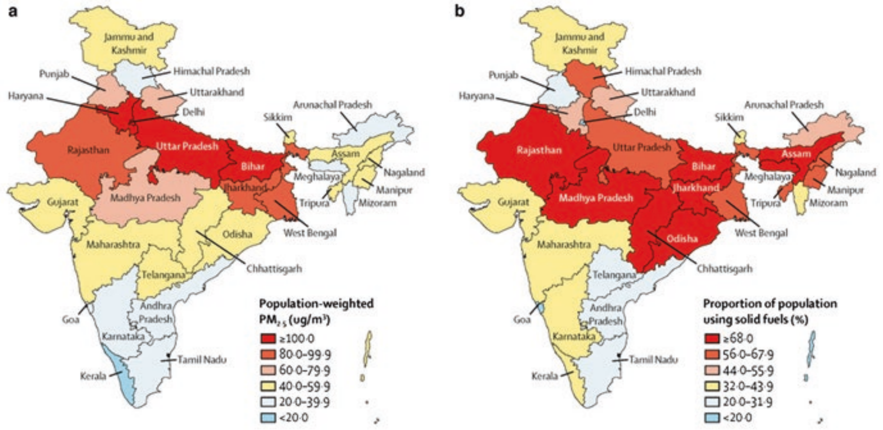

Fig. 13.5 $PM_{2.5}$ concentration and use of solid fuels in the states of India, 2017. (**a**) Population-weighted mean ambient air $PM_{2.5}$ (**b**) Proportion of the population using solid fuels. (Source: Balakrishnan et al., 2019)

eutrophication, are continuing to grow, and putative feedbacks between these gases and climate change could drive overall emissions higher (Fowler et al., 2013). World emissions of CH_4 and VOC are also increasing. Despite the worldwide high levels of $PM_{2.5}$, statistics from the global burden of disease study suggest that death rates from outdoor $PM_{2.5}$ and ground-level ozone may be on the decline globally. As a result, given the current magnitude of air pollution's effects on human health and ecosystems, as well as measurement and modeling limitations, it is premature to rejoice about a reduction in global emissions of two of the most critical air pollutants (SO_2 and NO_x). To conclude, the current status of the global AQI is shown in Fig. 13.4 (WAQI.Info: World Air Quality Index).

Air Quality Status over the Indian Region

India, a growing country, heavily reliant on its cities for growth; confronts significant issues in preserving good air quality in cities. According to the Press Trust of India, by 2030, 40% of India's population will be living in cities (PTI, 2018). Because of a huge number of emission sources, pollutant transportation, high emission rates, and unfavorable emission sources, Indian cities are experiencing the world's worst type of atmospheric pollution (Guttikunda et al., 2014). Furthermore, in emerging countries such as India, the lack of effective enforcement of environmental legislation has only exacerbated pollution problems. With the rising of pollutants such as PM, CO, NO_x, O_3, and SO_2 in Indian cities, air quality is becoming a major problem. Ten Indian cities were on the list of cities with the worst $PM_{2.5}$ pollution levels (WHO, 2018). In Fig. 13.5, the population-weighted average ambient $PM_{2.5}$ and the proportion of the population using solid fuels in 2017 are presented to give an idea of human-induced particle pollution in India.

The Central Pollution Control Board (CPCB) has set up 591 monitoring stations around the country to track air pollution trends (CPCB, 2008). In 2015, for example, typical SO_2 and NO_2 concentrations in major cities in India did not exceed the NAAQS in any of the country's main cities. Even the 8-h O_3 and CO concentrations in major cities in northern (47.8 and 1.26 mg/m^3), eastern (48.1 and 1.73 mg/m^3), western (58.6 and 1.27 mg/m^3), and southern (58.6 and 0.94 mg/m^3) India were lower than the NAAQS requirements (100 and 2 mg/m^3) (CPCB, 2015). Dust emissions, automobile emissions, biomass burning, and other sources of pollution concentrations are mostly to blame for the exceedance of air pollutant concentrations (CPCB, 2016). In 2015, India was responsible for 25.7% of global $PM_{2.5}$-related premature mortality (IHME, 2017). Excess mortality in the Indian capital was 6.5% due to $PM_{2.5}$ concentrations that exceeded WHO guidelines (Sahu & Kota, 2017).

Another matter of concern is the rising levels of air pollution in megacities (with a population of greater than ten million), also known as urban air pollution. The level of pollution surpasses national and international ambient air quality requirements as well as health-based air quality standards (Gurjar et al., 2008; Marlier et al., 2016). The increase in urban population and the resulting increase in motorized traffic in cities are the primary causes of severe air pollution (Singh et al., 2007; Wang et al., 2010; Kumar et al., 2017). The movement of vehicles is non-uniform across cities as a result of the heterogeneous and uncontrolled growth of cities in developing nations, resulting in substantial spatial fluctuations in pollutant emissions and the formation of urban hot spots. Due to high source activity, bad climatic circumstances, or both, an urban hotspot is a site in the city where air pollution levels are already failing or expected to fail to satisfy national ambient air quality standards (NAAQS). The majority of urban hotspots are key commercial centers, busy traffic crossroads, and heavily frequented congested roadways (Gokhale & Khare, 2007; Tiwari et al., 2012), experiencing extreme air pollution episodes due to a sudden increase in vehicle exhaust emissions during peak traffic periods (Chelani, 2013; Pant et al., 2015). Furthermore, in metropolitan settings, topographical and meteorological fluctuations cause complicated spatial and temporal variations in pollution concentrations (Gokhale & Khare, 2007).

Generally, poor air quality and atmospheric pollution plague the northern portions of India, owing to emissions from automobiles, industries, brick kilns, coal-fired power stations, and agricultural residue burning (Singh et al., 2004; Venkataraman et al., 2018). For example, New Delhi, India's capital, has consistently poor air quality, with pollution levels higher than those in Beijing (Zheng et al., 2017). In recent years, China's air quality and atmospheric pollution have improved; however, in India, poor air quality has steadily worsened over the previous several decades as a result of increasing anthropogenic activity (Chauhan & Singh, 2017; Sarkar et al., 2018). Since the early 1990s, air pollution levels in the Indian National Capital Territory of Delhi (NCT-Delhi) have exceeded those in most other developing countries. Many distinct factors influence air pollution levels in NCT-Delhi, including unrestrained emission sources in the surrounding area where city regulations are either not applicable or not strictly enforced, a large number of uncontrolled sources within the city, unfavorable local meteorological conditions such as extreme summers and extreme winters, which govern particle suspension in the air, and periodic agricultural pollutant transport from the outskirts (Guttikunda & Gurjar, 2012).

Motorized vehicles have emerged as one of the biggest contributors to growing levels of urban air pollution in India, out of all the sources of air pollution (Sharma & Dikshit, 2015; Dhyani et al., 2017; Kumar et al., 2017). According to figures from 2012 to 2013, India's total diesel and petrol consumption was 69.74 million tonnes and 15.7 million tonnes, respectively, with the transportation sector accounting for almost 70% of diesel and 99.6% of petrol use (MoPNG, 2013). Ambient PM concentrations in Indian metropolises (Delhi, Mumbai, Kolkata, and Chennai) routinely exceed NAAQS and WHO guideline standards (Gupta & Kumar, 2006; Singh et al., 2007; CPCB, 2010a, 2010b; Gupta et al., 2010). According to Ramachandra, 2009, India's transportation sector produces 258.10 Tg of CO_2, with motorized road transport accounting for 94.5%. According to the Central Pollution Control Board (CPCB) of Delhi, automobile emissions contribute approximately 76–90% of CO, 66–74% of NO_x, 5–12% of SO_2, and 3–12% of PM to overall urban air pollution in Delhi and Mumbai (CPCB, 2010a). Sharma and Dikshit (2015) calculated that in-use road cars in Delhi emit approximately 12.9 Ton/day, 11.6 Ton/day, 113.4 Ton/day, 1.2 Ton/day, and 322.4 Ton/day of PM_{10}, $PM_{2.5}$, NO_x, SO_2, and CO, respectively. This suggests that poor urban air quality in developing countries is a result of increased motor activity and accompanying ineffective management strategies. The next paragraphs describe the sources of air pollution and other related difficulties in two Indian megacities, Delhi and Chennai, which have also been used as case studies for air quality in Indian megacities.

Regardless of the type of site, Delhi, India's national capital, has significant PM_{10} and $PM_{2.5}$ concentrations in its ambient air (Sharma et al., 2013; Mandal et al., 2014; Pant et al., 2015; Tiwari et al., 2014). Delhi is the "worst" polluted city in the world, based on an environmental performance index (Hsu & Zomer, 2014). The increase in air pollution levels is mostly due to increasing emissions of pollutants such as $PM_{2.5}$, PM_{10}, and NO_x (nitrogen oxides) as a result of significant traffic congestion and a drop in vehicular speed on the roads (CPCB, 2010a; Dhyani et al., 2017). Mohan & Kandya, 2007 collected data from seven distinct places in Delhi for 9 years (1996–2004) and generated an air quality index (AQI). During the period from 1996 to 2004, the annual average NO_2 concentrations at one ITO crossing were found to be in the range of 50–90 μg/m^3. Between 1997 and 2016, PM and gaseous pollutant concentrations in ambient air surpassed the NAAQS, according to reports. It is further reported that a rise in particulate matter (PM) concentrations in Delhi city cause tens of thousands of premature deaths and six million asthma episodes each year (Guttikunda & Goel, 2013; Lelieveld et al., 2015). PM_{10}-related mortality increased by 1.6 and 2.5 times in 2015 in Mumbai and Delhi, respectively, compared to 1995 (Maji et al., 2017).

Compared to other Indian cities, Chennai had a vehicle population of approximately 3.7 million in 2015, with the highest vehicle density of 2093 per kilometer road length (Gupta, 2015). PM levels surpass the NAAQS at selected urban places in

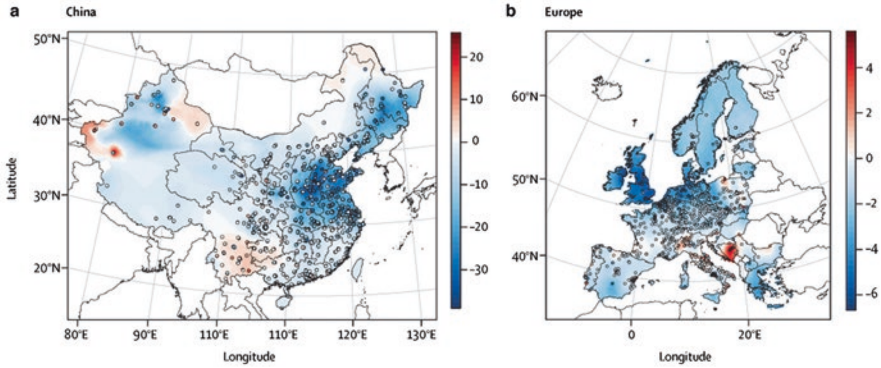

Fig. 13.6 Effect of lockdown on surface $PM_{2.5}$ concentrations. (Source: Giani et al., 2020)

Chennai city where vehicular movement was found to be highest, according to Sivaramasundaram & Muthusubramanian, 2010 and Srimuruganandam & Nagendra, 2011. Furthermore, at one of the curb sites in Chennai city, diesel exhausts (43–52% in PM_{10} and 44–65% in $PM_{2.5}$) and gasoline exhausts (6–16% in PM_{10} and 3–8% in $PM_{2.5}$) are shown to be significant source contributors (Srimuruganandam & Nagendra, 2012). Madala et al., 2016 used a Lagrangian particle dispersion model (LPDM) to simulate NO_x levels at seven different locations in Chennai city, taking into account all point, area, and line sources, and showed considerable seasonal fluctuation in NO_x concentration at all locations. Finally, in 2015, yearly average mortality attributable to $PM_{2.5}$ was found to be 10,880 and 10,900 in Mumbai and Delhi, respectively. They also projected that the total economic impact of rising PM_{10} concentrations increased from US$ 2680.87 million to US$ 4269.60 million for Mumbai and US$ 2714.10 million to US$ 6394.74 million for Delhi from 1995 to 2015. As a result, there is a need to reduce air pollution-related health effects, which can be accomplished by controlling/managing increasing urban air pollution loads through an integrated management plan that is efficient and effective.

The Brighter Side of COVID-19

With the first case of SARS-COVID-19 reported in China on the 17th of November, 376,000 people had died as a result of 6.3 million illnesses reported in 188 countries and territories by June 2020. Lockdown procedures have had a significant impact on industrial and transportation activity, as well as a reduction in emissions of many of the key pollutants that cause poor air quality. While it is too early for a full analysis, there are a number of preliminary reports available, including surface data from monitoring networks and satellite remote sensing. CO_2 flux measurements in major cities reveal lower combustion-related emissions, including a 55% drop in central London (Jenkins et al., 2020). The 20–30% reductions in urban NO_2 in the UK during the first weeks of lockdown (Jenkins et al., 2020) are comparable to reductions in other large cities across the world. Certain COVID-19-affected cities in China reported decreases in PM_{10} on a scale equivalent to NO_2 reductions but for a shorter length of time (Cole et al., 2020). Personal exposure to $PM_{2.5}$ in London during the lockdown was reduced by 5–25% depending on the mode of transport, according to the analysis, while effects on ambient PM were minimal and varied. A reduction in $PM_{2.5}$ concentrations was also observed in parts of China and Europe during the COVID-19 lockdown duration (Fig. 13.6). The pandemic's global scope had a noticeable impact on global emissions of combustion-related pollutants, with projected health and environmental advantages owing mostly to lower NO_x emissions. It is unclear whether these gains will result in longer-term emissions savings, as transportation and industry emissions have increased as a result of the extensive population lockdown. As transportation and combustion emissions are reduced, COVID-19 is likely to lower net acidity and increase the gaseous alkaline percentage (Sutton et al., 2020), with a minimal expected reduction in NH_3 emissions from agriculture. While this may have health benefits, it is equally important to consider the negative impacts of 'alkaline air' on ecosystems.

13.7 Impact of Degrading Air Quality on Human Health

Regardless of how wealthy a region is, air pollution is difficult to avoid. It can be found everywhere around us. Airborne pollutants can get past our bodies' defenses, penetrating deep into our respiratory and circulatory systems and causing damage to our lungs, heart, and brain. Climate change and air pollution are inextricably linked; the main driver of climate change is fossil fuel combustion, which is also a major source of air pollution, and efforts to mitigate one can help the other. The UN Intergovernmental Panel on Climate Change cautioned that coal-fired electricity must be phased out by 2050 if global warming is to be kept below 1.5 °C. In 2019, global air quality caused massive destruction in East Asia, Europe, and North America, taking away the lives of seven million people, extensive damage to crops, and a rapid reduction in biodiversity (Fowler et al., 2020). Approximately 4.3 million people die from household air pollution and 3.7 million from ambient air pollution, most of whom (3.3 and 2.6 million, respectively) live in Asia (Lancet, 2016). Within India, 1.24 million total deaths were recorded due to air pollution in 2017, among which 0.67 million deaths were recorded due to exposure to hazardous ambient particle concentrations (Balakrishnan et al., 2019).

Exposure to Air Pollutants

There are two types of air pollution: outdoor (or ambient) pollution and indoor (or household) pollution. Household combustion of fuels using open fires or basic stoves in poorly ventilated buildings causes pollution. Because air travels from within buildings to the outside and vice versa, both indoor and outdoor air pollution can contribute to each other. Indoor pollution kills four million people every year, mostly in Africa and Asia, where polluting fuels and technologies are used on a daily basis, especially at home for cooking, heating, and lighting (WHO, 2021). Women and children, who spend more time indoors, are the most vulnerable.

As per the World Health Organization's (WHO) air pollution program, 91% of the world's population breathes contaminated air, and 4.2 million people die each year as a result. It shows that air pollution is responsible for more than one-third of all deaths due to lung cancer, strokes, and chronic respiratory problems. $PM_{2.5}$ can get through the lungs and into the bloodstream. Furthermore, air pollution has a negative impact on young people. Air pollution-induced asthma affects up to 14% of children aged 5–18 years worldwide. Pregnant women are exposed to pollutants, which might influence the development of the unborn brain. Older people, children, and people with diabetes and predisposing heart or lung disease, particularly asthma, are vulnerable groups. People who are exposed to high levels of air pollutants develop disease symptoms and states of varying severity. These health impacts are divided into two categories: short term and long term. The relative magnitudes of the short- and long-term effects have not been completely clarified (Kloog et al., 2013) due to different epidemiological methodologies and exposure errors, according to a recent epidemiological study from the Harvard School of Public Health. New models are presented for more effectively analyzing short- and long-term human exposure data (Kloog et al., 2013). As a result, this section discusses the more prevalent short- and long-term health consequences, as well as general concerns about both types of impacts because these are typically reliant on environmental factors, dose, and individual sensitivity.

Short-term effects are temporary in nature and range from minor irritation of the eyes, nose, skin, and throat to more serious conditions such as asthma, pneumonia, bronchitis, and lung and heart problems. However, long-term exposure to pollutants can exacerbate these issues by harming the neurological, reproductive, and respiratory systems, as well as causing cancer and, in rare cases, death. The consequences are chronic, lasting up to several years or even a lifetime. Furthermore, the long-term toxicity of various air contaminants may cause a variety of malignancies (Nakano & Otsuki, 2013). Country, region, season, and time all have an impact on one's health. In connection with the foregoing criteria, prolonged exposure to the pollutant should predispose individuals to long-term health impacts.

Health Hazards

The human respiratory, cardiovascular, ophthalmologic, dermatologic, neuropsychiatric, hematologic, immunologic, and reproductive systems are the most affected by air pollution. However, long-term molecular and cell toxicity may result in a variety of cancers (Kampa & Castanas, 2008; Nakano & Otsuki, 2013). However, even small amounts of air toxicants are harmful to vulnerable groups such as children and elderly individuals, as well as patients with respiratory and cardiovascular diseases.

Respiratory Disorders The respiratory system is the first line of defense in the onset and progression of diseases caused by air pollutants because most pollutants enter the body through the airways. Inhaled pollutants produce varied levels of harm inside the respiratory system. The initial consequence in the upper respiratory system is inflammation, particularly in the trachea. Some respiratory disorders, such as asthma and lung cancer, are linked to air pollution as a key environmental risk factor (Brunekreef et al., 2009). The respiratory tract is severely harmed by air pollutants, particularly PM and other respirable chemicals such as dust, O_3, and benzene (Tam et al., 2012; Valavanidis et al., 2013; Bahadar et al., 2014; Johannson et al., 2014). People with a predisposed illness state are more likely to experience long-term repercussions. When contaminants poison the trachea, voice changes can occur after a short period of time. Some research has found links between traffic-related and/or industrial air pollution and an increased risk of chronic obstructive pulmonary disease (COPD) (Chung et al., 2011; Zeng et al., 2012). COPD can be caused by air pollution, which increases morbidity and mortality (Jiang et al., 2016). COPD risk is mostly influenced by long-term consequences from traffic, industrial air pollution, and fuel combustion (Jiang et al., 2016).

Cardiovascular Dysfunctions A direct link between air pollution exposure and cardiac-related disorders has been demonstrated in several experimental and epidemiologic investigations (Brook, 2008; Andersen et al., 2012). Changes in blood cells as a result of long-term exposure may have an impact on cardiac function. Long-term exposure to traffic emissions has been linked to coronary arteriosclerosis (Hoffmann et al., 2007), while short-term exposure has been linked to hypertension, stroke, myocardial infarction, and heart failure. Right and left ventricular hypertrophy are linked to traffic-related air pollution, particularly long-term exposure to high levels of NO_2 (Leary et al., 2014; Van Hee et al., 2009). Aside from antidote therapy, which is only available for a few cardio-toxic chemicals such as CO, standard cardiovascular disease treatment should be carried out.

Neuropsychiatric Complications Long-term exposure to air pollution has been linked to neurological consequences in both adults and children. The link between exposure to toxic materials suspended in the air and the nervous system has long been debated. These toxic substances, however, are now thought to have negative effects on the nervous system. Neurological problems and psychiatric diseases are among the damaging effects of air pollution on the nervous system. Neurological disability, especially in babies, can have fatal effects. Air pollution has been linked to neurobehavioral hyperactivity, criminal activity, and age-inappropriate behaviors in recent studies (Newman et al., 2013; Haynes et al., 2011) and an increased risk of neuroinflammation, Alzheimer's disease, and Parkinson's disease (Calderón-Garcidueñas et al., 2008). According to some studies, high levels of air pollutants are linked to aggression and anxiety in megacities (Evans, 2003; Jones & Bogat, 1978).

Damage to Exterior Organs As the most external layer of our body, the skin serves as protection against ultraviolet radiation (UVR) and other contaminants. Pollutants from traffic, such as PAHs, VOCs, oxides, and PM, can produce pigmentation on our skin (Drakaki et al., 2014). Skin aging, psoriasis, acne, urticaria, eczema, and atopic dermatitis (Drakaki et al., 2014) are usually caused by exposure to oxides and photochemical smoke via dermal contact (Drakaki et al., 2014). Acting as skin-aging agents, PM and cigarette smoke cause spots, dyschromia, and wrinkles (Manisalidis et al., 2020). The eye is another external organ that can be damaged via air pollutants. The clinical impact of air pollution on the eyes might range from asymptomatic eye issues to dry eye syndrome. Contamination is most commonly caused by suspended contaminants, which might cause asymptomatic eye results, irritation (Weisskopf et al., 2015), retinopathy or dry eye syndrome (Mo et al., 2019). Furthermore, there is now evidence that there is a link between air pollution and eye irritation, dry eye syndrome, and even serious blindness (West et al., 2013). Air pollution is associated with short-term increases in the number of patients attending the ophthalmological emergency room, according to data (Chang et al., 2012).

Other Long-Term Complications Toxic air pollutants, when inhaled or absorbed through the skin, can theoretically cause organ damage (Potera, 2007). Hepatocarcinogen compounds are present in several of these contaminants (Ito et al., 2011). There is some evidence that air pollutants, particularly traffic-associated air pollution, play a role in the occurrence of autism and related diseases in fetuses and children (Becerra et al., 2013; Roberts et al., 2013; Volk et al., 2013). The disruption of endocrine function by chemical pollutants has been proposed as a possible mechanism for autism and other neurological disorders (Calderón-Garcidueñas et al., 2008; De Cock et al., 2012). Through rigorous research, links have been established between air pollution exposure and fetal head size in late pregnancy, fetal growth (Liu et al., 2007), and low birth weight (Yucra et al., 2014). Several environmental factors, such as poor air quality, can affect many of the diseases linked to immune system dysfunction (Behrendt et al., 2014; Vawda et al., 2014). Finally, pollution has been linked to skin cancer (Drakaki et al., 2014). When fetuses and children are exposed to the risks listed above, they have a higher rate of morbidity. There have been reports of fetal growth problems, low birth weight, and autism (Weisskopf et al., 2015).

Overall Health Effects

Even healthy people can be harmed by polluted air, which can cause respiratory irritation or breathing difficulties while exercising or participating in outdoor activities. The real risk of negative impacts is determined by the existing health status of a person, the type and concentration of pollutants, and the length of time for which a person was exposed to polluted air.

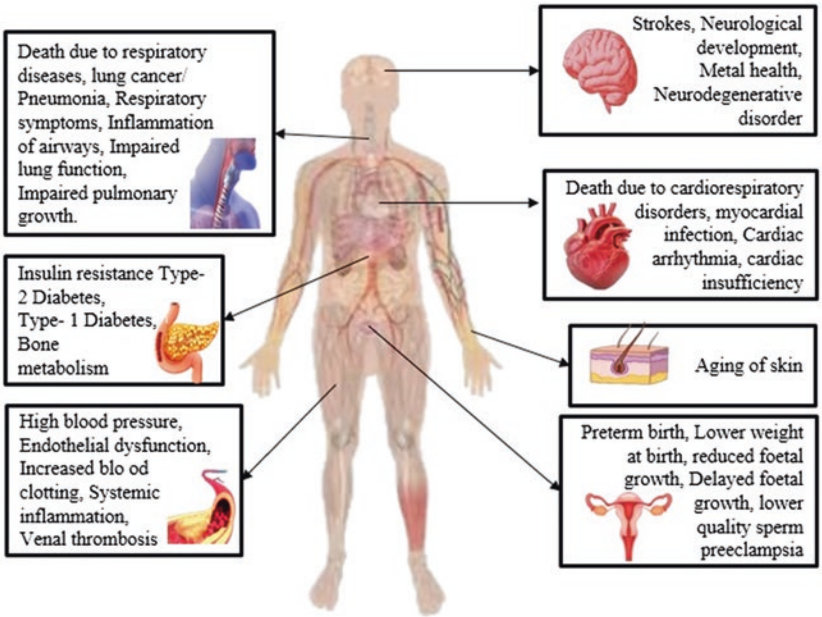

Fig. 13.7 Detrimental effects imparted by degrading air quality on human health

Those most susceptible to severe health problems from air pollution are as follows (Spare the Air, 2021):

- Individuals with heart disease, coronary artery disease or congestive heart failure
- Individuals with lung diseases such as asthma, emphysema, or chronic obstructive pulmonary disease (COPD)
- Pregnant women
- Outdoor workers
- Older adults and the elderly
- Children under the age of 14
- Athletes who exercise vigorously outdoors

People belonging to these population groups may have health problems at lower levels of air pollution exposure, or their health effects may be more severe. Particulate matter is a complicated mixture that includes soot, smoke, metals, nitrates, sulfates, and dust. The potential for particles to cause health problems is directly proportional to their size. Small particles (also known as $PM_{2.5}$ or fine particulate matter) are the most dangerous because they circumvent the body's natural defenses and can penetrate deep into the lungs and possibly into the circulatory system. Such particles can harm both the lungs and heart if exposed to them. To provide an overall perspective, the detrimental effects imparted by degrading air quality on human health are summarized in Fig. 13.7.

13.8 Conclusion

To convey a timeline of what has become a very large and complex field, the story recounted in this chapter has to be selective. It gives a complete and up-to-date picture of air quality and its effects on human health. It covers everything from discussing the AQI determination factor, various indexing systems, and air quality status to the negative effects of poor air quality on human health, including allergic reactions and respiratory, cardiovascular, and related problems. It has extensive international coverage, with sections on air pollution sources, criteria for selecting the best air quality index, and air quality improvement during the COVID-19 lockdown. This chapter is an essential read for anybody interested in air pollution monitoring and regulation, as well as those worried about its influence on human health. It takes a multidisciplinary approach and covers a wide range of topics. The claim that the world's air pollution problems have reached a trough is bold, and it could be proven incorrect. $PM_{2.5}$, haze, winter pollution, heat-related mortality, and aerosols are only a few examples from around the world. Current research and laboratory-based, observation-based, and modeling-based analyses are used to solve these difficulties.

Concerns about the effects of air pollution have prompted governments and locals all over the world to impose restrictions on the burning of fossil fuels, industrial effluent, cigarette smoke, and aerosols, among other things. This legislation has frequently been enacted in response to shocking findings concerning the impact of pollution on health. Simultaneously, there have been considerable advancements in our ability to identify and quantify pollutants, as well as an increase in the number of urban and rural air pollution networks that monitor levels of contamination in the atmosphere. This chapter combines current knowledge of air pollution, climate change, and human health to present a complete review of these concerns, allowing readers to better grasp how they interact and affect air quality and public health. This is an additional essential resource for anyone researching the effects of climate change or air pollution on human health, as well as those developing policies to address the problem.

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Chapter 14
Significance of Geo-Visualization Tools for Pollution Monitoring

Fayma Mushtaq and Majid Farooq

Abstract Geo-visualization tools have become of paramount significance in pollution monitoring, revolutionizing the way to comprehend and combat environmental challenges. By seamlessly integrating geographic information systems (GIS) with interactive mapping technologies, these tools provide real-time visualization of pollution data, offering valuable insights into the spatial patterns and trends of pollutants across various regions. Such accessibility and immediacy empower researchers, policymakers, and the public to make well-informed decisions and undertake targeted actions to address pollution effectively. Through the overlaying of diverse data layers encompassing meteorological information, industrial zones, population density, and more, geo-visualization facilitates a comprehensive understanding of the multifaceted factors influencing pollution levels. By identifying pollution hotspots and tracking changes over time, these tools aid in developing evidence-based environmental policies and formulating strategic pollution control measures. As technology continues to advance, the future of geo-visualization in pollution monitoring holds tremendous promise. The integration of cutting-edge technologies, such as artificial intelligence and machine learning, can enhance predictive capabilities, enabling proactive responses to potential environmental threats. Moreover, the widespread adoption of geo-visualization tools promotes transparency, citizen engagement, and a sense of collective responsibility in safeguarding the environment. Hence, these developments can lead to a healthier, more sustainable world to combat pollution and preserve the planet for future generations.

Keywords Geo-visualization tools · Pollution monitoring · Real-time visualization · Spatial data

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14.1 Introduction

Pollution monitoring refers to the systematic and continuous collection, analysis, and evaluation of various pollutants in the environment to assess their concentrations, distribution, and impacts on human health, ecosystems, and natural resources. This process involves the measurement and tracking of pollutants, such as air pollutants (e.g. particulate matter (PM), nitrogen dioxide, and sulphur dioxide), water pollutants (e.g. heavy metals, nutrients, and organic contaminants), and soil pollutants (e.g. pesticides and industrial chemicals) (Chrabąszcz & Mróz, 2017; Manisalidis et al., 2020; Khan & Ali, 2018). The primary goal of pollution monitoring is to provide reliable and up-to-date data that inform environmental policies, regulatory measures, and pollution control strategies. Timely and accurate data collection, analysis, and visualization are essential for understanding the scope and impact of pollution on our planet (Blaschke et al., 2011; Pellerin et al., 2016).

Importance of Real-Time Data and Spatial Analysis in Pollution Monitoring

(i) *Timely Decision-Making:* Real-time data allow for immediate identification of pollution spikes or incidents, enabling prompt responses to mitigate potential hazards. For instance, in the case of air pollution, real-time data can help trigger alerts for vulnerable populations or initiate measures to curb emissions during adverse air quality events.

(ii) *Early Detection of Pollution Sources:* Real-time monitoring helps detect pollution sources and patterns as they emerge, allowing authorities to investigate and address the root causes promptly. This is particularly crucial in the case of industrial accidents or spills that can have immediate and severe consequences on the environment.

(iii) *Understanding Pollution Transport and Dispersion:* Spatial analysis of pollution data helps to model the transport and dispersion of pollutants in the environment. This information is valuable for assessing the potential impacts of pollution on nearby communities and ecosystems, as well as predicting the spread of pollution over larger areas.

(iv) *Identifying Pollution Hotspots:* Geo-visualization tools and spatial analysis techniques assist in identifying pollution hotspots and areas with elevated pollutant concentrations. This knowledge enables targeted pollution control measures and resource allocation to areas that need immediate attention.

(v) *Assessing Environmental Impact:* Real-time data, combined with spatial analysis, allows for a comprehensive assessment of pollution's impact on the environment. This assessment helps in evaluating the effectiveness of pollution control measures and identifying areas where further actions are needed.

(vi) *Public Awareness and Engagement:* Accessible real-time pollution data empower the public to stay informed about environmental conditions in their surroundings. This awareness can lead to greater public engagement and advocacy for pollution reduction efforts.

(vii) *Integrating Diverse Data Sources:* Spatial analysis facilitates the integration of data from various sources, such as ground-based monitoring stations, satellite observations, and citizen science initiatives. This integration provides a more comprehensive and accurate view of pollution dynamics.

(viii) *Improving Environmental Modelling:* Real-time data aid in refining environmental models used to predict pollution trends and future scenarios. Such models are crucial for formulating long-term pollution control strategies and policies.

(ix) *Emergency Response and Disaster Management:* In the event of pollution-related emergencies, real-time data and spatial analysis play a crucial role in coordinating emergency responses, evacuations, and containment efforts.

14.2 Geo-Visualization Tools

Geo-visualization tools, also known as geospatial visualization tools, refer to a class of software applications and techniques that combine geographical data with visualization methods to represent and display spatial information in a visual format (Nöllenburg, 2007). These tools aim to enhance the understanding, analysis, and communication of spatial patterns, relationships, and trends by presenting data on interactive maps, charts, graphs, and 3D models (MacEachren et al., 2004). Geo-visualization tools are used in various fields, including geography, environmental sciences, urban planning, public health, transportation, and natural resource management (Tao, 2013). They play a crucial role in harnessing the power of geographical information and aiding decision-making processes related to location-based data (Wu et al., 2013). These tools typically rely on geographic information system (GIS) technology, which allows for the integration, storage, analysis, and visualization of spatial data from different sources. Geospatial visualization tools can work with diverse datasets, including satellite imagery, aerial photographs, topographic maps, geographic databases, GPS data, and real-time sensor data. Figure 14.1 shows various key features and functionalities of geo-visualization tools (Chen, 2019; Deng et al., 2019; Liao et al., 2016; Taştan & Gökozan, 2019; Zhao et al., 2020):

(i) *Data Visualization:* Presenting spatial data using maps, charts, graphs, and other graphical representations.

(ii) *Interactive Mapping:* Allowing users to interact with the data and maps, zoom in/out, pan, and click on map features to access detailed information.

(iii) *Spatial Analysis:* Conduct various spatial analyses, such as proximity analysis, overlay analysis, and spatial statistics, to derive meaningful insights.

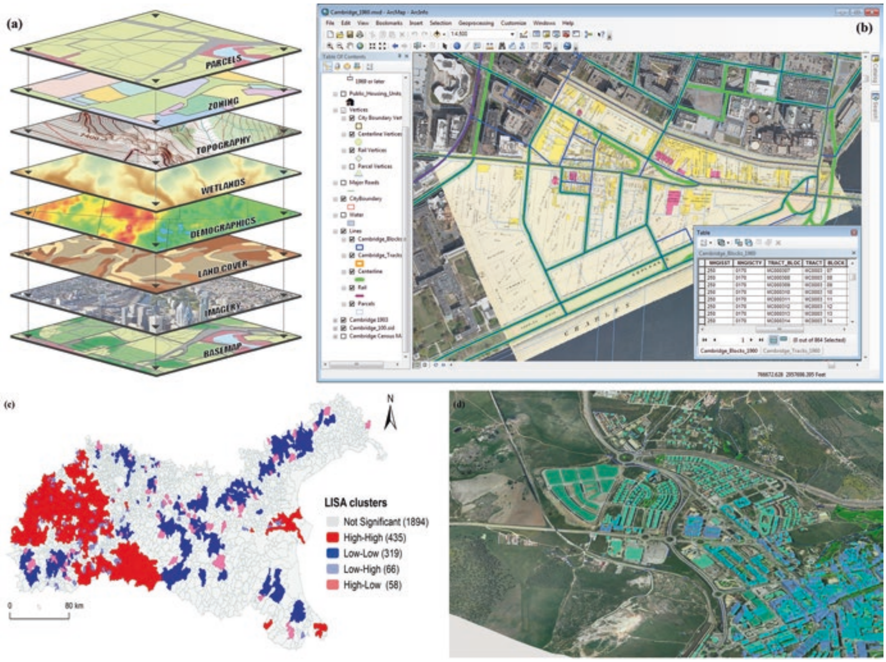


Fig. 14.1 Key features and functionalities of geo-visualization tools: (**a**) data visualization, (**b**) interactive mapping, (**c**) spatial analysis, and (**d**) data mashups

(iv) *3D Visualization:* Creating three-dimensional representations of landscapes, buildings, and terrain for immersive experiences. 3D visualization in pollution monitoring is a cutting-edge approach that leverages the power of three-dimensional representation to enhance the understanding, analysis, and communication of pollution data (Liu et al., 2019; Wang et al., 2013).

(v) *Real-Time Data Integration:* Handling real-time data feeds and updating visualizations in real-time for dynamic and up-to-date information.

(vi) *Web-Based and Mobile Platforms:* Enabling access to geo-visualizations through web-based applications and mobile devices, making it accessible to a wider audience.

(vii) *Storytelling and Presentation:* Supporting the creation of interactive and engaging visual narratives to convey complex spatial information effectively.

(viii) *Data Mashups:* Integrating spatial data with non-spatial datasets from other sources to create comprehensive visualizations.

Fig. 14.2 (**a**) 3D visualization, (**b**) web-mapping platforms, (**c**) virtual reality, and (**d**) augmented reality

Types of Geo-Visualization Tools

Geo-visualization tools encompass a variety of technologies and techniques that integrate geographical data with visualization methods (Kwan, 2004). Some of the main types of geo-visualization tools (Fig. 14.2) (Bwambale et al., 2022; Kulawiak et al., 2010; La Guardia et al., 2022) include the following:

Geographic Information Systems (GIS) GIS is one of the foundational geo-visualization tools. It is a software system designed to capture, store, manipulate, analyse, and present spatial and geographic data. GIS allows users to create, edit, and analyse digital maps, enabling them to gain insights into spatial relationships, perform spatial queries, and conduct spatial analysis.

Remote Sensing Remote sensing involves the use of satellites, aircraft, drones, or other platforms to capture data about the Earth's surface from a distance. The data collected through remote sensing, such as satellite imagery and aerial photographs, are crucial for creating maps, monitoring environmental changes, and conducting land-use studies.

Web-Based Mapping Platforms Web-based mapping platforms, also known as online mapping tools, provide users with the ability to create and share interactive maps over the Internet. These platforms typically offer a user-friendly interface, making it easy for individuals and organizations to visualize spatial data without the need for advanced GIS skills. Examples include Google Maps, OpenStreetMap, Leaflet, and Mapbox.

3D Visualization Tools 3D visualization tools enable the creation of three-dimensional representations of landscapes, buildings, and terrain. These tools are used in urban planning, architecture, and environmental modelling to create immersive and realistic visualizations. Applications such as Google Earth and CityEngine are examples of 3D visualization tools.

Data Visualization Libraries and Software Various data visualization libraries and software, such as D3.js, Matplotlib, Tableau, and Microsoft Power BI, provide functionalities to create interactive and static visualizations using spatial data. These tools can be integrated with GIS and other data sources to produce dynamic and informative visualizations.

Augmented Reality (AR) and Virtual Reality (VR) AR and VR technologies are emerging as powerful geo-visualization tools that overlay digital information onto the real world or create entirely virtual environments. They are being used in fields such as urban planning, cultural heritage preservation, and environmental education to offer immersive and interactive experiences.

Earth Observation and Sensor Networks Earth observation systems and sensor networks gather data from various environmental sensors, such as air quality monitors, weather stations, and water quality sensors. The data collected from these systems are visualized on maps and used for real-time monitoring, early warning systems, and environmental research.

Story Maps Story maps are a form of geo-visualization that combines maps with multimedia content such as images, videos, and text to tell engaging and informative stories. These narrative-driven maps are commonly used for educational purposes, storytelling, and public awareness campaigns.

14.3 Integration of Spatial Data with Pollution Monitoring via Geo-Visualization Tools

Geo-visualization tools play a pivotal role in pollution monitoring by seamlessly integrating spatial data and pollution-related information. These tools serve as a fundamental framework, allowing for the storage, management, and analysis of diverse datasets from various sources, including remote sensing satellites, ground-based sensors, weather stations, and mobile devices. Pollution-related data, such as air quality measurements, water quality samples, and soil contamination levels, are georeferenced and organized in geographic information system (GIS) databases. This spatial integration enables the creation of interactive and dynamic pollution maps, where pollution concentration levels are represented using colour gradients, symbols, or choropleth maps, providing a clear spatial representation of pollution distribution. Moreover, geo-visualization tools facilitate temporal visualization, animating pollution data to observe changes over time, identify seasonal variations, and track long-term trends. Spatial analysis techniques, such as interpolation methods and clustering algorithms, are employed to estimate pollution levels at unsampled locations and identify pollution hotspots with elevated pollutant concentrations (Çöltekin et al., 2020). Additionally, some tools handle real-time data feeds from sensors, enabling continuous monitoring of pollution levels and prompt responses to sudden pollution spikes or incidents. By integrating multiple layers of spatial data, such as land use, population density, and transportation networks, with pollution data, these tools create multilayered maps that help identify potential pollution sources, vulnerable populations, and areas of concern (Badach et al., 2020). With their interactive features, users can explore pollution data dynamically, zoom in/out, click on map features, and filter data based on specific criteria, gaining deeper insights into pollution patterns. Geo-visualization tools go beyond data analysis and visualization, empowering stakeholders, policymakers, and the public through storytelling and communication. By creating interactive story maps and dashboards, these tools combine pollution data with multimedia content to effectively communicate pollution-related information. This communication enhances public awareness, fosters engagement, and promotes informed decision-making in environmental management and policy formulation. The significance of geo-visualization tools in pollution monitoring lies in their ability to seamlessly integrate spatial data, provide real-time monitoring, facilitate interactive exploration, and create comprehensive visualizations (Brovelli et al., 2017; Xu et al., 2011). By harnessing the power of geographical information, these tools enable researchers, environmentalists, and policymakers to understand pollution distribution, identify sources, and develop targeted pollution control strategies for a sustainable and healthier environment.

14.4 Real-Time Data Collection and Visualization

Real-time data collection and visualization are essential components of modern pollution monitoring systems. With the advent of advanced sensors and Internet of Things (IoT) devices (Fig. 14.3), environmental data can now be collected and transmitted in real time, allowing for immediate analysis and visualization (Montanaro et al., 2022). This capability enables researchers, policymakers, and the public to stay informed about pollution levels and respond promptly to changing environmental conditions. Sensors and IoT devices for pollution data collection

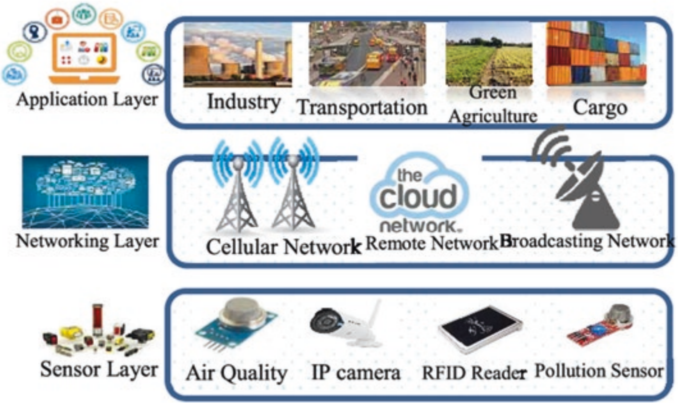


Fig. 14.3 Layered structure of the Internet of Things (IoT). (Source: Dhingra et al., 2019)

(Cloete et al., 2016; Pau & Arena, 2022; Rollo et al., 2021; Yin et al., 2021) are described below:

Air Quality Sensors These sensors measure various air pollutants, such as particulate matter (PM), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), ozone (O_3), carbon monoxide (CO), and volatile organic compounds (VOCs). They are commonly deployed in urban areas and industrial zones to monitor air quality.

Water Quality Sensors Water quality sensors (Fig. 14.4) assess parameters such as pH, dissolved oxygen, turbidity, temperature, and concentrations of contaminants such as heavy metals, nutrients, and organic pollutants. They are used in rivers, lakes, and coastal regions to monitor water pollution.

Soil Sensors Soil sensors measure soil moisture, temperature, and nutrient levels. They are used to assess soil health, nutrient content, and potential contamination.

Weather Stations Weather stations collect meteorological data, including temperature, humidity, wind speed, and direction. Weather conditions can influence pollution levels and need to be considered in pollution monitoring.

Remote Sensing Satellites Satellites equipped with remote sensing instruments capture data on a global scale. They provide valuable information for large-scale pollution monitoring and environmental assessment.

Advantages of Real-Time Data for Pollution Monitoring

Real-time data collection and visualization have revolutionized pollution monitoring, providing critical advantages in addressing environmental challenges. One of the key benefits is the prompt detection of pollution events and incidents. Real-time

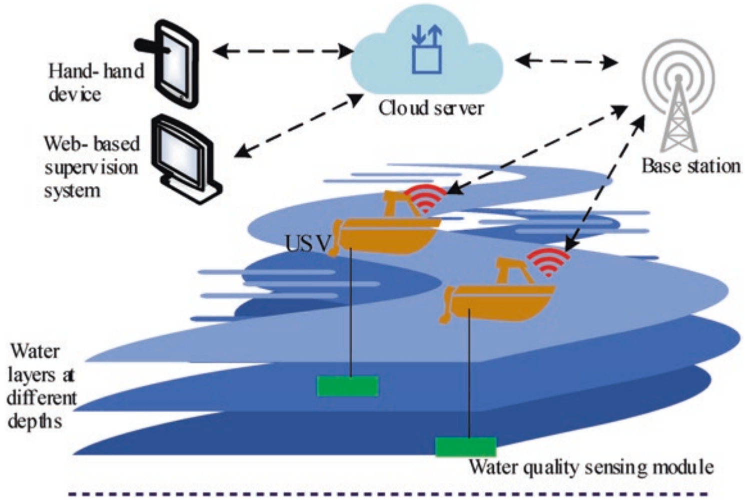


Fig. 14.4 In situ sensor-based real-time mapping and monitoring of water quality

data enable rapid identification of sudden spikes in pollution levels, which is crucial during emergencies to initiate swift responses and minimize the impact on human health and the environment. Additionally, this capability facilitates the development of early warning systems for pollution. Alerts can be generated when pollution levels surpass predetermined thresholds, empowering authorities to take preventive actions or issue public advisories, further enhancing preparedness and response measures. Continuous monitoring is another significant advantage of real-time data collection. The ability to monitor pollution levels continuously offers a more comprehensive and accurate understanding of pollution patterns over time (Dias & Tchepel, 2018). This continuous stream of data provides researchers, policymakers, and environmentalists with a real-time view of pollution dynamics, enabling them to detect trends, identify potential pollution sources, and assess the effectiveness of pollution control measures. The power of real-time data lies in its ability to drive data-driven decision-making. Decision-makers are empowered with up-to-date information to make informed choices regarding pollution control measures, resource allocation, and the formulation of environmental policies. With access to real-time data, stakeholders can respond more effectively to changing pollution conditions and prioritize actions that have the most significant impact on pollution reduction (Tang et al., 2022). Moreover, real-time data can be made accessible to the public through interactive web platforms and mobile applications, fostering public awareness about pollution issues. This increased awareness encourages community engagement in environmental protection efforts, as citizens become actively involved in understanding pollution trends, reporting incidents, and supporting pollution reduction initiatives. Furthermore, real-time data play a crucial role in validating pollution models and predictions. By comparing real-time data with model outputs, researchers can ensure the accuracy and reliability of their predictive models, enhancing their ability to forecast future pollution trends and potential scenarios accurately (Nourani et al., 2014). Real-time data serve as a valuable resource for conducting scientific research and studies on pollution's short-term and long-term impacts. Researchers can analyse real-time data to assess the environmental and health implications of pollution, aiding in the development of evidence-based strategies for pollution mitigation and sustainable environmental management. Real-time data collection and visualization offer a range of interconnected advantages, from prompt detection and early warning systems to continuous monitoring, data-driven decision-making, public engagement, model validation, and scientific research. These benefits underscore the critical role of real-time data in addressing pollution challenges and advancing environmental protection efforts.

14.5 Spatial Analysis and Data Integration

Spatial analysis and data integration are two essential components of the geo-visualization process that enhance our understanding of spatial patterns, relationships, and trends in various environmental phenomena, including pollution. These methodologies are used to analyse and interpret spatial data, allowing researchers and decision-makers to gain valuable insights and make informed decisions. Common spatial analysis techniques (Janssen et al., 2008; Lawson & Waller, 1996; Liu et al., 2013, 2022; Zhang, 2006) used for pollution data are described below:

Spatial Interpolation Spatial interpolation methods estimate pollution values at unsampled locations based on measured data from nearby sampling points. Techniques such as inverse distance weighting (IDW), kriging, and radial basis functions are commonly used for this purpose. Spatial interpolation helps create continuous pollution maps, providing a more comprehensive view of pollution distribution across the study area (Fig. 14.5).

Spatial Clustering Spatial clustering techniques identify clusters or groups of locations with similar pollution characteristics. Clustering algorithms, such as K-means clustering and hierarchical clustering, are employed to group spatially related pollution data. Identifying pollution hotspots through clustering is crucial for prioritizing pollution control measures in areas with elevated pollutant concentrations (Fig. 14.6).

Buffer Analysis Buffer analysis involves creating proximity zones, or buffers, around specific points or features, such as pollution sources or sensitive areas. This technique assesses the influence of pollution sources on nearby regions and helps identify potential areas at risk of pollution exposure.

Spatial Autocorrelation Spatial autocorrelation measures the degree of similarity between pollution values at different locations. Positive spatial autocorrelation

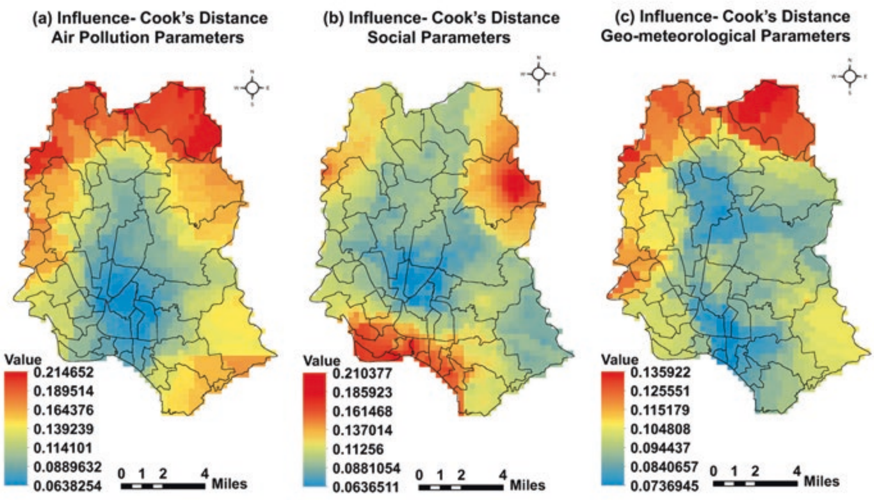


Fig. 14.5 IDW-based spatial interpolation and distribution of influence on air pollution, social, and geo-meteorological parameters. (Source: Hassan et al., 2021)

indicates that similar pollution levels tend to occur near each other, while negative spatial autocorrelation suggests dissimilar values are adjacent (Fig. 14.7). Understanding spatial autocorrelation helps identify spatial trends and patterns in pollution data.

Point Pattern Analysis Point pattern analysis evaluates the distribution of pollution data points in space to detect clusters, regular patterns, or random arrangements. It is particularly useful for studying the spatial distribution of pollution sources and understanding their potential impact on the surrounding environment.

Overlay Analysis Overlay analysis involves overlaying multiple spatial datasets to identify areas with overlapping attributes. By combining pollution data with other environmental factors, such as land use, vegetation, or hydrological features, researchers can identify areas of potential concern or areas where pollution sources coincide with vulnerable populations.

Spatial Statistics Spatial statistics techniques, including spatial correlation, spatial regression, and geographically weighted regression (GWR), are used to analyse the relationship between pollution and other spatial variables. These methods help researchers uncover spatially varying relationships and assess the influence of environmental factors on pollution levels.

Spatial Join and Aggregation Spatial join and aggregation techniques link pollution data to specific geographic areas, such as administrative boundaries or grid

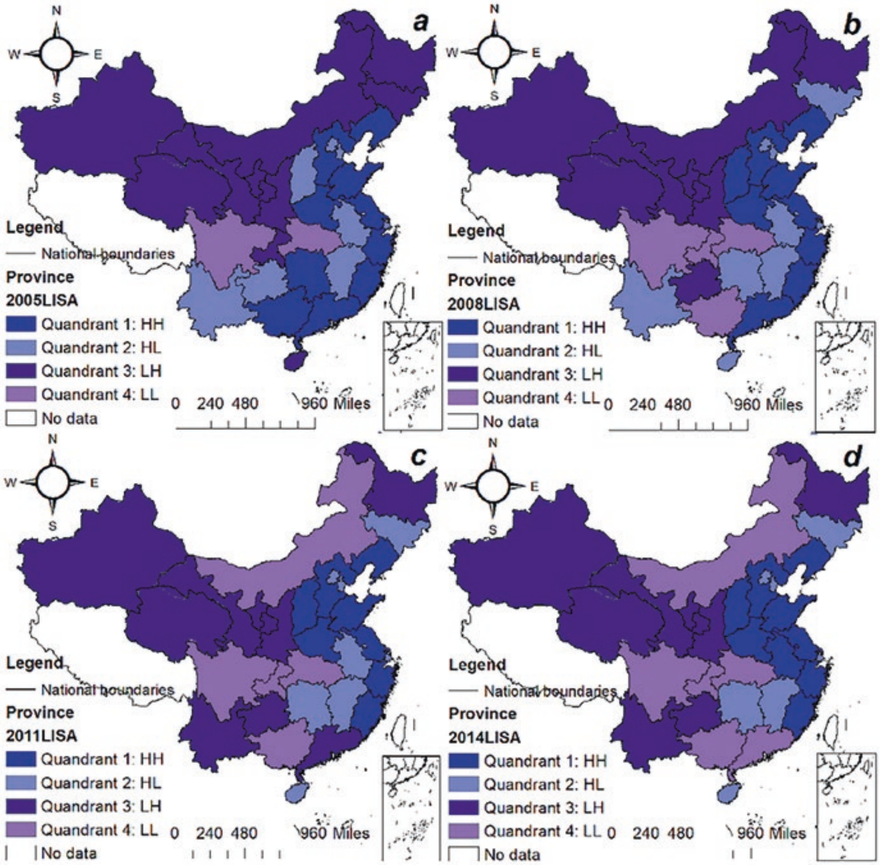


Fig. 14.6 The global Moran scatter plot displayed spatial clustering in different years. (Source: Peng et al., 2023)

cells. This allows for data aggregation and analysis at different spatial scales, facilitating comparisons and identifying regional variations in pollution levels.

14.6 Creating Pollution Maps Using Geo-Visualization Tools

Creating pollution maps using geo-visualization tools is a powerful and effective way to visualize and communicate pollution data in a spatial context (Balla et al., 2022; Xu et al., 2011). These maps provide a clear and intuitive representation of pollution patterns, trends, and hotspots, enabling researchers, policymakers, and the public to understand the distribution of pollutants across a specific area. A step-by-step guide to creating pollution maps using geo-visualization tools is described in Table 14.1.

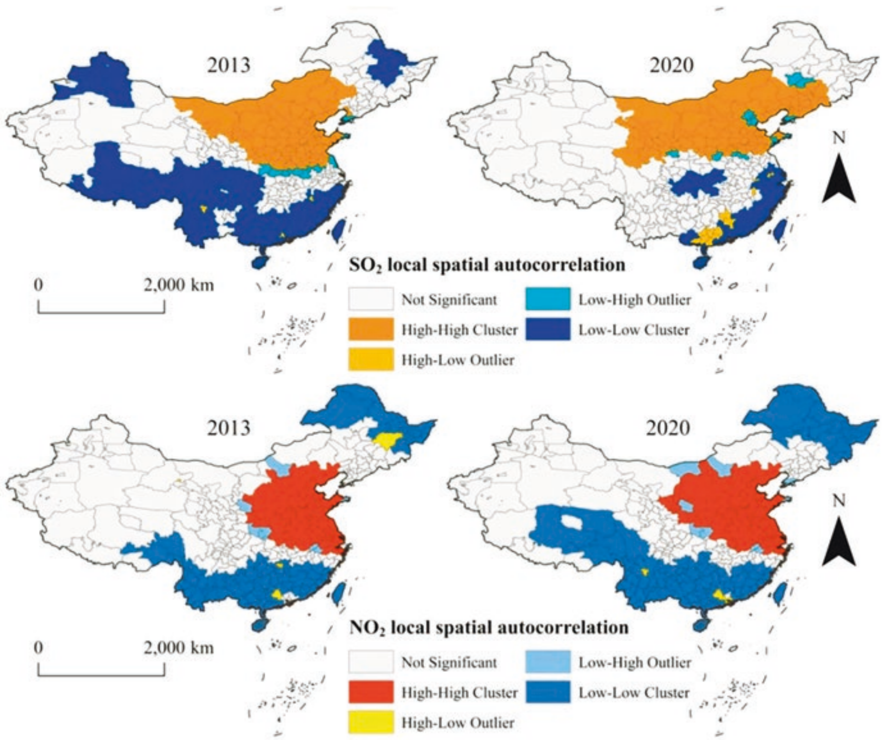


Fig. 14.7 Spatial autocorrelation of air pollution in China. (Source: Qi et al., 2022)

14.7 Visualization Techniques for Different Types of Pollution (Air, Water, Soil, and Noise)

Visualization techniques for different types of pollution (air, water, soil, and noise) are essential for effectively communicating the complex spatial patterns and variations of pollutants in the environment. Different types of pollution require specific visualization methods to showcase their unique characteristics. The visualization techniques for each type of pollution are described below:

Air Pollution Visualization

Heatmaps Heatmaps (Fig. 14.8) are commonly used to visualize air pollution data (Li et al., 2016). They use colour gradients to represent pollution concentration levels, with hotter colours (e.g. red) indicating higher pollutant levels and cooler colours (e.g. blue) representing lower concentrations. Heatmaps provide an intuitive representation of pollution hotspots and spatial patterns.

Table 14.1 Steps to prepare pollution maps using geo-visualization tools

Steps	Description
Step 1: Data Collection and Preparation	Collect pollution data from various sources, such as air quality monitors, water quality sensors, and other environmental monitoring devices. Ensure that the data are properly formatted and georeferenced with latitude and longitude coordinates. If needed, transform and standardize the data to ensure consistency.
Step 2: Choose a Geo-Visualization Tool	Select a geo-visualization tool that best suits your needs and proficiency level. Popular tools include ArcGIS, QGIS, Carto, Mapbox, and Google Earth, among others. Some tools are more user-friendly, while others offer advanced capabilities for spatial analysis and data visualization.
Step 3: Import Data into the Geo-Visualization Tool	Import the pollution data into the chosen geo-visualization tool. Most tools support various data formats, such as CSV, Excel, shapefile, or GeoJSON. Georeferenced data will be automatically plotted on the map.
Step 4: Styling and Symbology	Customize the appearance of the pollution data on the map using styling and symbology options. Choose a suitable colour scheme or gradient to represent pollution levels. For example, use a colour ramp to display varying levels of pollution concentration, with red indicating high levels and green indicating low levels.
Step 5: Spatial Interpolation (Optional)	If pollution data are sparse or have missing values at specific locations, consider using spatial interpolation techniques provided by the geo-visualization tool. Spatial interpolation will estimate pollution values at unsampled locations, creating a continuous and smooth pollution surface for the map.
Step 6: Overlay with Basemaps and Other Data	Overlay the pollution data with relevant basemaps, such as satellite imagery or street maps, to provide geographical context. Additionally, consider overlaying other spatial datasets, such as land use, population density, or transportation networks, to understand potential correlations between pollution and environmental factors.
Step 7: Add Interactive Elements (Optional)	Enhance the map's interactivity by adding elements like tooltips or pop-ups that display detailed information about pollution levels when users click on data points. This helps users gain more insights into specific pollution measurements.
Step 8: Time Series Visualization (Optional)	If pollution data have a temporal component, create time series visualizations to show how pollution levels change over time. Animating the map or using a time slider allows users to see temporal trends and seasonal variations in pollution.
Step 9: Publish and Share	Once the pollution map have been created, consider publishing it on interactive web platforms or embedding it in presentations or reports. Web-based maps are easily shareable and allow others to explore the pollution data and its spatial patterns.

Contour Maps Contour maps (Fig. 14.9) show lines connecting areas with the same pollutant concentration (Sivaraman et al., 2013). These lines, called contour lines, help visualize the elevation of pollution levels across the study area, providing insights into the spatial distribution of pollutants.

Animated Time Series Maps For air pollution data with a temporal component, animated time series maps are useful. These maps display changes in pollution levels over time, helping to identify temporal trends and seasonal variations in air quality (Rolph et al., 2017).

Water Pollution Visualization

Chloropleth Maps Chloropleth maps use colour shades to depict different levels of water pollution at various locations (Trombadore et al., 2020). This visualization technique allows users to quickly understand the spatial distribution of pollutants in water bodies.

Water Quality Index Maps Water quality index maps combine multiple water quality parameters into a single index, allowing for an overall assessment of water pollution (Wang et al., 2019). The index is then visualized on maps to indicate areas with good or poor water quality (Fig. 14.10).

Water Flow Animation In the case of river or stream pollution, water flow animation can show how pollutants disperse and move over time. This technique helps identify potential sources of pollution and how they affect downstream areas (Zhang et al., 2011).

Soil Pollution Visualization

3D Surface Visualization Soil pollution data can be visualized in 3D to represent the depth and distribution of contaminants within the soil profile. 3D surface visualizations provide a clear understanding of the extent of soil contamination (Fig. 14.11) (Seignez et al., 2010).

Contamination Plume Mapping Contamination plume maps illustrate the spatial distribution of soil contaminants from a specific source (Brahmi et al., 2021). These maps help identify the direction and extent of pollutant migration within the soil.

Risk Maps Soil risk maps combine soil contamination data with information about potential exposure pathways (e.g. agricultural activities and residential areas) to assess the risk of exposure to pollutants (Lourenço et al., 2010). These maps help prioritize areas for remediation efforts (Fig. 14.12).

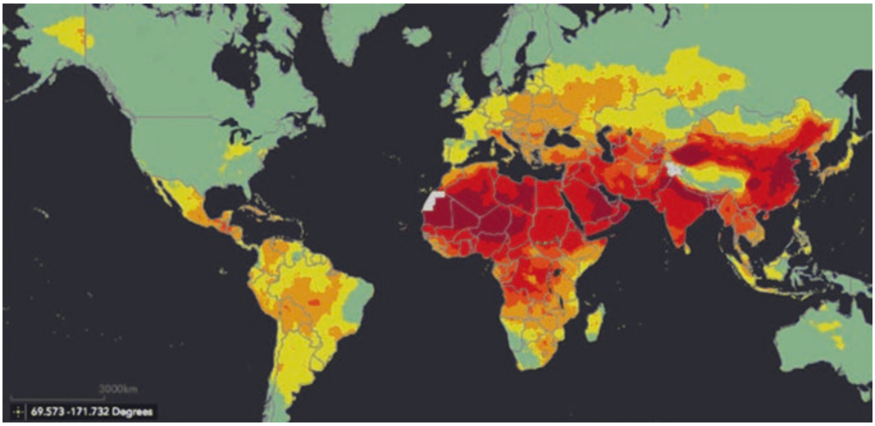
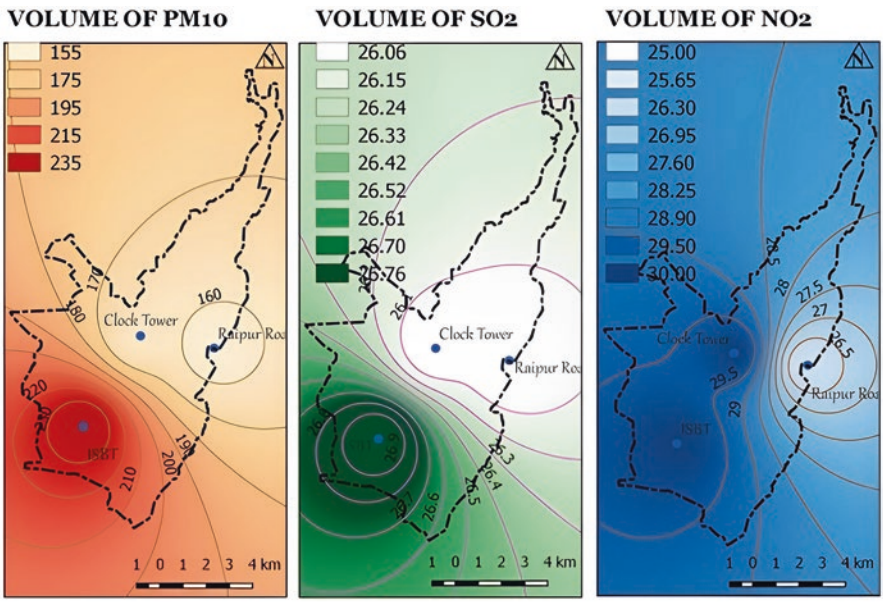


Fig. 14.8 A new air quality heatmap by the World Health Organization



id	Name	Air_PM10	Air_So2	Air_No2
1	Clock Tower	160	26	30
2	ISBT	238	27	30
3	Raipur Road	155	26	26

Standard as per CPCB for PM10 = 60 mug/ cum
Standard as per CPCB for SO2 = 20 mug/ cum
Standard as per CPCB for NO2 = 30 mug/ cum

Fig. 14.9 Ambient air quality interpolated contour map. (Source: UEPPCB Data)

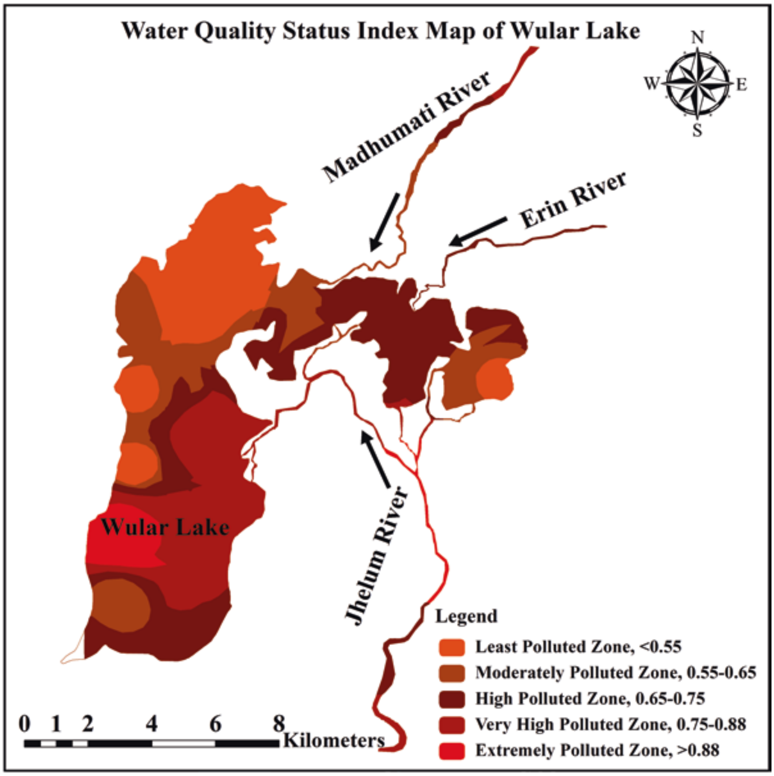


Fig. 14.10 Water quality index map showing different levels of pollution. (Source: Mushtaq et al., 2015)

Noise Pollution Visualization

Noise Contour Maps Noise contour maps use contour lines to depict areas with the same noise level (Merchan & Diaz-Balteiro, 2013). These lines connect locations with equal noise decibel (dB) values, allowing viewers to identify areas of high- and low-noise intensity. This visualization technique helps in understanding noise propagation and identifying noise hotspots near busy roads, airports, or industrial zones.

Heatmaps Similar to air pollution heatmaps, noise pollution heatmaps use colour gradients to represent noise levels. Hotter colours represent higher noise levels, while cooler colours indicate lower noise levels. Heatmaps provide an intuitive visual representation of noise distribution and help identify areas with excessive noise (Berger-Tal et al., 2019).

Time-Lapse Noise Maps Time-lapse noise maps show how noise levels change over time in a specific area. By animating noise data at different time intervals,

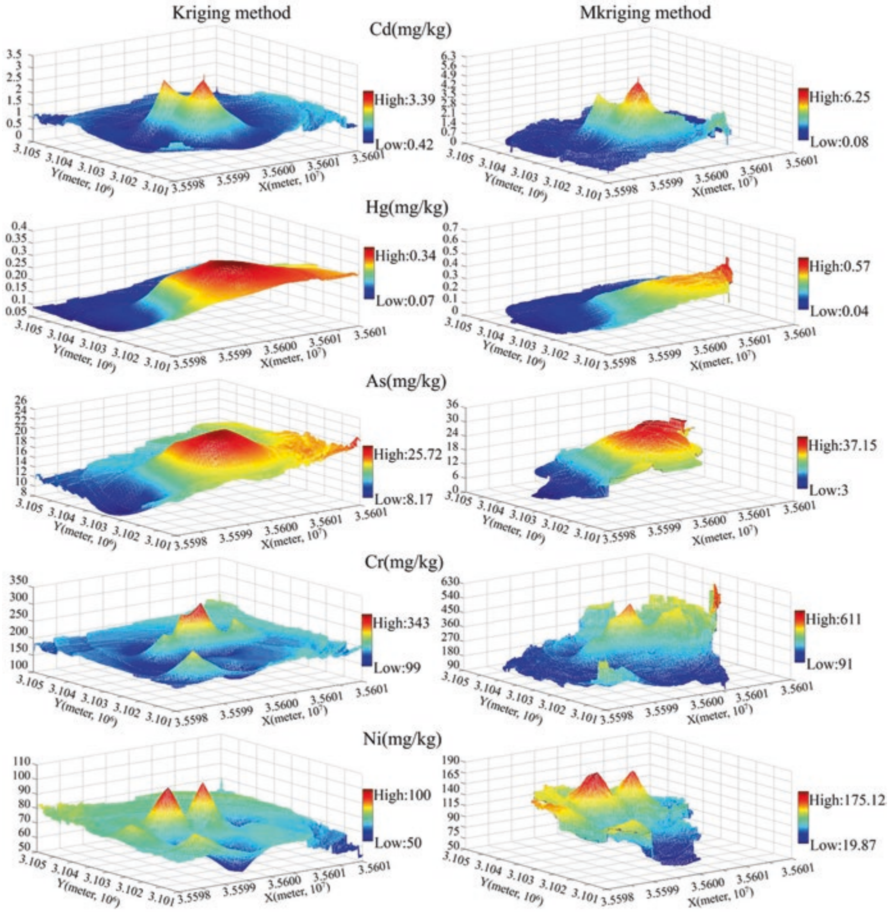


Fig. 14.11 3D representation of predicted distribution of heavy metals in reclaimed soil based on kriging and Mkriging method by Zhang et al., 2018 (Source: Zhang et al., 2018)

viewers can observe noise patterns during various hours of the day or days of the week. Time-lapse noise maps are valuable for understanding noise variations, especially in urban environments with fluctuating noise levels (Darbyshire et al., 2019).

Interactive Noise Monitoring Platforms Interactive web-based platforms allow users to access real-time noise data and explore noise levels in different locations. These platforms often provide interactive features, such as map zooming and filtering by time, enabling users to analyse noise data at specific locations and periods (Berti Suman & Van Geenhuizen, 2020).

Noise Source Mapping Noise source mapping involves plotting the locations of major noise sources, such as highways, railways, airports, and industrial facilities,

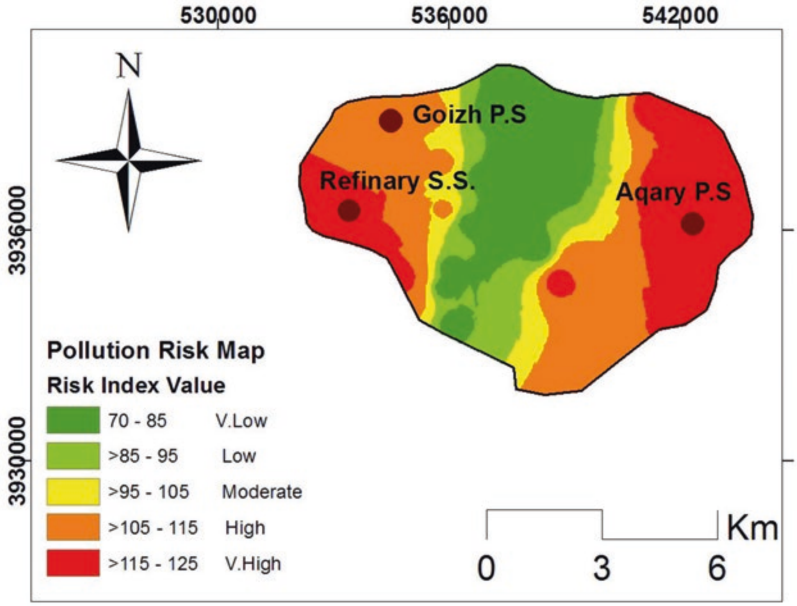


Fig. 14.12 Pollution risk map (Source: Amin Al Manmi et al., 2019)

on a map. By visualizing noise sources along with noise levels, decision-makers can assess the contribution of different sources to overall noise pollution.

Noise Pollution Severity Index (NPSI) Maps NPSI maps combine multiple noise indicators to create an overall index that represents the severity of noise pollution in an area. These maps provide a concise visualization of noise pollution levels across regions and help prioritize noise control measures (Fig. 14.13).

Noise Monitoring Network Visualization For cities or regions with a network of noise monitoring stations, visualizing these stations on a map helps to assess the spatial coverage of noise data collection. It also aids in identifying gaps in the monitoring network and the need for additional monitoring stations.

14.8 Empowering the Public Through Geo-Visualization Tools

Geo-visualization tools have become powerful instruments for empowering the public with valuable information and insights about their surroundings (Table 14.2). By making spatial data accessible and easy to understand, these tools bridge the gap

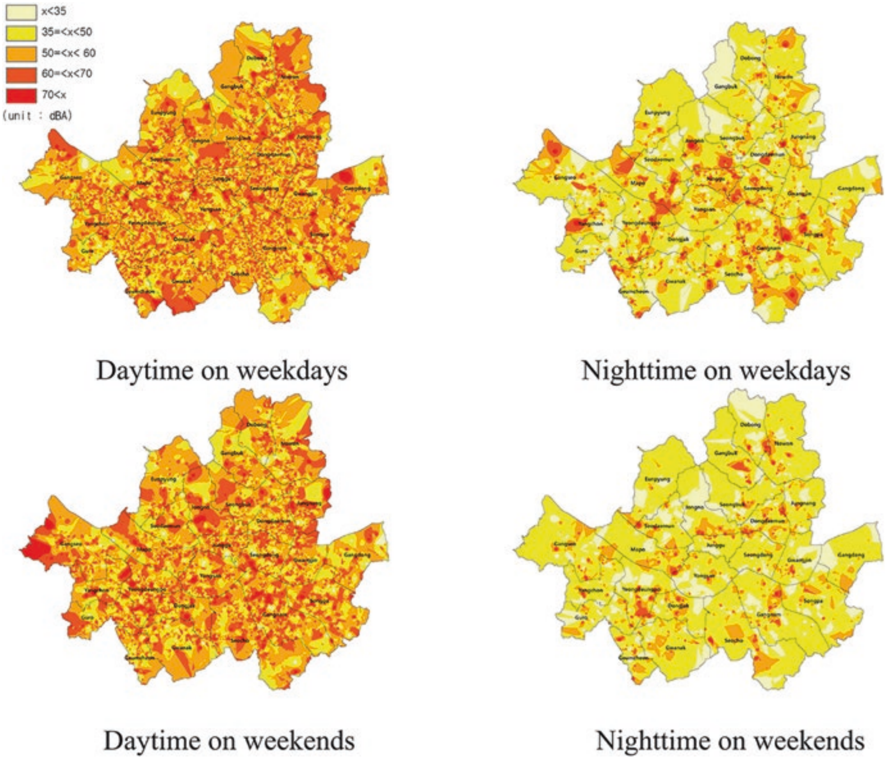


Fig. 14.13 Noise maps of Seoul, South Korea. (Source: Shim et al., 2016)

between complex data and public awareness, enabling individuals to actively engage in environmental, social, and civic matters.

14.9 Crowdsourced Pollution Data and Their Reliability

Crowdsourced pollution data refer to environmental information collected and contributed by the public through various means, such as mobile applications, online platforms, or community-based monitoring initiatives. While crowdsourcing offers many advantages, such as increased data coverage and real-time monitoring capabilities, the reliability of crowdsourcing pollution data can vary based on several factors:

Data Quality and Accuracy The reliability of crowdsourced pollution data heavily depends on the quality and accuracy of the information submitted by the public. Since crowdsourcing involves nonexperts, there is a risk of data errors, misinterpretations, or inconsistencies, which could affect the overall reliability of the data.

Table 14.2 Geo-visualization tools for empowering the public

Empowering the public with geo-visualization tools for pollution monitoring	
Accessible information	Geo-visualization tools provide a user-friendly interface that allows the public to access a wide range of geographic information. By presenting data through interactive maps and visualizations, complex datasets, such as environmental pollution levels, land use patterns, or transportation networks, become easily comprehensible to nonexperts.
Environmental awareness	With geo-visualization tools, the public can explore real-time environmental data, such as air quality, water pollution, and climate trends. This increased awareness empowers individuals to understand the environmental challenges faced by their communities, inspiring them to take action to protect and preserve their local ecosystems.
Community engagement	Geo-visualization tools encourage community engagement by enabling users to contribute data and share their observations. Citizen science initiatives and community mapping projects allow the public to participate actively in environmental monitoring, helping to identify pollution sources, track changes, and advocate for positive change.
Informed decision-making	Public access to spatial data through geo-visualization tools promotes informed decision-making. Whether it is choosing an eco-friendly transportation route, making land use planning decisions, or participating in community development projects, individuals armed with relevant spatial information can make more sustainable choices.
Disaster preparedness and response	During emergencies and natural disasters, geo-visualization tools play a crucial role in empowering the public with real-time information. By visualizing disaster-related data, such as flood maps, evacuation routes, or wildfire spread, individuals can take appropriate measures to protect their safety and assets.
Advocacy and policy support	The visual impact of geo-visualization tools can bolster advocacy efforts for environmental and social causes. By creating compelling maps and visualizations, individuals and organizations can communicate their concerns to policymakers and support evidence-based policy development.
Environmental education	Geo-visualization tools enhance environmental education by providing interactive learning experiences. Students can explore environmental phenomena, ecological systems, and climate change effects on a global scale, fostering a deeper connection with nature and encouraging a sense of responsibility for the planet
Transparent governance	Governments and public agencies can use geo-visualization tools to enhance transparency and citizen engagement. By sharing spatial data on infrastructure projects, public spending, or urban planning, governments foster public trust and encourage collaboration in decision-making processes.

Calibration and Standardization Ensuring consistency in data collection methods and units of measurement is crucial for reliable crowdsourced pollution data. Lack of calibration and standardization across different contributors may result in discrepancies and make data integration challenging.

Data Validation and Verification The absence of formal validation processes can raise concerns about the reliability of crowdsourced pollution data. Verification mechanisms, such as cross-referencing with official monitoring stations or comparing crowdsourced data with established datasets, can enhance data reliability.

Bias and Representation Crowdsourced data may exhibit geographical bias, as certain areas with a higher density of contributors may be overrepresented, while remote or less populated regions may be underrepresented. This bias can impact the accuracy and completeness of pollution data across different locations.

User Engagement and Participation Maintaining consistent user engagement and participation is essential for the reliability of crowdsourced data. If contributors lose interest or stop actively providing data, the coverage and continuity of pollution monitoring could be compromised.

Data Privacy and Security Ensuring data privacy and security is crucial for building trust and encouraging public participation. Inadequate measures to protect user data could deter people from contributing, potentially affecting data reliability.

Data Aggregation and Analysis Effectively aggregating and analysing crowdsourced pollution data requires robust methodologies. Without appropriate data processing techniques, the overall reliability and usefulness of the collected data could be limited.

14.10 Citizen Science Projects for Pollution Monitoring in India

Citizen science projects for pollution monitoring in India have gained momentum in recent years, empowering individuals to actively participate in environmental monitoring and contribute to data-driven decision-making. These initiatives leverage the power of public engagement and collaboration to collect pollution data from diverse locations across the country. Some notable citizen science projects for pollution monitoring in India are presented in Table 14.3.

14.11 Examples of Real-Time Monitoring/Visualization of Pollution

World's Air Pollution: Real-Time Air Quality Index (https://waqi.info/#/c/6.475/8.915/1.9z)

The "World Air Quality Index" (WAQI) website, a real-time air quality monitoring platform, offers air pollution data for locations worldwide (Fig. 14.14). The website displays an interactive map with a pin at the specified coordinates. Clicking on the

Table 14.3 Citizen science projects

Citizen science projects for pollution monitoring in India	
IndiaSpend Air Quality Project	IndiaSpend, a data-driven journalism platform, initiated the IndiaSpend Air Quality Project to engage citizens in monitoring air pollution. Through the use of low-cost, portable air quality monitors, volunteers collect real-time data on air quality parameters such as particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), and ozone (O_3). The collected data are then shared on a public platform to raise awareness about air pollution and advocate for cleaner air.
Care for Air Project (CAP)	Care for Air Project, initiated by the Centre for Environmental Health, monitors air pollution levels in various Indian cities. Citizen volunteers use portable air quality monitors to measure $PM_{2.5}$ levels at different locations. The data are aggregated and analysed to provide real-time air quality updates and identify pollution hotspots.
India Biodiversity Portal	The India Biodiversity Portal encourages citizen scientists to document and monitor various aspects of biodiversity, including pollution indicators. Users can report observations of pollution-affected flora and fauna, as well as document changes in ecosystems due to pollution stress.
Marine Debris Tracker	The Marine Debris Tracker app, although not specific to India, enables citizens to report and track marine litter and debris, which can include plastic pollution, on coastlines and beaches. This project helps raise awareness about marine pollution and its impact on coastal ecosystems.
Citizen Water Monitoring Network (CWMN)	The Citizen Water Monitoring Network, led by the Central Pollution Control Board (CPCB) in collaboration with various state pollution control boards, involves citizens in monitoring water quality across India. Volunteers collect water samples from rivers, lakes, and other water bodies, and the data are integrated into the national water quality database.
Water Warriors Project	The Water Warriors Project, initiated by the Wildlife Trust of India, engages local communities and volunteers in monitoring and conserving water resources, including assessing pollution levels in rivers and wetlands.

Fig. 14.14 Real-time air quality index (https://waqi.info/#/c/6.475/8.915/1.9z)

pin reveals air quality data for the corresponding location. The information typically includes the following:

(i) Air Quality Index (AQI): The AQI value provides an overall assessment of air quality at a specific location. It is calculated based on the concentrations of various air pollutants, such as $PM_{2.5}$, PM_{10}, NO_2, SO_2, O_3, CO, and VOCs.
(ii) Pollutant Concentrations: The website shows the current concentrations of individual air pollutants contributing to the AQI value. This information helps users understand the major contributors to air pollution at that particular location.
(iii) AQI Colour Code: The AQI value is colour-coded to indicate the level of air quality. Common colour categories are "Good" (Green), "Moderate" (Yellow), "Unhealthy for Sensitive Groups" (Orange), "Unhealthy" (Red), "Very Unhealthy" (Purple), and "Hazardous" (Maroon).
(iv) Health Impacts: The website provides descriptions of potential health impacts associated with each AQI level. This information helps individuals understand the health risks of exposure to varying air quality conditions.
(v) Time and Date: The time and date of the latest air quality data update are usually displayed, ensuring that users are aware of the data's freshness.

Bhuvan Ganga Geoportal (https://bhuvan-app1.nrsc.gov.in/mowr_ganga/)

The Bhuvan Ganga Geoportal is an initiative by the National Remote Sensing Centre (NRSC) under the Ministry of Water Resources, Government of India (Fig. 14.15). The Bhuvan Ganga Geoportal aims to provide comprehensive geospatial information related to the Ganga River Basin in India. This portal serves as a

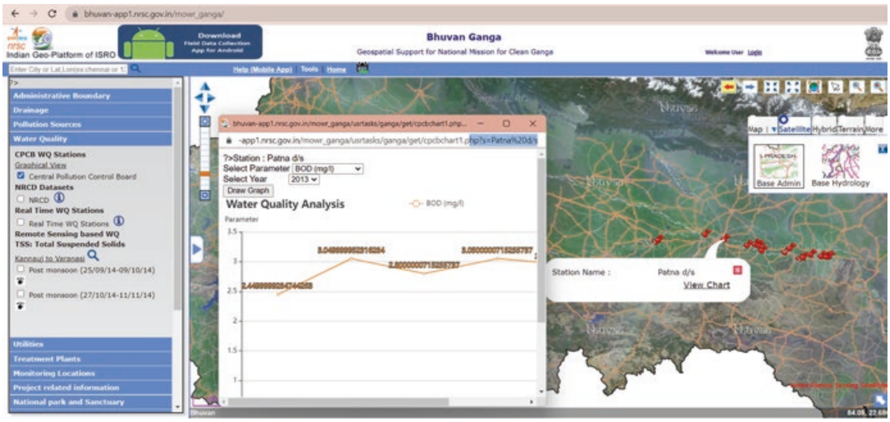


Fig. 14.15 Bhuvan Ganga Geoportal (https://bhuvan-app1.nrsc.gov.in/mowr_ganga/)

valuable resource for tracking water pollution and understanding various aspects of the Ganga River's hydrology and environment. Key features of the Bhuvan Ganga Geoportal include the following:

(i) Ganga River Basin Information: The portal offers detailed information about the Ganga River Basin, including its geographical extent, drainage patterns, and major river systems.
(ii) Water Quality Monitoring: The Bhuvan Ganga Geoportal provides access to water quality monitoring data for various stretches of the Ganga River and its tributaries. These data include measurements of key water quality parameters, such as dissolved oxygen (DO), biochemical oxygen demand (BOD), total coliforms, and other pollutants.
(iii) River Morphology and Geomorphology: The portal offers data on the morphology and geomorphology of the Ganga River, providing insights into river channel dynamics and sediment transport processes.
(iv) Flood Monitoring and Management: The Bhuvan Ganga Geoportal provides real-time flood monitoring information, including flood extent mapping and flood risk assessment for the Ganga River Basin.
(v) Satellite Imagery and Remote Sensing Data: The portal offers satellite imagery and remote sensing data, allowing users to analyse land cover, land use changes, and other environmental parameters within the Ganga River Basin.
(vi) Data Visualization: The portal provides interactive maps and data visualization tools to facilitate the exploration and analysis of various geospatial datasets related to the Ganga River.
(vii) Stakeholder Engagement: The Bhuvan Ganga Geoportal aims to engage various stakeholders, including researchers, policymakers, and the public, in understanding and managing the Ganga River Basin's water resources and environmental health.

SDG 6 – Hydrology Thematic Exploitation Platform (TEP) (http://sdg6--hydrology-tep.eu/) This is an online platform developed as part of the European Space Agency's (ESA) Earth Observation (EO) science for society program (Fig. 14.16). The main objective of this platform is to support the United Nations Sustainable Development Goal 6 (SDG 6), which focuses on ensuring the availability and sustainable management of water and sanitation for all. SDG 6 – Hydrology TEP leverages Earth observation data and advanced hydrological models to provide valuable information and tools for water resource monitoring, assessment, and management. It offers a range of features and services, including access to satellite imagery, hydrological models, and data processing capabilities. By providing a wealth of hydrological data and analysis tools, SDG 6 – Hydrology TEP contributes to sustainable water management practices and helps address water-related challenges on a global scale.

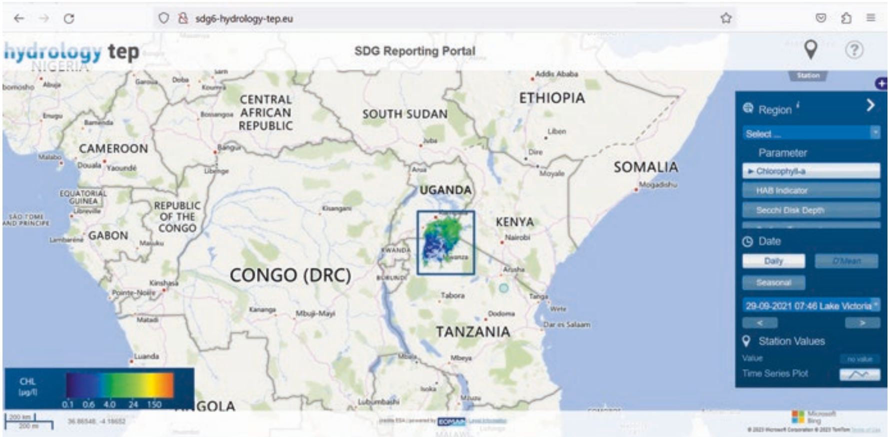


Fig. 14.16 SDG 6 – Hydrology Thematic Exploitation Platform (TEP) (http://sdg6-hydrology-tep.eu/)

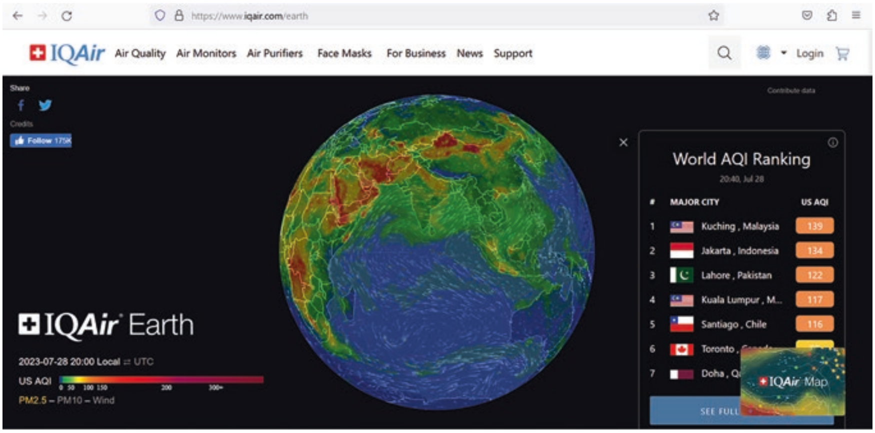


Fig. 14.17 Real time, 3D animated air pollution map (https://www.iqair.com/earth?nav=)

IQAir Earth (https://www.iqair.com/earth?nav=) This online platform provides real-time air quality data and information about air pollution on a global scale (Fig. 14.17). IQAir's Earth website offers a comprehensive platform for users to access real-time air quality data from locations worldwide. This data includes information on current air quality levels, types of pollutants present, and health recommendations derived from data collected by air quality monitoring stations. Additionally, the website employs interactive 3D maps, allowing users to visually analyze air quality information, including pollution levels, trends, and patterns across various regions. IQAir also provides valuable insights and educational resources regarding air quality, pollution sources, and the health consequences of poor air quality. Furthermore, IQAir is recognized for its air purification solutions,

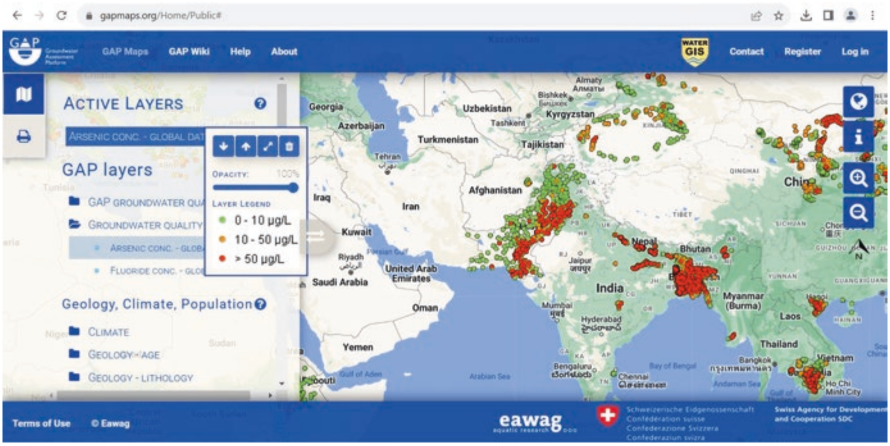


Fig. 14.18 Global arsenic concentration (https://www.gapmaps.org/Home/Public#)

including air purifiers, designed to enhance indoor air quality, and information about these products and related solutions may be available on the website. The site likely utilizes the Air Quality Index (AQI) to categorize and assess air quality, simplifying users' comprehension of the potential health impacts associated with the air in their respective areas. For convenient access to real-time air quality data, IQAir may also offer mobile apps that users can install on their smartphones or tablets.

Groundwater Assessment Platform (GAP Maps) (https://www.gapmaps.org/Home/Public#) Groundwater Assessment Platform (GAP) website hosts the information concerning geogenic groundwater contamination (Fig. 14.18). The platform offers opportunities for data sharing, sharing of case studies and field experiences, user interaction, and the ability to craft probabilistic maps for any global region. Within GAP Maps, users have the capability to visualize and print existing data and models, manipulate and model their own data, and produce hazard maps. Furthermore, the GAP Wiki encompasses a wide range of information pertaining to geogenic contamination.

14.12 Potential of AI and Machine Learning in Pollution Data Analysis and Visualization

In recent years, the field of pollution monitoring has seen remarkable advancements in geo-visualization technology, revolutionizing the way we perceive and analyse environmental data. Geo-visualization technology leverages geographic information systems (GIS) and interactive mapping tools to create dynamic, real-time visual representations of pollution levels across various regions. These advancements have enabled researchers, policymakers, and the general public to gain a deeper understanding of the spatial distribution and trends of pollution, making it easier to identify pollution hotspots and devise targeted interventions.

In addition, the potential of AI and machine learning in pollution data analysis and visualization has been a game-changer. AI algorithms can process vast amounts of pollution data quickly and efficiently, extracting valuable insights and patterns that were once difficult to discern. Machine learning models can predict pollution levels based on historical data and various environmental factors, aiding in the formulation of proactive strategies to combat pollution and minimize its adverse effects. The integration of AI and machine learning with geo-visualization technology has led to the development of sophisticated pollution monitoring systems that offer real-time updates and predictive capabilities. By combining data from multiple sources, such as satellite imagery, ground sensors, and citizen science contributions, these systems can generate comprehensive pollution maps with high accuracy and granularity. Furthermore, AI-powered pollution visualization tools have made environmental information more accessible to the public. Interactive dashboards and mobile applications allow individuals to explore pollution data in a user-friendly manner, empowering them to make informed decisions about their daily activities and lifestyle choices that can contribute to pollution reduction. The synergy between geo-visualization technology and AI-driven pollution data analysis has ushered in a new era of environmental awareness and action. With more precise monitoring, predictive capabilities, and user-friendly interfaces, these advancements hold tremendous potential in helping us address the global challenge of pollution and pave the way for a more sustainable future.

14.13 Conclusion

Geo-visualization tools have proven to be of paramount importance in pollution monitoring efforts. By integrating geographic information systems (GIS) and interactive mapping technologies, these tools enable us to gain valuable insights into the spatial distribution and trends of pollution. Real-time visualization of pollution data empowers researchers, policymakers, and the public to identify pollution hotspots, track changes over time, and assess the effectiveness of pollution control measures. The ability to overlay various data layers, such as industrial zones, population density, and weather patterns, enhances our understanding of the complex factors influencing pollution levels. This comprehensive approach to pollution monitoring fosters data-driven decision-making and supports targeted interventions to address environmental challenges.

The integration of geo-visualization tools in pollution monitoring has significant implications for environmental policies and decision-making. Access to real-time and easily accessible pollution data allows policymakers to develop more informed and evidence-based strategies for pollution control and environmental protection. By visualizing pollution data on interactive maps, policymakers can identify areas with high pollution concentrations, understand the sources of pollution, and prioritize interventions accordingly. Moreover, these tools facilitate cross-sectoral collaboration by providing a common platform for various stakeholders to share information and coordinate efforts. The insights gained from geo-visualization contribute to the formulation of effective policies that can lead to a healthier and more sustainable environment for present and future generations.

Looking ahead, the future of pollution monitoring through geo-visualization tools appears promising and transformative. Advancements in technology, such as the Internet of Things (IoT), 5G connectivity, and improved data processing capabilities, will enable more extensive data collection and faster dissemination. As sensor networks and satellite technology continue to evolve, we can expect even higher-resolution data, providing more detailed and accurate pollution maps. Furthermore, the integration of artificial intelligence and machine learning in pollution data analysis will enhance predictive capabilities, allowing us to anticipate pollution trends and proactively respond to potential environmental threats.

In the future, the widespread adoption of geo-visualization tools in pollution monitoring will democratize access to environmental information, enabling individuals and communities to actively participate in environmental stewardship. Citizen science initiatives will become more prevalent, with citizens contributing data and observations through mobile applications and other platforms. These collective efforts will not only strengthen pollution monitoring networks but also foster a sense of responsibility and ownership in safeguarding the environment. Geo-visualization tools have become indispensable in pollution monitoring, transforming the way we perceive, analyse, and respond to environmental challenges. The ongoing advancements in technology and the increasing awareness of environmental issues will continue to drive innovation in pollution monitoring and inspire collaborative efforts towards a more sustainable and ecologically balanced future.

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Chapter 15
Environmental Pollution Control Measures and Strategies: An Overview of Recent Developments

Zeba Khanam, Fatma Mehar Sultana, and Fayma Mushtaq

Abstract Environmental pollution continues to be a pressing global issue, posing significant threats to the health of ecosystems and human well-being. Urbanization, industrialization, and various other economic activities caused by human intervention contribute significantly to the overall environmental pollution experienced in the present day. In recent years, substantial progress has been made in understanding the complexities of pollution and developing innovative strategies for effective control and mitigation. This chapter provides an overview of the latest developments in environmental pollution control measures and strategies. It also delves into the significant strides made in adopting cleaner technologies, renewable energy sources, and water pollution control measures, where the latest innovations in wastewater treatment technologies are explored. The enforcement of stringent emission standards for industries and vehicles, in addition to the pivotal role of carbon capture and storage in combating climate change, is highlighted, underscoring its potential in curbing greenhouse gas emissions. Furthermore, this chapter addresses the importance of integrated water resource management strategies, which ensure sustainable water usage and minimize the environmental impact of pollution. Advancements in soil and land pollution control are also outlined, such as novel remediation methods, such as phytoremediation and bioremediation, which offer eco-friendly solutions for rehabilitating contaminated sites. The integration of cleaner technologies, innovative treatment methods, and advanced monitoring techniques holds great promise in safeguarding the environment and ecosystems and ultimately enhancing the quality of life for all inhabitants of our planet.

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15.1 Introduction

Environmental pollution is a multifaceted global challenge that has been escalating over the past few decades due to industrialization, urbanization, population growth, and unsustainable practices. The adverse effects of pollution on human health, biodiversity, and ecosystems have raised concerns worldwide and spurred the need for effective pollution control measures and strategies (Tietenberg and Wheeler, 2001). Air pollution, resulting from the release of harmful gases and particulate matter into the atmosphere, has been a prominent issue in urban areas and industrial regions (Anjum et al., 2021). The combustion of fossil fuels in power plants, vehicles, and industries has been a significant contributor to air pollution, leading to respiratory diseases, acid rain, and climate change (Manisalidis et al., 2020). To address this concern, international agreements such as the Paris Agreement have aimed to curb greenhouse gas emissions and promote the adoption of renewable energy sources (Sovacool et al., 2021).

Water pollution, on the other hand, arises from the discharge of untreated or inadequately treated wastewater, industrial effluents, and agricultural runoff into water bodies (Häder et al., 2020). This pollution not only threatens aquatic life but also jeopardizes the availability of clean drinking water, essential for human survival. Recent developments in wastewater treatment technologies have focused on advanced processes to efficiently remove pollutants and protect aquatic ecosystems (Gogoi et al., 2018). Soil and land pollution have emerged as significant environmental issues, with activities such as improper waste disposal, industrial contamination, and urbanization causing soil degradation and the loss of fertile land. Soil pollution adversely impacts agriculture and biodiversity, necessitating innovative methods such as phytoremediation and bioremediation to restore contaminated sites to a healthy state (Mani & Kumar, 2014).

As technological advancements continue, the integration of advanced monitoring systems, data analytics, and artificial intelligence has proven instrumental in pollution control efforts (Fig. 15.1) (Park et al., 2020). Real-time tracking and forecasting of pollution levels enable proactive responses and the formulation of evidence-based policies to combat pollution effectively (Adams & Kanaroglou, 2016; Xiaojun et al., 2015). Understanding the complex nature of environmental pollution and its far-reaching consequences is essential in devising appropriate measures and strategies. Recent developments have shown promise in mitigating pollution across air, water, and soil domains, while data-driven approaches offer a path towards sustainable environmental management and the preservation of our planet's delicate ecological balance (Bibri, 2022). Efforts in pollution control will continue

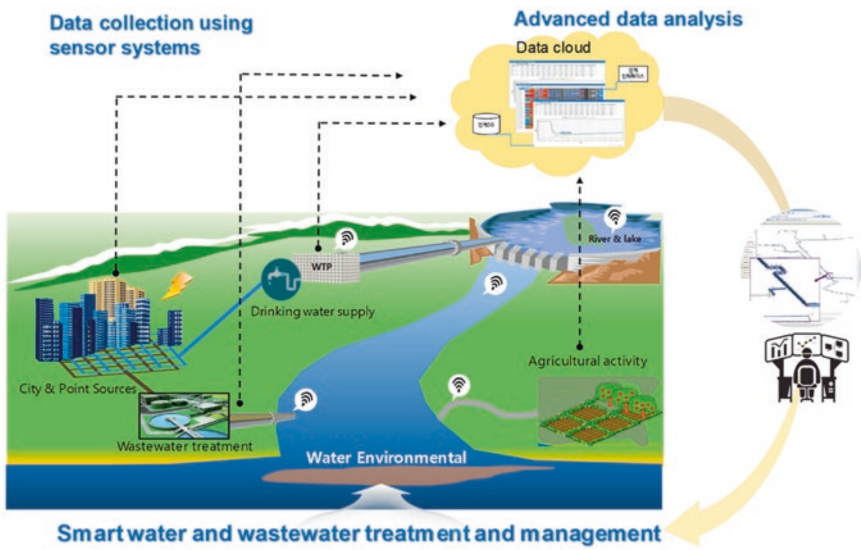

Fig. 15.1 Integrated solution that combines real-time monitoring, seamless transmission, and advanced data management to facilitate intelligent water and wastewater treatment and enhance their efficient management. (Source: Park et al., 2020)

to play a crucial role in ensuring a cleaner and healthier environment for present and future generations.

15.2 Significance of Pollution Control Measures

The significance of pollution control measures cannot be overstated in today's world. These measures play a crucial role in safeguarding the environment, protecting human health, and preserving the delicate balance of ecosystems. Several key reasons highlight the importance of pollution control measures:

Environmental Protection: Pollution control measures are essential in minimizing the release of harmful pollutants into the air, water, and soil. By reducing pollution levels, the negative impacts on natural habitats, wildlife, and plant life can be mitigated, thereby preserving biodiversity.

Human Health: Many pollutants have adverse effects on human health, leading to respiratory issues, cardiovascular diseases, and other illnesses. Implementing pollution control measures helps create cleaner and healthier living environments, enhancing the well-being of individuals and communities.

Climate Change Mitigation: Pollution, particularly greenhouse gas emissions, contributes significantly to climate change. By curbing these emissions and promoting cleaner technologies, pollution control measures are instrumental in mitigating global warming and its associated consequences.

Sustainable Development: Pollution control measures are integral to sustainable development. They enable economic growth and industrial progress without causing irreversible damage to the environment, ensuring that future generations can meet their needs as well.

Resource Conservation: Effective pollution control measures often involve recycling and responsible waste management, leading to the conservation of valuable resources and reducing the strain on natural ecosystems.

Compliance with Regulations: Many countries have established environmental regulations and standards to limit pollution levels. By adhering to these regulations, industries and individuals contribute to a cleaner environment and avoid potential legal repercussions.

International Cooperation: Pollution knows no boundaries, and its impacts can cross borders. Encouraging pollution control fosters international cooperation in tackling global environmental challenges as nations work together to address shared concerns.

Improved Quality of Life: Cleaner air, water, and surroundings directly translate to an improved quality of life. Pollution control measures create more pleasant living conditions, fostering a sense of well-being and pride in communities.

Protection of Ecosystem Services: Healthy ecosystems provide essential services such as water purification, pollination, and climate regulation. Pollution control measures safeguard these services, ensuring the continued resilience of ecosystems.

Long-term Economic Benefits: Although implementing pollution control measures may require initial investments, the long-term economic benefits outweigh the costs. Reduced healthcare expenses, enhanced productivity, and a sustainable environment contribute positively to economic growth.

15.3 Objectives

This chapter aims to provide a comprehensive overview of the latest advancements in pollution control technologies and strategies, focusing on cleaner technologies, renewable energy, and emerging techniques such as carbon capture and storage. Integrated water resource management and sustainable land use planning are discussed for effective water and soil pollution control. This chapter also highlights the role of advanced monitoring systems, data analytics, and international cooperation in pollution tracking and policy implementation.

15.4 Air Pollution Control Measures

Air pollution control measures play a crucial role in combating the harmful effects of air pollution on human health and the environment (Megahed & Ghoneim, 2021). These measures are designed to reduce the emissions of hazardous pollutants into the atmosphere, thereby promoting cleaner air quality. Governments enforce strict emission standards for industries, vehicles, and other pollution sources, pushing for the adoption of cleaner technologies and practices. Additionally, promoting the use of cleaner fuels, such as low-sulfur diesel and natural gas, helps to minimize the release of harmful pollutants such as sulfur dioxide and particulate matter. The transition from fossil fuels to renewable energy sources, such as solar, wind, and hydroelectric power, is encouraged to reduce greenhouse gas emissions and air pollution from power generation (Tripathi et al., 2016). Energy efficiency measures are also implemented in industries and buildings to decrease energy consumption and, consequently, air pollution. Furthermore, promoting the use of electric and hybrid vehicles, along with implementing regular vehicle inspections, helps to curb vehicular emissions and improve air quality in urban areas. Other essential measures include green transportation promotion, industrial upgrades, and best practices to minimize emissions (Chan & Lee, 2008). Proper urban planning can also contribute to reducing air pollution by optimizing traffic flow, creating green spaces, and controlling industrial activities in densely populated areas (Kumar et al., 2019; Sharifi & Khavarian-Garmsir, 2020; Yang et al., 2020). Addressing indoor air pollution through proper ventilation, air purifiers, and reduced use of indoor pollutants is essential for improving overall air quality. Finally, public awareness and education initiatives are vital in fostering responsible behavior and encouraging citizens to actively participate in air pollution reduction efforts. By implementing these air pollution control measures, societies can effectively mitigate the impact of air pollution, protect public health, and preserve the environment for the well-being of future generations.

National Clean Air Program (NCAP) The National Clean Air Program (NCAP) is an ambitious initiative launched by the Government of India in January 2019 (Ganguly et al., 2020) to address the growing problem of air pollution in the country (Fig. 15.2). The program aims to improve air quality in 102 cities across India, which were identified as having poor air quality based on their ambient air quality data. The primary objective of the NCAP is to reduce particulate matter (PM_{10} and $PM_{2.5}$) concentrations by 20–30% in target cities by 2024 compared to 2017 levels (Singh et al., 2021). The program focuses on collaborative efforts between central and state governments, local authorities, and various stakeholders to implement effective air pollution control measures. Some of the key strategies and initiatives under the NCAP include the following:

(i) *City-Specific Action Plans:* Each target city develops its own comprehensive action plan to tackle air pollution, considering the local sources of pollution and regional meteorology.

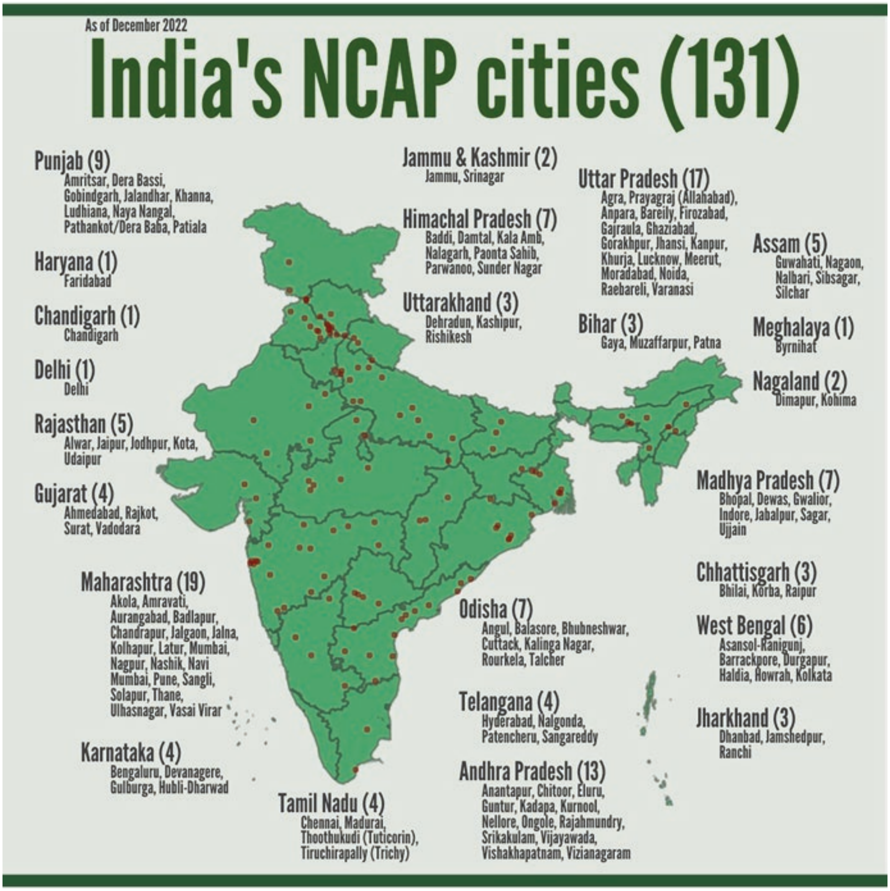

Fig. 15.2 India's NCAP cities. (Source: Urban emissions. Info, 2021)

(ii) *Strengthening Monitoring and Data Management:* The program aims to enhance air quality monitoring infrastructure to gather real-time data and improve data dissemination for public awareness.

(iii) *Source Apportionment Studies:* Identifying major sources of pollution in each city through source apportionment studies to formulate targeted mitigation measures.

(iv) *Promotion of Cleaner Technologies:* Encouraging the use of cleaner technologies and fuels in industries, transportation, and household activities to reduce emissions.

(v) *Strengthening Enforcement Mechanisms:* Improving compliance and enforcement of emission standards for industries, vehicles, and construction activities.

(vi) *Public Participation:* Involving citizens and civil society in creating awareness, encouraging public participation, and promoting behavioral changes to reduce pollution.

(vii) *Research and Innovation:* Supporting research and innovation in the field of air pollution control to develop cost-effective and sustainable solutions.

NCAP emphasizes a multisectoral approach to air quality management and recognizes the importance of cooperation between various levels of governance to achieve the desired air quality improvements. By implementing these measures, the National Clean Air Program aims to significantly reduce air pollution levels in target cities, leading to improved public health and a cleaner environment for the citizens of India.

Industrial Emission Standards and Regulations Industrial emission standards and regulations are essential tools used by governments to control and manage air pollution originating from industrial activities. These standards are designed to limit the release of harmful pollutants into the atmosphere, ensuring that industries operate in an environmentally responsible and sustainable manner. The components of industrial emission standards and regulations include the following:

(i) *Pollutant Limitations:* Industrial emission standards set specific limits on the amount of pollutants that industries are allowed to release into the air. These pollutants may include sulfur dioxide (SO_2), nitrogen oxides (NO_x), particulate matter (PM), volatile organic compounds (VOCs), and other hazardous substances.

(ii) *Compliance Monitoring:* Industries are required to install monitoring systems to track and report their emissions regularly. This allows regulatory authorities to ensure that companies are adhering to the prescribed emission limits.

(iii) *Technology Requirements:* Industrial emission standards often mandate the use of specific pollution control technologies to reduce emissions. Companies may be required to implement technologies such as scrubbers, catalytic converters, and particulate control devices to achieve compliance.

(iv) *Best Available Techniques (BAT):* Some regulations incorporate the concept of Best Available Techniques (BAT), which refers to the most effective and advanced pollution control measures that industries should adopt to minimize their environmental impact.

(v) *Sector-Specific Regulations:* Emission standards may vary according to the industry sector. Different industries have unique emissions profiles and challenges, and regulations are tailored to address their specific characteristics.

(vi) *Permitting and Compliance Mechanisms:* Industries typically require permits to operate, and compliance with emission standards is a prerequisite for obtaining and renewing these permits. Noncompliance can lead to penalties, fines, or even the suspension of operations.

(vii) *Continuous Improvement:* Emission standards are periodically reviewed and updated to reflect advancements in pollution control technologies and scientific knowledge. This ensures that industries continually strive to improve their environmental performance.

(viii) *International Commitments:* Many countries align their emission standards with international agreements and protocols, such as the Kyoto Protocol and the Paris Agreement, to fulfill their global commitments to reducing greenhouse gas emissions.

Urban Air Quality Management Urban air quality management is a multifaceted and crucial approach to address the pressing issue of air pollution in cities and urban areas (Pacione, 2003). As urbanization and industrialization continue to grow, cities face significant challenges in maintaining clean and healthy air for their residents. Urban air quality management encompasses a range of strategies aimed at improving air quality and reducing air pollution in urban areas (Gulia et al., 2015). These strategies are implemented by governments and local authorities to safeguard public health, enhance environmental sustainability, and create livable urban environments. By implementing these strategies, cities can significantly improve air quality, promote sustainable urban development, and create healthier living environments for their residents. Effective urban air quality management is crucial for achieving environmental sustainability and ensuring the well-being of urban populations. Some key urban air quality management strategies include the following:

(i) *Emission Standards and Regulations*: Governments set and enforce strict emission standards for industries, vehicles, and other pollution sources. These regulations limit the release of harmful pollutants into the atmosphere, encouraging the adoption of cleaner technologies and practices.
(ii) *Air Quality Monitoring*: Establishing and maintaining air quality monitoring networks allows continuous tracking of pollutant levels. Real-time data help identify pollution sources and assess the effectiveness of control measures.
(iii) *Source Apportionment Studies*: Governments conduct source apportionment studies to determine the contributions of different pollution sources to overall air pollution. This information aids in formulating effective pollution control strategies by targeting the significant contributors.
(iv) *Low-Emission Zones (LEZ)*: Establishing low-emission zones in congested urban areas restricts the entry of high-polluting vehicles. Only vehicles meeting specific emission standards are allowed to operate within these zones, reducing vehicular emissions in highly populated areas.
(v) *Public Transportation Promotion*: Governments prioritize and enhance public transportation systems to encourage citizens to use buses, trains, and other mass transit options. By reducing the reliance on private vehicles, this strategy lowers traffic-related emissions.
(vi) *Active Transportation Infrastructure*: Creating pedestrian-friendly sidewalks, bike lanes, and dedicated cycling paths promotes walking and cycling as eco-friendly transportation alternatives.
(vii) *Green Infrastructure*: Investing in green spaces, urban parks, and green belts helps absorb pollutants and improve air quality. Green infrastructure also mitigates the urban heat island effect and enhances the aesthetic value of the city.
(viii) *Clean Energy Initiatives*: Governments encourage the adoption of clean and renewable energy sources for power generation and heating. Incentives and subsidies are provided to promote solar, wind, and other sustainable energy technologies.

(ix) *Waste Management and Control*: Effective waste management practices, such as proper waste disposal and recycling, reduce the release of pollutants from open burning and uncontrolled waste.
(x) *Industrial Upgrades and Best Practices*: Industries are encouraged to adopt pollution control technologies and best practices to minimize emissions. Regular inspections ensure compliance with emission standards.
(xi) *Public Awareness and Education*: Governments conduct public awareness campaigns to educate citizens about air quality issues, the health impacts of pollution, and individual actions they can take to reduce emissions.
(xii) *Research and Innovation*: Supporting research and innovation in pollution control technologies and sustainable urban planning leads to the development of more effective and efficient solutions.

Renewable Energy Promotion and Energy Efficiency Measures Renewable energy promotion and energy efficiency measures are two crucial components of sustainable energy transition and environmental protection (Del Río, 2010; Marques & Fuinhas, 2011). These strategies aim to reduce greenhouse gas emissions, enhance energy security, and mitigate the adverse effects of climate change.

Renewable Energy Promotion: Renewable energy sources, such as solar, wind, hydroelectric, geothermal, and biomass, are abundant and have a significantly lower carbon footprint than fossil fuels (Rahman et al., 2022). Promoting renewable energy involves various initiatives and policies to increase the share of renewable sources in the energy mix described in Table 15.1.

Energy Efficiency Measures: Energy efficiency measures focus on optimizing energy use to reduce consumption and waste (Nižetić et al., 2019). These measures are critical in lowering greenhouse gas emissions and reducing dependence on energy-intensive resources. The details are presented in Table 15.2.

Air Quality Standards in India In India, air quality standards are set and regulated by the Central Pollution Control Board (CPCB) under the Air (Prevention and Control of Pollution) Act, 1981 (Mahato et al., 2020). These standards define the permissible limits of various air pollutants to safeguard public health and the environment. India follows ambient air quality standards, which specify the maximum allowable concentration of pollutants in the outdoor air. The National Ambient Air Quality Standards (NAAQS) in India cover a range of pollutants, including particulate matter (PM10 and $PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO), ammonia (NH_3), lead (Pb), and benzene (Agrawal et al., 2021; Singh et al., 2010). The NAAQS in India is based on the World Health Organization (WHO) guidelines and takes into account the health impacts of air pollution (Beig et al., 2010). The standards are divided into different categories, such as industrial, residential, rural, and ecologically sensitive areas, with varying permissible limits depending on the severity of pollution and the sensitivity of the location. The National Ambient Air Quality Standards (NAAQS) followed in India are given in Table 15.3. The timeline of air quality regulations in India is presented in Fig. 15.3.

Table 15.1 Description of initiatives and policies to promote renewable energy

Renewable energy promotion	Description
Incentives and subsidies	Governments provide financial incentives, tax breaks, and subsidies to encourage investments in renewable energy projects. These measures make renewable energy more economically viable and attract private-sector participation
Renewable portfolio standards (RPS)	RPS mandates require utilities to generate a certain percentage of their electricity from renewable sources. Compliance with RPS regulations ensures a steady growth of renewable energy in the energy portfolio
Feed-in tariffs (FIT)	FIT programs provide fixed, premium prices for renewable energy producers, guaranteeing a stable revenue stream and encouraging the development of renewable energy projects
Net metering	Net metering allows renewable energy producers, such as rooftop solar panel owners, to sell excess electricity back to the grid, incentivizing small-scale renewable energy generation
Public–private partnerships	Collaborative efforts between governments, private companies, and nongovernmental organizations accelerate the deployment of renewable energy projects and share resources and expertise

Table 15.2 Details of energy efficiency measures

Energy efficiency measures	Description
Energy-efficient building codes	Governments establish energy-efficient building standards that mandate the use of energy-saving technologies and materials in construction, promoting sustainable infrastructure
Energy audits	Conducting energy audits in industries, buildings, and institutions helps identify energy inefficiencies and implement energy-saving measures
Energy-efficient appliances and lighting	Encouraging the use of energy-efficient appliances, LED lighting, and smart technologies reduces energy consumption in households and commercial establishments
Industrial process optimization	Implementing energy-efficient practices and upgrading industrial processes reduces energy waste and enhances productivity
Demand-side management	Demand-side management programs encourage consumers to shift energy usage during off-peak hours or curtail consumption during periods of high demand, reducing strain on the grid
Energy-efficient transportation	Promoting fuel-efficient vehicles, public transportation, and electric mobility reduces energy consumption and air pollution from transportation
Training and capacity building	Educating consumers, businesses, and industries about energy-efficient practices fosters a culture of energy conservation

15.5 Water Pollution Control Measures

Water pollution control measures are crucial for preserving freshwater sources, protecting aquatic ecosystems, and ensuring access to clean drinking water (Gleick, 1998). Governments and communities worldwide implement a range of strategies to prevent, reduce, and remove pollutants from water bodies. Wastewater treatment plays a central role in this effort, utilizing advanced processes such as biological treatment and membrane filtration to remove organic matter and harmful substances before discharge (Gunatilake, 2015). Managing nutrient runoff, particularly nitrogen and phosphorus, is vital to combat algal blooms and eutrophication (Zhang et al., 2008). Industrial regulations ensure that industries treat their effluents and adhere to strict discharge standards, limiting the release of harmful chemicals and heavy metals. Additionally, stormwater management with green infrastructure reduces urban runoff pollution. Source water protection efforts, such as riparian zone management, safeguard water quality at its origin, while comprehensive watershed management addresses nonpoint source pollution (Shepard, 2006). Groundwater protection involves managing land use in recharge areas and regular monitoring to detect contamination. Educating the public about the impact of water pollution and individual responsibilities is essential for long-term sustainable water management. International cooperation is necessary to address transboundary water pollution issues effectively (Uitto & Duda, 2002). Investing in research and innoation supports the development of advanced water treatment technologies and sustainable management practices. By implementing these comprehensive water

Table 15.3 National Ambient Air Quality Standards (NAAQS) followed in India

Air quality parameter	Permissible limits
Particulate matter (PM_{10})	Annual average: 60 μg/m^3
	24-h average: 100 μg/m^3
Particulate matter ($PM_{2.5}$)	Annual average: 40 μg/m^3
	24-h average: 60 μg/m^3
Sulfur dioxide (SO_2)	Annual average: 20 μg/m^3
	24-h average: 50 μg/m^3
Nitrogen dioxide (NO_2)	Annual average: 40 μg/m^3
	24-h average: 80 μg/m^3
Ozone (O_3)	8-h average: 100 μg/m^3
Carbon monoxide (CO)	8-h average: 2 mg/m^3 (1.7 ppm)
	1-h average: 4 mg/m^3 (3.4 ppm)
Ammonia (NH_3)	Annual average: 100 μg/m^3
	24-h average: 400 μg/m^3
Lead (Pb)	Annual average: 0.5 μg/m^3
	24-h average: 1 μg/m^3
Benzene	Annual average: 5 μg/m^3
	24-h average: 10 μg/m^3

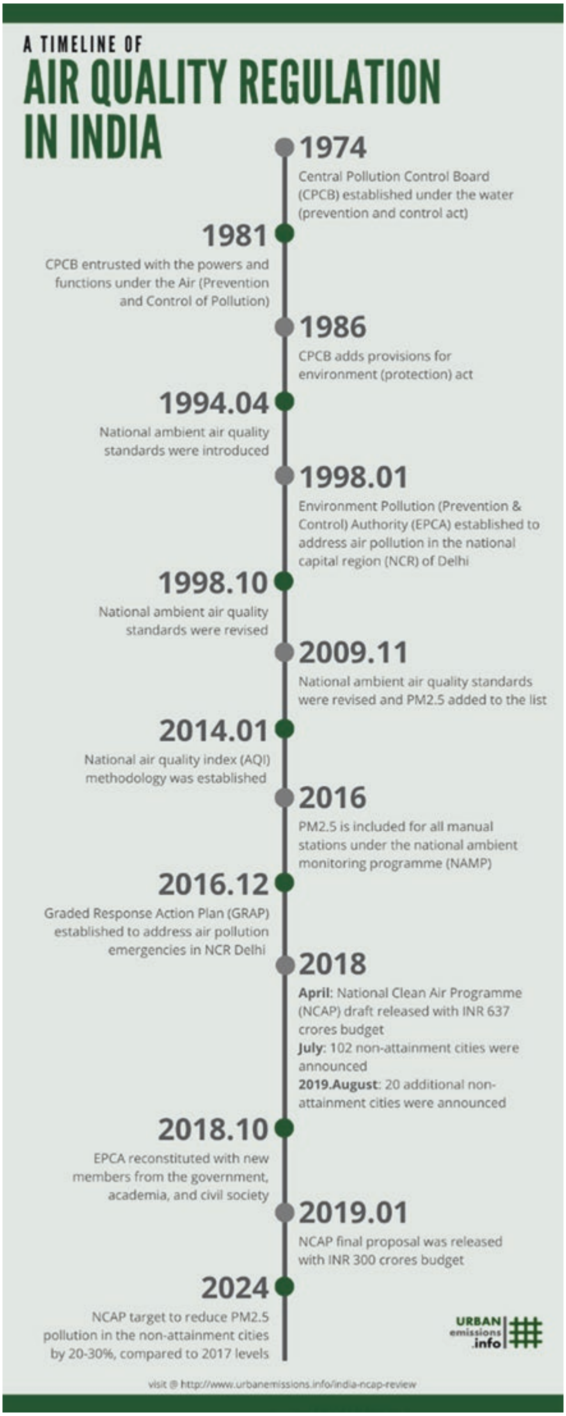

Fig. 15.3 A timeline of air quality regulation in India. (Source: Urban emissions. Info, 2021)

pollution control measures, societies can secure clean and healthy water resources, ensuring a sustainable future for all.

Clean Ganga Mission (Namami Gange): The Clean Ganga Mission, also known as Namami Gange, is a flagship program launched by the Government of India in 2014 with the aim of rejuvenating the river Ganga (Ganges) (Simon & Joshi, 2022). The mission's primary objective is to restore and conserve the ecological and cultural significance of the Ganga River basin, promote sustainable water resource management, and improve the overall quality of river water. Namami Gange has witnessed significant progress in its efforts to clean and rejuvenate the Ganga River (Sharma & Shekhar, 2021). However, it remains an ongoing and challenging task due to the complex nature of river pollution and the need for long-term sustainable management. The mission reflects the government's commitment to conserving one of India's most revered rivers, ensuring that its cultural heritage and ecological significance are preserved for future generations. The components and strategies of the Namami Gange program include the following:

(i) *Wastewater Treatment*: One of the primary focuses of the mission is to set up and upgrade sewage treatment infrastructure in cities and towns along the Ganga River. This helps in treating domestic and industrial wastewater before it is discharged into the river, significantly reducing pollution levels.
(ii) *Riverfront Development*: The mission includes plans for the beautification and development of riverfronts to enhance public access and promote tourism while ensuring ecological sustainability.
(iii) *Afforestation and Biodiversity Conservation*: Plantation drives and biodiversity conservation efforts are undertaken to restore and protect the natural habitats along riverbanks, promoting the ecological health of the river basin.
(iv) *Industrial Effluent Control*: Strict regulations and standards are enforced on industries located near the Ganga River to ensure proper treatment of their effluents, preventing industrial pollution.
(v) *Public Awareness and Participation*: The Clean Ganga Mission involves public awareness campaigns to engage citizens in conservation efforts and encourage responsible behavior toward the river.
(vi) *River Surface Cleaning*: The mission includes regular cleaning drives to remove floating debris and solid waste from the river surface to improve its visual appeal and environmental condition.
(vii) *Geospatial Monitoring*: The use of geospatial technology and real-time data monitoring is employed to track pollution sources and assess the progress of the mission.
(viii) *Innovation and Research*: Research and innovation are promoted to develop sustainable solutions and technologies for river conservation.
(ix) *International Collaboration*: To address transboundary pollution challenges, the Clean Ganga Mission collaborates with neighboring countries sharing the Ganga River basin.

Industrial Effluent Treatment and Discharge Standards: Industrial effluent treatment and discharge standards are crucial regulations set by governments to manage the release of industrial wastewater into the environment. These standards are designed to protect water bodies, prevent water pollution, and ensure the well-being of human health and the ecosystem. The specific standards may vary from country to country or regionally based on local environmental conditions and industrial activities. However, common components of these standards include limits on various pollutants, such as suspended solids, biochemical oxygen demand (BOD), chemical oxygen demand (COD), nitrogen compounds, phosphorus, heavy metals, and toxic substances. pH and temperature ranges are also specified to prevent drastic changes in water quality due to effluent discharge (Kanu & Achi, 2011). Controlling the amount of oxygen-consuming organic matter and total suspended solids in effluents helps maintain dissolved oxygen levels in water bodies, which are vital for aquatic life. To prevent excessive dilution of pollutants, some standards may set dilution ratios relative to the volume of receiving water bodies.

In India, industrial effluent treatment and discharge standards are regulated by the Central Pollution Control Board (CPCB) and State Pollution Control Boards (SPCBs) under the Water (Prevention and Control of Pollution) Act, 1974, and the Environment (Protection) Act, 1986 (Rajaram & Das, 2008). These standards aim to control and manage the release of industrial wastewater to protect water quality, aquatic ecosystems, and public health. The industrial effluent treatment and discharge standards in India cover various parameters, including the physical, chemical, and biological characteristics of the effluents. The CPCB and SPCBs regularly monitor industrial discharges and enforce compliance with the effluent treatment and discharge standards. Noncompliance may lead to penalties, closure of facilities, or legal actions.

Some key parameters and their permissible limits for industrial effluents in India are described in Table 15.4.

Municipal Wastewater Management Municipal wastewater management is a crucial process that involves the collection, treatment, and disposal of wastewater generated from residential, commercial, and institutional sources within a city or municipality. This comprehensive management approach is essential to protect public health, prevent water pollution, and maintain the ecological balance of natural water bodies. The process starts with the collection system, which gathers wastewater through a network of underground pipes and sewer systems and transports it to treatment plants. At these plants, the collected sewage undergoes a series of treatment processes, including physical, chemical, and biological methods, to remove contaminants and pollutants (Elbeshbishy & Okoye, 2019) (Fig. 15.4). Primary treatment separates large solids and debris, while secondary treatment employs microorganisms to breakdown organic pollutants, significantly reducing harmful substances. Some advanced plants implement tertiary treatment to further enhance effluent quality. Sludge generated during treatment is also managed, reducing its volume and stabilizing it for safe disposal or beneficial reuse (Ahmad et al., 2016).

Table 15.4 Parameters and their permissible limits for industrial effluents in India

Parameters	Limits
pH	The permissible pH range for industrial effluents is generally between 6.0 and 9.0
Total suspended solids (TSS)	The maximum limit for TSS in industrial effluents varies depending on the industry but is generally in the range of 100–600 milligrams per liter (mg/L)
Biological oxygen demand (BOD)	The BOD limit varies depending on the type of industry but typically ranges from 30 to 350 mg/L
Chemical oxygen demand (COD)	The COD limit also varies for different industries and is typically between 250 and 2500 mg/L
Temperature	The maximum permissible temperature of industrial effluents for discharge varies depending on the receiving water body but is generally approximately 40 °C
Oil and grease	The permissible limit for oil and grease in industrial effluents is generally in the range of 10–50 mg/L
Heavy metals	Specific limits are set for various heavy metals such as lead, cadmium, chromium, mercury, and arsenic, depending on the industry and type of effluent

The treated effluent is either discharged into nearby water bodies in compliance with water quality standards or reused for nonpotable purposes such as irrigation and industrial processes. Additionally, municipal wastewater management focuses on resource recovery, harnessing nutrients and biogas for agricultural use, and energy production. Regular monitoring ensures compliance with discharge standards and tracks treatment effectiveness. Integrated planning is crucial to address future challenges, promote sustainability, and optimize resource utilization, making municipal wastewater management an indispensable component of responsible urban development.

Rainwater Harvesting and Water Conservation Initiatives in India In India, rainwater harvesting and water conservation initiatives (Glendenning et al., 2012) have gained significant importance due to the country's water scarcity challenges and increasing demand for water resources (Pani et al., 2021). The government, along with various organizations and communities, has been actively promoting these initiatives to address water shortages and ensure sustainable water management. Rainwater harvesting and water conservation initiatives carried out in India are presented in Table 15.5. In addition, various rainwater harvesting and water conservation initiatives have been implemented to address water scarcity and promote sustainable water management. Community-driven rainwater harvesting projects have gained momentum, encouraging collective efforts toward water conservation and efficient water resource management. Additionally, industries are adopting water recycling and reuse systems to reduce freshwater consumption and minimize wastewater discharge. In urban areas, cities are implementing rainwater harvesting policies and offering incentives to promote rainwater harvesting in buildings and public spaces. To raise awareness about water conservation practices, public

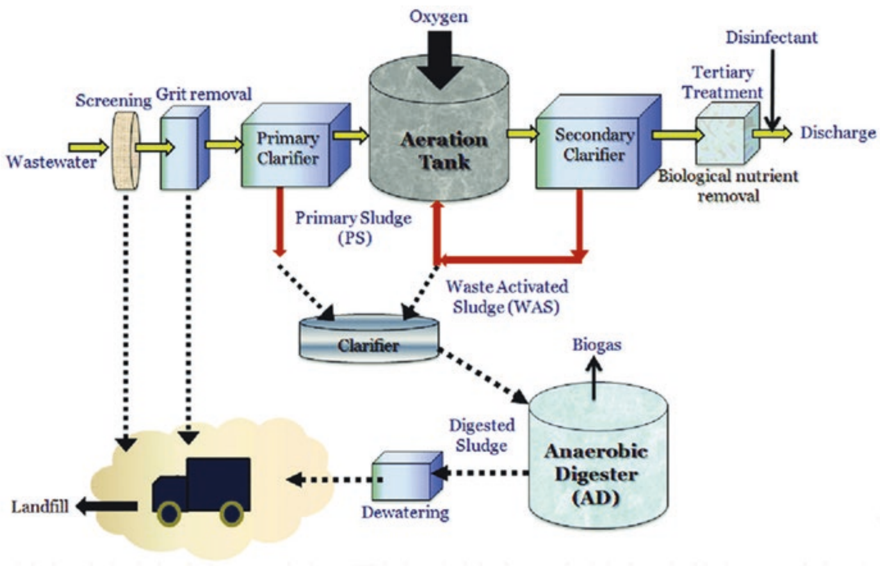

Fig. 15.4 Wastewater treatment process. (Source: Elbeshbishy & Okoye, 2019)

awareness campaigns, workshops, and seminars are regularly conducted, educating citizens about the significance of sustainable water use. The government has played a significant role by introducing regulations and incentives to encourage rainwater harvesting and water conservation in residential, commercial, and industrial sectors. Educational institutions also actively participate in fostering responsible water use by incorporating water conservation into their curriculum and organizing awareness activities for students. In some regions, water budgeting systems have been adopted to manage water allocation and consumption based on available resources and needs. These combined efforts are essential for achieving water security and environmental sustainability and ensuring a more water-resilient future for India.

15.6 Soil Pollution Control Measures

Soil pollution control measures are essential to prevent and mitigate the contamination of soil by pollutants and hazardous substances. Regular soil testing and monitoring are conducted to identify the presence of pollutants. Source control measures focus on reducing or eliminating the use of hazardous chemicals in various activities. Proper hazardous waste management and secure landfill design help prevent soil contamination from improper waste disposal. Additionally, adopting sustainable agricultural practices and promoting soil conservation techniques contribute to maintaining soil health and fertility, safeguarding ecosystems, and ensuring a

Table 15.5 Rainwater harvesting and water conservation initiatives in India

Rainwater harvesting and water conservation initiatives	
Jal Shakti Abhiyan	Launched by the Government of India, the Jal Shakti Abhiyan is a nationwide campaign to raise awareness about water conservation and promote water-saving practices. The campaign emphasizes rainwater harvesting, groundwater recharge, and water resource management at the community level
Traditional water harvesting methods	India has a rich history of traditional water harvesting techniques like "Johads" in Rajasthan, "Kunds" in Gujarat, and "Bawdis" in Karnataka. These ancient practices have been revitalized and incorporated into modern water conservation efforts
Water conservation in agriculture	The "Per Drop More Crop" initiative promotes water-efficient agricultural practices, such as drip and sprinkler irrigation, and encourages farmers to adopt water-saving technologies
Watershed development projects	Government and nongovernmental organizations undertake watershed development projects to enhance rainwater infiltration, soil moisture conservation, and groundwater recharge
Roof rainwater harvesting	Many urban and rural households in India have adopted rooftop rainwater harvesting systems, which involve capturing rainwater from rooftops and storing it in tanks for domestic use and groundwater recharge

healthy environment for future generations (Montanarella & Vargas, 2012; Ronchi et al., 2019).

Soil Contamination Sources and Prevention Measures
Soil contamination can arise from various sources, including industrial activities, agricultural practices, improper waste disposal, and urban development (Havugimana et al., 2017; Zwolak et al., 2019). Industrial processes, such as mining, manufacturing, and chemical production, may release harmful chemicals and heavy metals into the soil (Wuana & Okieimen, 2011). Agricultural activities, such as the use of pesticides, fertilizers, and livestock waste, can also contribute to soil pollution. Improper disposal of hazardous waste and sewage sludge, as well as urban runoff containing pollutants, are additional sources of soil contamination.

Prevention measures for soil contamination involve a combination of regulatory actions, best practices, and public awareness. Implementing strict regulations and monitoring systems to control industrial emissions, waste disposal, and agricultural chemical use is crucial. Encouraging the adoption of sustainable agricultural practices, such as organic farming and integrated pest management, reduces the use of harmful chemicals and their impact on soil (Lefebvre et al., 2015). Proper management and treatment of hazardous waste, along with the promotion of recycling and safe disposal methods, prevent soil pollution. Additionally, urban planning that includes green spaces, permeable surfaces, and stormwater management systems helps mitigate urban runoff and its potential impact on soil quality. Public awareness and education campaigns play a vital role in fostering responsible waste management and soil conservation practices, contributing to the prevention of soil contamination. Addressing soil pollution necessitates more than just a firm stance

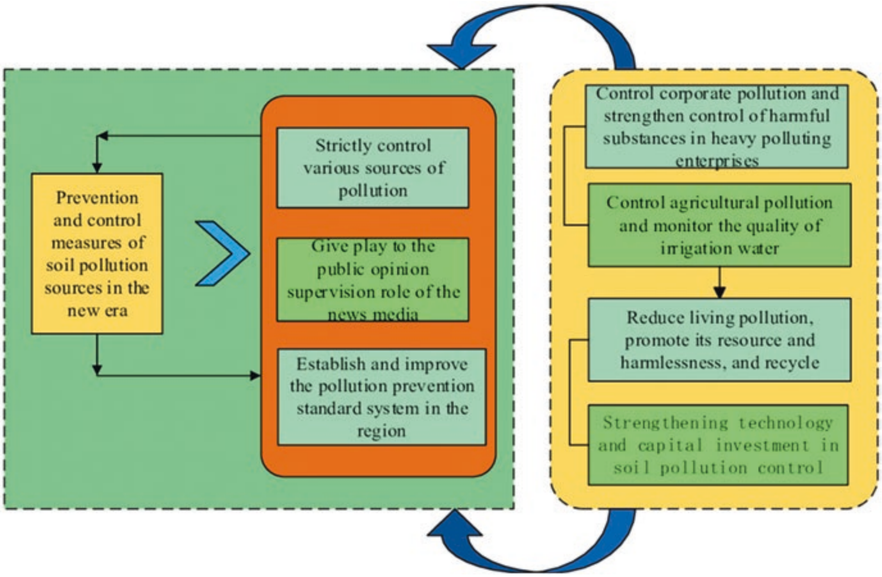

Fig. 15.5 Prevention and control measures of soil pollution by Guo et al., 2020. (Source: Guo et al., 2020)

from the government; it also calls for public awareness and concern regarding the issue of soil pollution (Guo et al., 2020) (Fig. 15.5).

Soil Remediation Technologies and Best Practices

Soil remediation technologies and best practices are essential for restoring and improving soil quality in areas affected by contamination (Azhar et al., 2022). Soil remediation is often a complex and site-specific process that requires careful planning, assessment, and implementation. A combination of remediation technologies and best practices tailored to specific contaminants and site conditions is crucial for successful soil restoration and sustainable land use. Various techniques are employed to remove, reduce, or neutralize pollutants, depending on the type and extent of contamination. Some common soil remediation technologies and best practices include the following (Ma et al., 2016):

(i) *Bioremediation*: This process uses microorganisms to breakdown or transform contaminants into less harmful substances. Bioremediation can be performed in situ (in the soil) or ex situ (outside the soil), depending on the specific situation.

(ii) *Phytoremediation*: Phytoremediation involves using plants to remove, stabilize, or degrade contaminants. Certain plants can absorb and accumulate pollutants, which can then be harvested and properly disposed of.

(iii) *Soil Vapor Extraction (SVE)*: SVE is a technique used to remove volatile organic compounds (VOCs) from the soil by applying a vacuum to extract the vapors from the soil.

(iv) *Soil Washing*: Soil washing is a physical separation process that uses water or other solutions to wash and separate contaminants from soil particles.
(v) *Thermal Desorption*: This method applies heat to the contaminated soil to volatilize the contaminants, which are then collected and treated.
(vi) *In Situ Chemical Oxidation (ISCO)*: ISCO involves injecting chemical oxidants into the soil to chemically degrade contaminants.
(vii) *Stabilization/Solidification*: This method involves adding materials to the contaminated soil to stabilize or solidify the pollutants, reducing their mobility and toxicity.
(viii) *Electrokinetic Remediation*: Electrokinetic remediation uses an electric field to move contaminants in the soil toward specific electrodes, where they can be collected for treatment.
(ix) *Encapsulation*: Encapsulation involves covering the contaminated soil with impermeable materials to prevent the spread of pollutants.
(x) *Soil Amendments*: Adding soil amendments, such as organic matter, lime, or activated carbon, can help improve soil structure and reduce the availability of contaminants.
(xi) *Proper Waste Management*: Implementing proper waste management practices prevents further soil contamination by ensuring safe disposal of hazardous materials.
(xii) *Environmental Site Assessment (ESA)*: Conducting an ESA before remediation helps identify the extent and nature of soil contamination, guiding the selection of appropriate remediation technologies.
(xiii) *Monitoring and Post-remediation Assessment*: Regular monitoring during and after remediation ensures the effectiveness of the chosen techniques and verifies that the soil meets acceptable cleanup standards.

Agricultural Practices for Soil Health Improvement Improving soil health is vital for sustainable agriculture and ensuring the long-term productivity of farmland. Several agricultural practices can help enhance soil health and fertility, such as crop rotation, cover cropping, reduced tillage or no-tillage farming, organic matter management, green manure, mulching, nutrient management, integrated pest management (IPM), agroforestry (Fig. 15.6), soil pH management, irrigation management, crop residue management, soil testing and monitoring, and livestock integration (Balota et al., 2003; Ehler, 2006; Wade & Sanchez, 1983; Zikeli & Gruber, 2017). Several agricultural practices to enhance soil health and promote sustainable farming practices are described in Table 15.6.

In India, improving soil health is of utmost importance due to the country's heavy reliance on agriculture for food security and livelihoods. Several schemes and initiatives have been introduced by the government of India to promote agricultural practices for soil health improvement. These schemes aim to enhance soil fertility, water retention, and overall soil health. Some of the notable schemes for agricultural practices for soil health improvement in India are as follows:

(i) *Soil Health Card Scheme (SHCS)*: Launched in 2015, this scheme provides farmers with personalized soil health cards that contain information about the nutrient status of their soil and recommendations for appropriate nutrient management practices. It helps farmers make informed decisions regarding fertilizers and soil amendments, leading to improved soil health.
(ii) *Paramparagat Krishi Vikas Yojana (PKVY)*: This scheme encourages farmers to adopt organic farming practices and traditional agricultural methods. It promotes the use of organic manures, green manure, and biofertilizers to enhance soil fertility and reduce chemical input usage.
(iii) *Rashtriya Krishi Vikas Yojana (RKVY)*: Under this scheme, financial assistance is provided to states and union territories to support various agricultural development projects, including those aimed at improving soil health through sustainable practices.
(iv) *National Mission on Sustainable Agriculture (NMSA)*: NMSA focuses on promoting climate-resilient and sustainable agricultural practices. It encourages the adoption of integrated nutrient management, crop residue management, and organic farming to improve soil health.
(v) *Sub-Mission on Agricultural Mechanization (SMAM)*: This scheme aims to increase farm mechanization and implement the practice of residue management. It helps retain crop residues on the field, which enriches soil organic matter and enhances soil health.
(vi) *Pradhan Mantri Krishi Sinchayee Yojana (PMKSY)*: PMKSY promotes efficient water management practices, such as drip irrigation and sprinkler irrigation, to prevent waterlogging and soil degradation.
(vii) *National Food Security Mission (NFSM)*: While primarily focused on increasing food grain production, NFSM also encourages the adoption of improved agricultural practices that positively impact soil health.

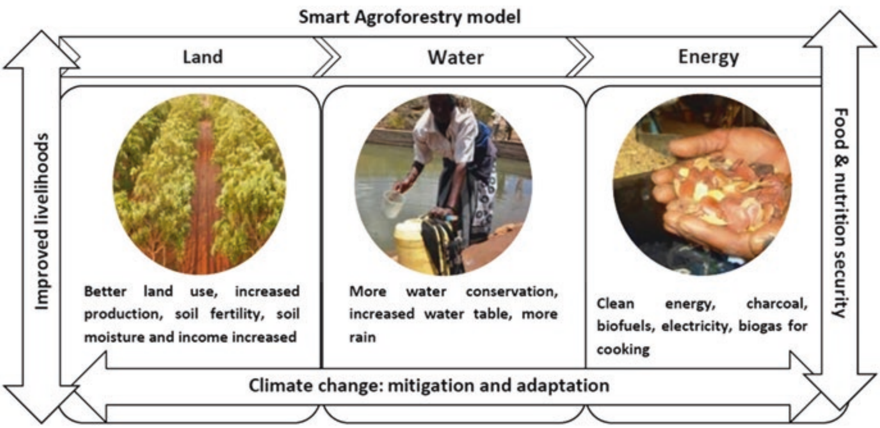

Fig. 15.6 Smart agroforestry model presenting an integrated approach to address both energy and food security concerns. (Source: Sharma et al., 2016)

Table 15.6 Agricultural practices to enhance soil health and promote sustainable farming practices

Practice	Description
Organic farming	Organic farming methods, which avoid the use of synthetic chemicals, focus on enhancing soil fertility through the application of organic matter, compost, and green manure
Crop rotation	Farmers in India practice crop rotation to break pest and disease cycles, improve soil structure, and maintain soil health
Cover cropping	Planting cover crops, such as legumes and grasses, during fallow periods or after main crops helps protect the soil from erosion and add nutrients through biomass incorporation
Vermicomposting	Vermicomposting, the use of earthworms to decompose organic waste, is widely used in India to produce nutrient-rich compost for soil enrichment
Integrated nutrient management	A balanced approach to nutrient management is followed, combining chemical fertilizers, organic manures, and biofertilizers to improve soil fertility
Integrated Pest Management (IPM)	IPM practices are employed to reduce reliance on chemical pesticides, promote natural pest control, and preserve soil health
Water management	Efficient irrigation techniques, such as drip irrigation and sprinklers, are adopted to prevent waterlogging and soil degradation
Sustainable rice-wheat cropping system	In regions with rice-wheat cropping systems, sustainable practices like direct-seeding of rice and residue retention are encouraged to improve soil health
Microbial inoculants	Biofertilizers and microbial inoculants are used to introduce beneficial microorganisms into the soil, promoting nutrient cycling and organic matter decomposition
Nutrient recycling	Farmers in India utilize crop residues, animal manure, and other organic waste to recycle nutrients back into the soil
Zero-tillage or reduced tillage	Adopting zero-tillage or reduced-tillage practices minimizes soil disturbance, reduces erosion, and conserves soil moisture
Mulching	Applying organic mulch or crop residues as mulch helps retain soil moisture, suppress weed growth, and enhance soil health
Agroforestry	Agroforestry systems, combining trees or shrubs with agricultural crops, are practiced to improve soil structure, conserve water, and enhance biodiversity
Soil testing and balanced fertilization	Soil testing is done to assess nutrient levels, and balanced fertilization is practiced to optimize nutrient application based on crop requirements

(viii) *National Mission on Oilseeds and Oil Palm (NMOOP)*: NMOOP promotes oilseed cultivation using sustainable agricultural practices, including organic farming and integrated nutrient management.

Land Reclamation and Restoration Approaches In India, several land reclamation and restoration approaches are implemented to rehabilitate degraded land and restore ecosystems. Afforestation and reforestation initiatives involve massive tree-planting drives to combat deforestation and enhance biodiversity. Watershed development projects aim to conserve degraded land by implementing soil and water conservation measures and rainwater harvesting. Wetland conservation and restoration efforts protect important wetlands and rejuvenate damaged areas. Soil and land remediation techniques, such as bioremediation and phytoremediation, are used to clean up contaminated land. Coastal erosion control measures include beach nourishment and mangrove restoration to protect shorelines and preserve coastal ecosystems. Regenerative agriculture practices, urban green spaces, and river restoration are also adopted to improve soil health, preserve urban biodiversity, and protect aquatic habitats. Community participation plays a crucial role in these initiatives, ensuring the success of land reclamation and restoration projects across the country. In India, several land reclamation and restoration schemes have been implemented by the government to rehabilitate degraded land and restore ecosystems (Dhyani et al., 2023; Shanwad et al., 2008). Some notable schemes include the following:

(i) *Green India Mission (GIM)*: Launched as part of the National Action Plan on Climate Change, GIM aims to increase forest cover, improve ecosystem services, and enhance carbon sequestration through afforestation and reforestation activities.
(ii) *National Afforestation Programme (NAP)*: This scheme focuses on afforestation and reforestation efforts on degraded forest and nonforest lands to increase green cover and support sustainable forest management.
(iii) *Watershed Development Programme*: Various watershed development schemes are implemented to conserve soil and water resources, enhance agricultural productivity, and promote ecological restoration in rain-fed areas.
(iv) *National Mission for a Green India (GIM-Ganga)*: This mission targets the rejuvenation of the Ganga River basin through afforestation and soil conservation activities to reduce soil erosion and improve water quality.
(v) *National Mission for Sustainable Agriculture (NMSA)*: NMSA promotes climate-resilient and sustainable agricultural practices, including soil health management and organic farming, to enhance agricultural productivity and soil fertility.
(vi) *National Mission on Himalayan Studies (NMHS)*: This mission focuses on restoring degraded lands and conserving biodiversity in the Himalayan region, which is prone to ecological fragility and environmental degradation.
(vii) *National Coastal Zone Management Programme (NCZMP)*: NCZMP aims to conserve and restore coastal ecosystems, including mangroves and wetlands, to protect coastlines and preserve marine biodiversity.
(viii) *Integrated Coastal Zone Management (ICZM) Projects*: ICZM projects are implemented in specific coastal areas to address coastal erosion, restore degraded coastal habitats, and promote sustainable coastal development.
(ix) *National River Conservation Plan (NRCP)*: The NRCP focuses on restoring the water quality of major rivers by implementing pollution control measures and ecosystem restoration activities.
(x) *Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS)*: While not exclusively a land reclamation scheme, MGNREGS

provides employment opportunities to rural communities through various activities, including afforestation, soil and water conservation, and land development.

15.7 Noise Pollution Control Measures

Noise pollution control measures are essential to mitigate excessive and harmful noise levels in the environment, promoting public health and overall well-being (Fig. 15.7). To achieve this, governments set noise regulations and standards for various sources, such as industries, vehicles, construction sites, and commercial establishments, aiming to limit noise emissions to acceptable levels. Proper urban planning and zoning play a vital role in segregating noisy activities from residential areas and sensitive locations such as hospitals and schools. Constructing noise barriers, such as sound walls or berms, along highways or busy roads helps shield nearby communities from traffic noise, while sound insulation in buildings reduces indoor noise levels. Traffic management measures, such as speed limits, the use of quieter pavement materials, and traffic flow optimization, help reduce noise from vehicles. Public awareness campaigns and educational programs inform people about the harmful effects of noise pollution and promote responsible noise behavior (Garg et al., 2021). Technological advancements have led to the development of quieter machinery and equipment for industrial and commercial use, contributing to noise abatement efforts. Regular noise monitoring ensures compliance with regulations, and strict enforcement measures, including penalties for violators, discourage noise pollution. By incorporating these noise pollution control measures, communities can create a quieter and more peaceful environment, enhancing the quality of life for residents and protecting public health.

Noise Standards and Regulations Noise standards and regulations are essential tools used by governments to manage and control noise pollution in various settings (Chauhan et al., 2021). These guidelines aim to protect public health, preserve environmental quality, and ensure a harmonious living environment for residents. Noise standards encompass a wide range of aspects, including ambient noise limits, industrial noise emission standards, vehicle noise regulations, and construction site noise limits. Additionally, they address noise levels from commercial establishments, recreational activities, and aircraft operations. Community noise assessment and mapping help identify high-noise areas, enabling targeted noise reduction efforts. Noise monitoring and enforcement mechanisms are implemented to ensure compliance with the set standards and regulations (Hunashal & Patil, 2012). By adhering to these guidelines, industries, businesses, and individuals can actively contribute to reducing noise pollution, enhancing overall well-being, and fostering a more tranquil and peaceful society.

In India, noise standards and regulations are formulated and enforced by various government authorities to address noise pollution and its impact on public health

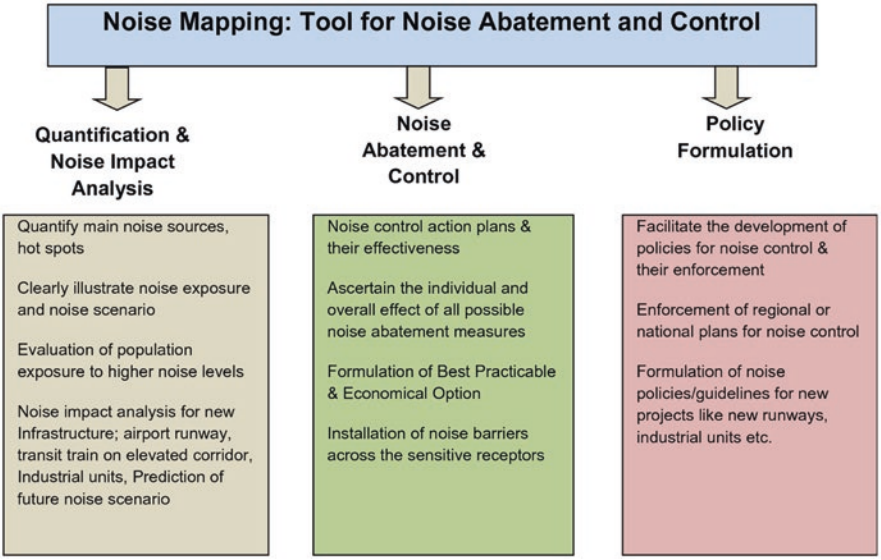

Fig. 15.7 Steps to control noise pollution. (Source: Garg et al., 2021)

and the environment. The key noise standards and regulations in India include the following:

(i) *The Environment (Protection) Rules, 1986*: These rules, under the Environment (Protection) Act, set ambient air quality standards, including permissible noise levels for different zones, such as industrial, commercial, residential, and silence zones. Silence zones are areas near hospitals, educational institutions, and courts where strict noise limits are maintained to ensure a peaceful environment.

(ii) *Motor Vehicle Rules*: India has regulations governing vehicle noise emissions to curb excessive noise from motor vehicles. Vehicle manufacturers must adhere to prescribed noise limits during the design and manufacturing process.

(iii) *Construction and Demolition Activities*: The Central Pollution Control Board (CPCB) issued guidelines for noise levels at construction sites and during demolition activities. These guidelines aim to reduce noise disturbances for nearby residents.

(iv) *Firecracker Regulations*: During festivals and celebrations, noise pollution from firecrackers can become a significant concern. Some states and cities have imposed restrictions on the use of loud or high-decibel firecrackers to limit noise pollution.

(v) *Aircraft Noise Regulations*: The Directorate General of Civil Aviation (DGCA) has guidelines to control aircraft noise during take-off, landing, and taxiing. These measures help reduce the impact of aircraft noise on communities near airports.

(vi) *Indian Standards for Machinery and Equipment*: The Bureau of Indian Standards (BIS) sets noise emission standards for various machinery and equipment used in industries and construction activities.

(vii) *Noise Pollution (Regulation and Control) Rules, 2000*: These rules were formulated to regulate and control noise pollution in specific areas, including residential, commercial, and industrial zones, as well as silence zones. The rules specify permissible noise levels during different times of the day.

(viii) *State-Specific Regulations*: Some states have their own specific noise regulations to address local noise pollution issues, which may be more stringent than national regulations.

International Cooperation and Knowledge Sharing

The preservation of the environment has become a paramount concern for nations worldwide due to increasing population, industrialization, air pollution, deteriorating water quality, and environmental degradation. Countries, including India, actively participate in local and global environmental protection initiatives to address these pressing issues at various levels. At the national and regional levels, India collaborates with institutions such as the Asia-Pacific Network for Environmental Compliance and Enforcement (AECEN) to promote adherence to environmental legal standards and share innovative policies and practices. Additionally, India engages in dialogues facilitated by organizations such as the OECD and AECEN to develop cost-effective enforcement strategies and tools for environmental compliance. The World Bank and the US Environmental Protection Agency (EPA) have also conducted extensive studies evaluating India's environmental compliance, enforcement, and institutional reforms. These efforts aim to enhance effective environmental compliance and enforcement, ensuring a sustainable and greener future for the nation and the world.

15.8 Challenges and Future Prospects

Enforcement and Compliance Enforcement and compliance issues are significant challenges in the realm of environmental pollution control. Despite the existence of regulations and standards, ensuring that industries, businesses, and individuals adhere to these measures can be complex. Inadequate enforcement mechanisms, lack of resources, and bureaucratic hurdles can hinder effective implementation. Noncompliance may result from a variety of factors, such as cost considerations, limited awareness, or a lack of motivation to change established practices. Additionally, the presence of informal or unregulated sectors can further complicate enforcement efforts. To address these challenges, governments need to strengthen enforcement capacities, increase transparency, and streamline regulatory processes. Public awareness campaigns can play a crucial role in educating communities about the importance of pollution control and the consequences of noncompliance. Furthermore, incentivizing compliance through rewards or penalties and fostering collaboration between regulatory agencies, industries, and the public can foster a culture of environmental responsibility and ultimately lead to better enforcement and compliance outcomes.

Technological Advancements and Innovation Technological advancements and innovation hold immense potential for revolutionizing environmental pollution control measures. Rapid developments in various fields, such as renewable energy, waste management, and pollution monitoring, offer promising solutions to address environmental challenges. The integration of cleaner technologies, such as solar and wind energy, can reduce reliance on fossil fuels and mitigate greenhouse gas emissions. Advanced waste treatment technologies, including recycling and waste-to-energy processes, contribute to waste reduction and resource conservation. Smart sensors, drones, and satellite imaging enable real-time pollution monitoring, facilitating data-driven decision-making for better pollution control strategies. Artificial intelligence and machine learning applications can analyze vast amounts of environmental data, providing valuable insights for targeted interventions. Moreover, innovations in green building materials and energy-efficient designs enhance sustainability in construction and urban development. Embracing technology-driven solutions not only improves pollution control efficiency but also boosts economic growth by fostering a green and sustainable industry. Collaboration between governments, research institutions, and the private sector is essential to foster technological advancements and harness innovation for effective environmental protection and sustainable development.

Integration of Pollution Control with Sustainable Development The integration of pollution control with sustainable development is a fundamental approach to achieving long-term environmental protection and balanced socioeconomic growth. Sustainable development aims to meet the needs of the present generation without compromising the ability of future generations to meet their own needs. By integrating pollution control measures into sustainable development strategies, we can address environmental challenges while promoting social equity and economic prosperity. This integration involves adopting environmentally friendly practices across various sectors, such as energy, transportation, agriculture, and industry. For instance, transitioning to renewable energy sources reduces greenhouse gas emissions and air pollution, contributing to both environmental and economic sustainability. Sustainable urban planning emphasizes eco-friendly infrastructure, green spaces, and efficient public transport, creating cities that are less polluted, more livable, and economically vibrant. In agriculture, promoting sustainable farming practices, such as organic farming, agroforestry, and water-efficient irrigation, reduces soil and water pollution, conserves biodiversity, and ensures food security. Integrating waste management with sustainable practices, such as recycling and waste-to-energy technologies, minimizes landfill usage, conserves resources, and reduces pollution. The integration of pollution control with sustainable development also considers the social dimension, ensuring that environmental benefits are equitably distributed among communities. Environmental justice and inclusivity become crucial considerations in the decision-making process. To achieve successful integration, policy coherence and cross-sectoral collaboration are essential. Governments, businesses, civil society, and academia must work together to develop and implement comprehensive strategies that prioritize environmental protection and social well-being while fostering economic growth. Public awareness and education play a vital role in promoting sustainable practices and garnering public support for pollution control efforts. By embracing this holistic approach, societies can create a more resilient and sustainable future where environmental protection, social equity, and economic prosperity go hand in hand, safeguarding the planet for present and future generations.

15.9 Conclusion

In conclusion, environmental pollution control measures are vital for safeguarding the health of our planet and its inhabitants. Recent advancements in technology and innovative approaches offer promising solutions to combat pollution effectively. However, enforcement and compliance issues remain significant challenges that need to be addressed through stronger regulatory measures and public awareness campaigns. Integrating pollution control with sustainable development is a key aspect of creating a harmonious balance between environmental protection, social equity, and economic progress. By adopting cleaner technologies, promoting renewable energy, and implementing sustainable practices in various sectors, we can pave the way for a greener and more sustainable future. International cooperation and knowledge sharing further strengthen global efforts to address environmental challenges and create a healthier planet for all. It is essential that governments, industries, communities, and individuals work together, taking decisive actions to preserve the environment, conserve natural resources, and ensure the well-being of current and future generations. Through collective efforts and a commitment to responsible environmental stewardship, we can create a world where pollution is minimized, ecosystems thrive, and the beauty of our planet endures for generations to come.

The implications of effective environmental pollution control measures extend far beyond immediate benefits. By curbing pollution and adopting sustainable practices, we promote environmental sustainability on multiple fronts. Reduced emissions and pollution lead to improved air and water quality, benefiting human health and biodiversity. Preservation of natural habitats and ecosystems helps maintain ecological balance and protect endangered species. Sustainable land and water management practices contribute to soil health, water conservation, and enhanced agricultural productivity. Moreover, the integration of pollution control with sustainable development fosters economic resilience by promoting green industries and creating green jobs. Embracing environmental sustainability not only secures the well-being of current generations but also ensures a viable and thriving planet for future generations. The commitment to environmental sustainability is a shared responsibility that transcends borders, requiring collective action and collaboration to protect our precious planet and secure a sustainable and prosperous future.

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Chapter 16
Environmental Legislation and Global Initiatives

Aabid Hussain Naqash and Bilal Bashir Bhat

Abstract The environment is comprised of air, water, and land, and it is crucial to ensure that human activities do not pose a threat to the environment from which we derive our food. With the advent of globalization, environmental issues have transcended national boundaries and become transnational in nature. Consequently, the importance of protecting the natural environment has grown significantly in recent decades. Environmental law encompasses a collection of regulations and legal principles that tackle various aspects of the environment, including air and water quality, the preservation of endangered species, and other related matters. At the national level, environmental laws are formulated in the form of acts, rules, and regulations, while at the international level, they take the shape of treaties, protocols, and conventions. Multilateral environmental agreements (MEAs) specifically incorporate or rely on data and information obtained through space-based technologies. Remote sensing, without infringing on legal provisions or violating national sovereignty, can offer a comprehensive range of relevant information synoptically.

Keywords Environmental law · Globalization · Transnational environmental issues · Multilateral environmental agreements · Space-based technologies · Remote sensing

16.1 Introduction

Air, water, and land together form the environment as well as their interaction with one another, with people, with other living beings, and with physical objects. We must ensure that the environment from which we obtain our food is not threatened by human demands that exceed its capacity to sustain both the present and the coming generations. An environmental catastrophe that endangers life on earth has been

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brought on by environmental deterioration, population explosion, extensive urbanization, indiscriminate exploitation of natural resources, etc. Today, key global challenges include conservation, improvement, and protection of the human environment (Kanga et al., 2022). Additionally, environmental issues are becoming transnational as a result of globalization. The global environment is also impacted when the environment of one nation deteriorates. Therefore, it is imperative to think about the possible effects before they turn into absolute problems. The urge to protect the natural environment has increased during the past few decades (Christmann & Taylor, 2002).

16.2 Types of Environmental Legislation and International Agreements

National environmental laws are in the form of acts, rules, regulations, etc. At the international level, it is in the form of treaties, protocols, conventions, etc. Environmental law is a body of rules and laws that address issues including air quality, water quality, threatened and endangered species, and several other aspects of the environment. Environmental legislation aims to control human-nature interactions to lessen environmental dangers and enhance public health. The two pillars of environmental law are management and conservation. The way environmental laws are put into practice largely determines their effectiveness (Gunningham, 2009). An agreement between many governments or enterprises of several countries is known as international law and differs from national laws passed by the government of a single nation, whether they are referred to as treaties, conventions, accords, or variants of these arrangements. Agreements are the written records of legally binding agreements reached between two or more nations (Mitchell, 2003). A treaty, as defined, "is an intercontinental agreement settled between governments in writing and administered by global law" as per the Vienna Convention on the Treaties of Law of 1969. In an agreement, governments affirm their "approval to be bound." A sort of treaty that is legally required under transnational law and that enables us to accomplish conservation goals is an international environmental accord, commonly referred to as an environmental protocol. A convention is a conference or gathering intended to create or consider a generally accepted concept, a framework in which the parties select the key elements. Since the convention's outcome document is given during the conference, the line between a conference and a convention can occasionally be blurred, and the terms are frequently used interchangeably.

United Nations Conference on the Human Environment

It was the first significant conference on global environmental concerns held by the UN and signaled a turning point in the evolution of global environmental politics, known as the Stockholm Conference informally, which took place in June

1972 in Stockholm, Sweden. The Stockholm Assertion, which set forth 26 principles, raised environmental apprehensions to the topmost transnational agenda and motioned the launch of a dialogue between technologically advanced and emerging states regarding the connection between inclusive financial development, contamination of the water and air, and human well-being (Caldwell & Weiland, 1996). The establishment of the UNEP was among the key outcomes of the Stockholm conference.

National Environmental Legislation

Some remarkable efforts at the national level have been made by incorporating amendments into the Indian constitution for the protection and improvement of the environment. Initially, the Indian constitution did not directly provide for the protection of the natural environment. However, after the 1972 United Nations Conference on the Human Environment in Stockholm, the Indian constitution was amended to include environmental protection as a constitutional mandate (Niyati, 2015). After the Stockholm Conference, the Department of Science and Technology established the National Council for Environmental Policy and Planning in 1972 as a regulatory agency to handle environment-related concerns. Following this, the Ministry of Environment and Forest (MoEF) was established in India in 1980. The Ministry of Environment and Forest (MoEF) has overall responsibility for the management and implementation of environmental legislation and policies. The constitutional provisions are backed by several laws, acts, rules, and notifications (Fig. 16.1), and some are as follows:

The Water (Prevention and Control of Pollution) Act, 1974

The Water Prevention and Control of Pollution Act, 1974, was enacted to provide for the following:

(i) Prevention and control of water pollution.
(ii) Maintain or restore the wholesomeness of water purity in the various sources of water.
(iii) It further provides for the establishment of the Centre Pollution Control Board (CPCB) and State Pollution Control Board (SPCB) for the prevention and control of water pollution.
(iv) It empowers CPCB and SPCB authorities to lay down effluent standards for factories discharging pollutants into water bodies.
(v) CPCB and SPCB control sewage and industrial effluent discharge by approving, rejecting, and granting consent to discharge (Yadav, 2016).

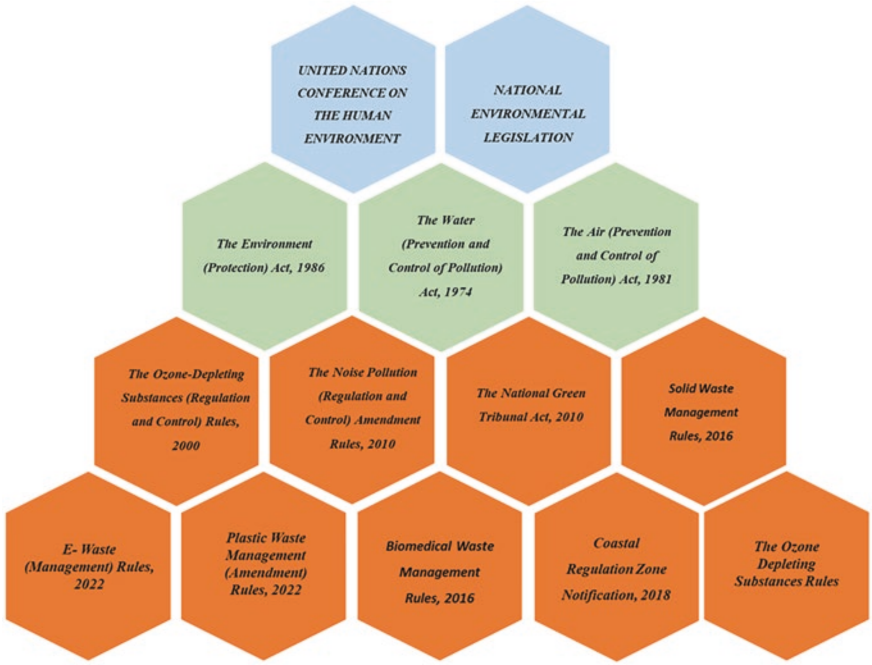

Fig. 16.1 Laws, acts, rules, and notifications for regulation of environmental pollution in India

The Air (Prevention and Control of Pollution) Act, 1981

The act was passed to control air pollution and was subsequently amended in 1987. The Act is an outcome of the Stockholm Conference of 1972. Its main objectives are to:

(i) Prevent, control, and abatement of air pollution.
(ii) Prohibit the use of polluting substances and regulate the appliances that give rise to air pollution.
(iii) Provide for the establishment of CPCB and SPCB to implement the provisions of the act.
(iv) As per the act, the CPCB and SPCB were given the responsibility to:
(v) Stipulate that the sources of air pollution, such as industries and power plants, are not permitted to release particulate matter, CO, CO_2, lead, volatile organic compounds (VOCs), sulfur dioxide, nitrogen oxides, or other toxic substances beyond the permissible limit.
(vi) Allow the state government to identify air pollution areas (Chand, 2018).

The Environment (Protection) Act, 1986

The EPA of 1986 was passed under Article 253 of the Indian Constitution. After the Bhopal gas tragedy in December 1984, this law was passed. It was implemented to achieve the goals of the UN conference on the human environment of the 1972 Stockholm Declaration. Under the EPA of 1986, which mandates a 10 km buffer zone around protected sites, the Ministry of Environment, Forest and Climate change (MoEF&CC) notifies eco-sensitive zones or environmentally vulnerable areas (Agarwal, 2005).

The statutory bodies under the EPA of 1986 are as follows:

(i) Genetic Engineering Appraisal Committee
(ii) National Coastal Zone Management Authority (now National Ganga Council)

The Ozone-Depleting Substances (Regulation and Control) Rules, 2000

The Ozone-Depleting Substances (Regulation and Control) Rules, 2000, and their amendments have been published by the Central Government in the Gazette of India under the Environment Protection Act, 1986. These rules forbid the use of ozone-depleting substances (ODS), such as carbon tetrachloride and methyl chloroform, SFC, CFCs, and halons, *e*xcept for metered-dose inhalers and other medical purposes. The Act sets timelines for the phase-out of several ozone-depleting substances (ODS) and controls the manufacturing, commercial import, and export of goods containing ODS (Weatherhead & Andersen, 2006).

The Noise Pollution (Regulation and Control) Amendment Rules, 2010

Key features of the amendment are as follows:

(i) Loudspeakers, sound systems, or amplifiers should not be used at night except in enclosed spaces such as auditoriums, meeting rooms, community halls, and banquet halls, or during public emergencies (Mangalekar et al., 2012).
(ii) Noise levels in public spaces where loudspeakers or public address systems are being used should not exceed 10 dB or 75 dB of the area's ambient noise standard, whichever is less.
(iii) No horn should be used in the residential area except during an emergency.
(iv) Sound emitted from construction-related equipment shall not be used at night.

The National Green Tribunal Act, 2010

Following the NGT Act of 2010, the National Green Tribunal (NGT) was established on October 18, 2010 as a specialized body for addressing any environmental disputes, including multidisciplinary concerns. It also draws inspiration from Article 21 of the Indian Constitution, which assures a healthy environment for the citizens of India (Shrotria, 2015). Some of the major objectives of the National Green Tribunal (NGT) are as follows:

(i) Effective and expeditious disposal of cases related to the protection and conservation of the environment, forests, and other natural resources.
(ii) To give relief and compensation for any damage caused to persons and properties.
(iii) To handle various environmental disputes that involve multidisciplinary issues.

Plastic Waste Management Rules, 2016

The Plastic Waste Management Rules, 2016, have been published by the government through the MoEF&CC, replacing the preceding Plastic Waste (Management and Handling) Rules, 2011.

(i) Every day, 15,000 tonnes of plastic waste are generated, of which 9000 tonnes are collected and processed, but 6000 tonnes are not collected.
(ii) The updated Waste Management Rules, which will aid in accomplishing the goals of Swacch Bharat and cleanliness as a necessity for health and tourism, include the new Plastic Waste Management Rules.

Solid Waste Management Rules, 2016

The Municipal Solid Waste (Management and Handling) Rules, 2000, have been replaced by these regulations. Its key characteristics consist of the following:

(i) The restrictions now apply to urban agglomerations, census towns, notified industrial townships, and other locations outside of municipal boundaries.
(ii) Waste source segregation has been made mandatory.
(iii) The generator will be required to pay the garbage collection "User Fee" and "Spot Fine" for littering and improper segregation.
(iv) The Ministry of Urban Development (MoUD) is responsible for developing the nation's solid waste management policy and strategy.
(v) The Ministry of Chemicals, Department of Fertilizers, shall support compost commercialization and use.
(vi) They also encourage building waste-to-energy facilities (Sudha, 2008).

E-Waste Management Rules, 2016

(i) The term "electronic waste" refers to old, obsolete, or abandoned electronic appliances.
(ii) The Ministry of Environment, Forests, and Climate Change issued the E-Waste Management Rules, 2016, which replaced the E-Waste (Management & Handling) Rules, 2011.
(iii) Every year, 17 lakh tonnes of e-waste are generated, with an annual increase of 5% in e-waste generation.
(iv) The revised rules provide stricter standards and reflect the government's greater commitment to environmental control.

Biomedical Waste Management Rules, 2016

Important elements of the rules include the following:

(v) The scope of the regulations has been widened to cover any healthcare-related activity, including immunization camps, blood donation camps, and surgery camps.
(vi) Within 2 years, the usage of chlorinated plastic bags, gloves, and blood bags is to be phased out.
(vii) For the purpose of disposal, it aims to create a bar-code system for bags or containers carrying biomedical waste.
(viii) According to the regulations, biomedical wastes are divided into four groups: soiled trash, biotechnology waste, animal anatomical waste, and untreated human anatomical waste.
(ix) The state government is required by law to provide land for the construction of a facility for the treatment and disposal of biomedical waste (Pandey et al., 2016).

Coastal Regulation Zone Notification, 2018

The Ministry of Environment, Forest and Climate change (MOEF&CC) under the Environment Protection Act of 1986 constituted the Shailesh Nayak Committee in June 2014, and based on the committee, CRZ notification 2018 was notified. While the CRZ Rules are made by the union environment ministry, implementation is to be ensured by state governments through their Coastal Zone Management Authorities (Chinnasamy & Parikh, 2021).

The CRZs have been classified into four zones for regulation:

(i) CRZ I – includes ecologically sensitive areas such as mangroves, coral reefs, salt marshes, turtle nesting ground, and the intertidal zone.
(ii) CRZ II – includes areas close to the shoreline that have been developed.
(iii) CRZ III – includes coastal areas that are not substantially built up, including rural coastal areas.
(iv) CRZ IV– includes the water area from the Low Tide Line (LTL) to the limit of the territorial waters of India.

16.3 Global Environmental Initiatives

In order to address global environmental issues, world leaders have signed Multilateral Environmental Agreements (MEAs) (Fig. 16.2) between three or more countries that assist with addressing specific environmental problems at national, regional, and global levels. Examples include the pollution of rivers and seas that are part of several countries (e.g. the Mediterranean Sea or the Great Lakes in the United States and Canada) and air pollution dispersed from one or more countries over several other countries (e.g. sulfur dioxide and dust from power plants in Europe).

These kinds of environmental issues require multilateral action in order to be effective, and MEAs set out the rules describing what each country is expected to do.

The best-known MEAs are those that deal with global problems, such as the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, and the Convention on Biological Diversity.

Key features of MEAs include the following:

- A primary objective is to address one or more clearly defined environmental problems. An MEA may also have a secondary objective, such as poverty reduction or sustainable development.
- They are expressed in written form in a document that is approved by each country's parliament (or similar).
- They are governed by international law.

Some of the global initiatives have been touched upon in the blow sections.

Initiatives Related to Abating the Effects of Climate Change

Rio Earth Summit The Rio Summit, sometimes referred to as the Earth Summit, was a notable UN conference that transpired in Rio de Janeiro, Brazil, in June 1992. The Earth Summit's main motive was to create an inclusive program and worldwide action plan on environmental and development challenges (Conca & Dabelko, 2018). The summit concluded that everyone on earth could achieve knowledge of sustainable development. This summit resulted in the creation of the following documents:

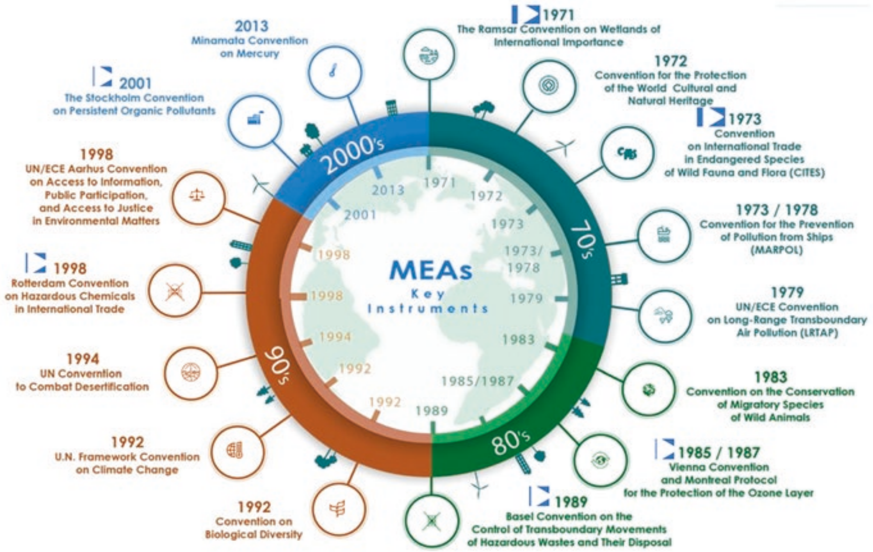

Fig. 16.2 Key multilateral environmental agreements

(i) The United Nations Framework Convention on Climate Change (UNFCCC)
(ii) The Convention on Biological Diversity (CBD)
(iii) The Statement on Forest Principles
(iv) The Rio Declaration
(v) Agenda 21

United Nations Framework Convention on Climate Change (UNFCCC) The UNFCCC was established in Rio de Janeiro, Brazil, in 1992 as a result of the first multinational meeting on climate change, which transpired in Stockholm, Sweden, in 1972. The Earth Summit took place in 1992, and that year witnessed the ratification of the UNFCCC, which was the chief multinational pact and controlling step to contest climate change through its creativities of vindication and adaptation, which aimed at a decrease in the release of greenhouse gases (GHGs), contributing to global warming (Najam & Cleveland, 2005). A total of 197 countries accepted the UNFCCC, which entered into power in 1994. India endorsed the UNFCCC in 1993.

Kyoto Protocol It is an intercontinental pact to diminish the release of greenhouse gases. Nitrous oxide, methane, carbon dioxide, perfluorocarbons, sulfur hexafluoride, and hydrofluorocarbons are greenhouse gases that are covered by the Kyoto Protocol. Industrialized countries are chiefly held responsible for the elevated values of GHG emissions in the Earth's atmosphere (Iwata & Okada, 2014). The Kyoto Protocol was ratified in 2005 after being signed in Kyoto, Japan, in 1997. Phase 1 of the Kyoto Protocol (2005–12) specified an emission reduction target of 5% from 1990 levels, whereas Phase 2 (2013–20) set an emission reduction objective of at least 18% for industrialized countries.

Paris Agreement The Paris Agreement, sometimes referred to as COP 21, is an international climate change treaty that was enacted to diminish and alleviate greenhouse gas emissions. It replaced the earlier climate change pact known as the Kyoto Protocol (Ourbak & Magnan, 2018). It attempts to keep a check on the global average temperature for the current century to considerably less than 2 °C over preindustrial scales by reducing GHG emissions on a worldwide scale. 196 Parties ratified it in Paris on December 12, 2015, and on November 4, 2016, it entered into power.

Ramsar Convention The Ramsar Convention took place in the Iranian city of Ramsar to protect wetlands and their resources. It was ultimately put into operation in 1975. At least 2453 Ramsar sites have been designated globally as of August 2022, covering 255,792,244 hectares, with participation from 171 national governments (Gardner & Davidson, 2011). On February 1st, 1981, the Ramsar Convention entered into force in the country. There are 75 Ramsar sites in India. These wetlands are deemed to be of "international significance" by the Ramsar Convention.

The Ramsar Convention was created with three pillars as its foundation:

(i) Work to ensure that all wetlands are used wisely
(ii) Designate appropriate wetlands on the Ramsar List to manage those wetlands efficiently
(iii) To promote international cooperation for common species, shared wetland systems, and transboundary wetlands

Initiatives Related to the Abatement of Air Quality

Vienna Convention To stop the ozone layer from being destroyed, this convention was established. The ozone layer of the planet is protected by the said Convention and its Montreal Protocol on materials that diminish the ozone layer. The Convention aims to encourage international collaboration by exchanging data on how human activity affects the ozone layer (Sand, 1985). This convention entered into force in 1988 and was completely ratified in 2009. On March 22nd, 1985, 28 nations approved the pact for the first time. India also signed the Vienna Convention. It ratified the agreement in 1991.

Montreal Protocol The said Protocol is a significant global pact that regulates the manufacture, use, and emissions of chemicals that harm the ozone layer. Scientists were able to demonstrate in the late 1970s that chemicals used in air conditioners, refrigerators, and aerosol cans were harming the ozone layer (Levy, 1997). Member states of the UN agreed to avoid ozone layer depletion when they ratified the Vienna Convention in 1985. The Protocol was retained in 1987 and came into power in January 1989.

Initiatives Related to the Protection of Freshwater Resources

Convention on the protection and use of transboundary watercourses and international lakes (ECE water convention) A worldwide environmental agreement, also known as the Water Convention, is one of the five environmental treaties that the UNECE has negotiated. The management and protection of transboundary surface waters and groundwaters are the goals of this convention, which seeks to reinforce national efforts and legislation in these areas. The convention has provisions on information sharing as well as research, monitoring, consultations, development, alarm systems and warning, mutual aid, and access (Contartese, 2017). It became formally enforceable on October 6, 1996, and was made available for signature in Helsinki on March 17, 1992.

Initiatives Related to Protection from Land Degradation/Nature Conservation and Terrestrial Living Resources

UN Convention to Combat Desertification (UNCCD) Its purpose is to lessen the detrimental effects of desertification and drought. The drylands, which are made up of barren, semibarren, and dry submoist regions and are home to some of the most vulnerable ecosystems and inhabitants, are the core focus of the UNCCD (Stringer, 2008). The draft of the convention was made available for signing in 1994. It became effective in 1996 after receiving 50 ratifications. India adopted the Convention to Combat Desertification in December 1996. A comprehensive worldwide commitment to accomplish land degradation neutrality (LDN) is made in the convention's 2018–2030 tactical structure, which aims to:

(i) Reinstate the efficiency of degraded land
(ii) Improving the standard of living for those who depend on them
(iii) Minimizing the effects of droughts on population groups at risk

Initiatives Related to the Management of Hazardous Wastes

Basel Convention The meeting of delegates authorized the Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and the Disposal of Such Wastes in 1989. It aims to guard people and the ecology from the detrimental effects of hazardous waste that is created, managed, and disposed of on a worldwide scale (Kohler, 2017). Legislation was enacted in 1992. The Basel Convention secretariat is headquartered in Geneva, Switzerland. India is a member of the Basel Convention.

Stockholm Convention The meeting of delegates approved the Stockholm Convention in 2001, and the convention entered into force in 2004. It is a global agreement to safeguard substances (persistent organic pollutants) from damaging the health of humans or the environment by remaining in the atmosphere for an extended length of period, becoming largely dispersed in nature, and building up in the fatty tissues of both people and animals. Pesticides, industrial chemicals, and inadvertently created POPs are the three categories of POPs for which worldwide action is required (Hagen & Walls, 2005). India ratified the international agreement in May 2002, and it came into effect in January 2006.

Minamata Convention This convention on Mercury is a global environmental accord that targets protecting human health and the environment from the detrimental effects of mercury and its derivatives. The infamous Minamata disease, which first manifested in the Japanese city of Minamata in the 1950s, was due to industrial wastewater from a chemical factory containing methylmercury (Selin, 2014). Mercury is one of the top ten elements that the World Health Organization (WHO) lists as being of significant public health concern. The pact was executed in 2013 and entered into power in 2017. India ratified the Minamata Convention in 2018 and is a party to it.

Initiatives Related to the Oceans and Seas

London Convention The convention's primary goal is to prohibit careless dumping at sea of waste that might endanger human health and destroy living things and marine life. It includes the deliberate discharge of waste or other materials from ships and platforms into the ocean (Verlaan, 2011). Releases from sources based on land, such as pipelines and channels, are not covered under the convention. It became effective on August 30, 1975, after 15 countries approved it.

International Convention for the Prevention of Pollution of the Sea by Oil A global agreement was reached in London on May 12, 1954. It was amended in 1962, 1969, and 1971. The OILPOL Convention recognized that day-to-day shipboard activities, such as cargo tank washing, were the main contributors to the majority of oil pollution. The discharge of oily waste to the nearby land and in the locality where the surroundings are particularly at risk was prohibited by OILPOL 54 (Cremean & Techera, 2012).

Initiatives Related to Nuclear Safety

Comprehensive Nuclear-Test-Bans Treaty A universal treaty known as the CTBT prohibits the testing of atomic weapons and supplementary nuclear detonations for both armed and unarmed purposes in every condition. It was approved on September

10, 1996, but has not taken effect since eight specific nations have not ratified it (Ghosh, 1996).

Convention on Nuclear Safety The 1994 Convention on Nuclear Safety is a convention that defines safety standards for nuclear power facilities in governments that have accepted it. These include a selection of the location, design and construction, use and safety assurance, and emergency readiness (Kamminga, 1995). The pact was agreed on June 17, 1994, during an IAEA diplomatic meeting in Vienna, Austria. On September 20, 1994, it became available for signature.

16.4 National and International Environmental Organizations and Institutional Framework

At the National Level

The Ministry of Environment and Forest & Climate Change (MoEF&CC) The Ministry of Environment, Forest & Climate Change (MoEF&CC) is the nodal body in the Central Government's administrative structure responsible for organizing, coordinating, and monitoring the execution of the nation's environmental and forestry programs. The ministry's primary initiatives include the preservation and survey of India's flora and wildlife, forests and other wilderness regions, pollution prevention and management, afforestation, and minimizing land degradation (Officer, 2016). Additionally, the Ministry serves as the nation's focal point for the UN Environment Programme (UNEP).

Central Pollution Control Board The Water (Prevention and Control of Pollution) Act of 1974 created the Central Pollution Control Board (CPCB), a governmental organization, in September of that year. Additionally, the CPCB was given authority and responsibilities under the Air (Prevention and Control of Pollution) Act of 1981 (Chand, 2018). It performs the functions of a field formation and offers technical assistance to the Ministry of Environment and Forests on the guidelines set forth in the Environment (Protection) Act of 1986.

At the International Level

Intergovernmental Panel on Climate Change (IPCC) It operates under UN supervision. It was initially recognized in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). The UNFCCC is supported by reports from the IPCC. The IPCC reports provide all the information required to understand the threat posed by man-induced environmental changes, their possible repercussions, and methods for vindication and adaptation (Agrawala, 1998).

United Nations Environment Programme (UNEP) The UN General Assembly founded the UNEP as a result of the UN Conference on the Human Environment, which took place in Sweden. Its main office is in Nairobi (Kenya). UNEP is primarily responsible for coordinating the development of environmental policy, which is used to monitor the status of the environment across the globe (Ivanova, 2010).

World Health Organization (WHO) The WHO's goal is to ensure that every person has the greatest possible level of health. Fighting illness, especially deadly infectious diseases, is its key objective (Jong-Wook, 2003). One of the earliest organizations established by the United Nations, its charter was adopted by the 26th member state on April 7, 1948, the inaugural World Health Day. The WHO has 193 member nations.

International Union for Conservation of Nature (IUCN) The principal universal environmental network in the world is the IUCN. It is an independent membership organization with members exceeding 1000 from government and nongovernmental organizations, together with over 11,000 volunteer researchers from over 160 nations (Haas, 1990). The Union's main office is in Gland, Switzerland. IUCN aims to discover real-world resolutions to the most significant environmental issues.

Worldwide Fund for Nature (WWF) The WWF, previously known as the World Wildlife Fund, is an intercontinental NGO that deals with matters pertaining to environmental protection, research, and restoration (Curry-Lindahl, 1978). It operates in over 90 countries and is backing over 1300 environmental and preservation activities on a worldwide scale, making it the largest independent conservation organization in the world.

Food and Agriculture Organization of the United Nations (FAO) It is a UN organization with member countries that coordinates worldwide efforts to eliminate hunger. The FAO is a way of expertise and knowledge that assists emerging and transitional countries in technologizing and advancing their farming, forestry, etc., ensuring that everyone has access to a nutritious diet and food security (Ruane & Sonnino, 2011).

Global Environment Facility (GEF) The GEF supports national sustainable development initiatives while working with international organizations and the corporate segment to tackle global environmental issues. (GEF) is an organization with complete financial independence and provides funding for programs addressing persistent organic pollutants, international waterways, ozone depletion, land degradation, and biodiversity (Jordan, 1994).

Commission on Sustainable Development (CSD) It was recognized by the General Assembly Resolution in December 1992 to implement an endorsement in Chapter 38 of Agenda 21. It promotes sustainable development via capacity building and technical assistance at the regional, national, and global levels. The historic global agreement was reached at the Rio de Janeiro Earth Summit (Kaasa, 2007).

16.5 Remote Sensing & GIS in Relevance to National & Multinational Environmental Legislation/ Agreements

An unrivaled source of data that conveys environmental changes in a visually appealing manner is the use of remote sensing and GIS. As a result, it is very helpful for increasing awareness and building the political support required to enhance MEAs and environmental legislation. Spatial data on the earth's biophysical systems are becoming necessary as a result of the growth of environmental accords (Peter, 2004). Environmental legislation has a physical connection to space. Much environmental legislation effectively safeguards entire ecosystems, such as protecting endangered species by identifying their habitats or those that require permits for the dredging and filling of wetlands. Multilateral environmental accords (MEAs) specifically include or rely on data and information from space-based technologies, even though over 200 MEAs addressing a wide variety of environmental issues and concerns have been created over the previous few decades.

The use of remotely sensed information for many elements of MEAs has been emphasized by the American Institute of Aeronautics and Astronautics. Earth observation tools can be used for a variety of purposes to assist MEAs, including the detection of new environmental issues, their evaluation and monitoring of conformity testing, and eventual enforcement. Various projects specifically aim to use remote sensing data for environmental treaty needs. The Meso-American Biological Corridor, the Millennium Ecosystem Assessment (MEA) and the Global Monitoring for Environment and Security (GMES) of the European Commission are a few of the more significant (Kuriyama, 2005). At the national level, environmental remote sensing focuses on cutting-edge techniques, tools, and high-impact applications in practical, real-world contexts. It contains sensors for monitoring coastal subsidence, UAV-based data for assessing disaster damage and recovery, high-resolution multispectral data for assessing ecosystem vulnerability and rehabilitation, and hyperspectral data for evaluating and mapping biodiversity. On a modest scale, efforts are being made to investigate remote sensing uses in connection to MEAs, such as tracking carbon sequestration under the Kyoto Protocol (Perez et al., 2007). MEAs can be assisted by Earth observation (EO) information in a variety of ways, including state forest surveys and the use of GIS services. Remote sensing can help with global environmental assessments in support of MEAs by providing timely information on environmental concerns, including carbon-monoxide plumes and the carbon density of ecosystems.

Any effort to track trends in land degradation and desertification must include remote sensing images because it is crucial for understanding how land cover is changing. Estimates of land degradation based on remote sensing data are now present in many country reports submitted to the UN Convention to Combat Desertification. The information generated from satellites may be pertinent to the requirements of biodiversity-related accords such as the CBD and CITES (Huberman, 2009). The main reasons for the decline in biodiversity are loss of habitat and fragmentation. Satellite imagery may be used to properly monitor these factors. The incorporation of satellite data into maps of the appropriateness of animal habitats is another widely used application. The adequacy of habitats for black bears, moose, and waterfowl was assessed using satellite data. Generating vegetation maps employing spatial information and assessing habitat choices and circumstances of animal species utilizing field data are typical approaches for such an undertaking.

The frequent use of satellite data is for the mapping and surveillance of wetlands. Remotely sensed information may therefore be relevant to:

(i) Specify the migratory species habitat and migration path.
(ii) Regular assessments of the migratory species conservation status and the identification of potential threats to that status.

A range of GHG measures that can be entirely or partially acquired using remote sensing are required for the Kyoto Protocol. These include the emissions of nitrous oxide and methane, which are influenced by aspects of the land cover, such as soil moisture, rice paddies, and temperature. The type of land cover, aboveground biomass, and height are all important (Rosenqvist et al., 2003). Since tillage methods and crop varieties can be distinguished from one another by optical vision alone, current RS technology may be more easily used in calculating carbon sequestration in agricultural fields than in forested fields. The main marine aspects of remote sensing are ocean color (and therefore primary productivity) by spectrometers, sea-surface level by altimeters, sea-surface heat by infrared radiometers, and surface roughness by passive and active microwave systems. These in turn pertain to different aspects of maritime agreements that are important. The Global Ocean Observing System (GOOS) is an international tool for utilizing remote sensing to monitor the health of marine ecosystems (Barrerra et al., 2008). Monitoring protocols have been established in accordance with the Bonn Agreement to trace oil spills. SAR pictures have been shown to be helpful for spill assessment because oil slicks alter the roughness of water bodies. SAR has the benefit of being able to cover a large area of the ocean, and it allows for the targeted use of limited surveillance resources in areas where a spill is most definitely suspected to have occurred.

Without breaking the law and without violating national sovereignty, remote sensing may offer a wide variety of pertinent facts synoptically. In the context of agreements such as MEAs that need data on both human behavior and environmental change, remote sensing data have numerous advantageous characteristics.

16.6 Limitations and Problems

At the national level, the lack of coordination among government agencies, poor institutional capacity, lack of information access, corruption, and suppressed citizen involvement are the main causes of the ineffectiveness and inadequate execution of environmental rules. More than two-thirds of the states and union territories in the nation have not bothered to follow the Supreme Court's rulings or the Ministry of Environment, Forests and Climate Change's (MoEF&CC) directives. The efficacy of national and international environmental legislation has been weakened by the complexity of domestic and international affairs. Many aspects of multinational law, especially global environmental law, have a soft status due to concerns about sovereignty (Elliott, 2004). In general, governments are reluctant to hand over control of their internal affairs, inhabitants, and territories to unbiased international organizations. Even after joining international agreements, several nations have included reservations to preserve their right to reject particular clauses. When this ability is exercised, many international agreements suffer a small reduction in overall effectiveness (Gamble, 1980). In January 2019, the UN released a research report, a global assessment of the environmental rule of law. What they witnessed was that, despite a large increase in environmental protection organizations and laws, the global attempt to address a number of environmental challenges has been impeded by a general failure to successfully apply regulations.

16.7 Future Prospects

Environmental preservation and sustainability must become commonplace and an essential component of everything we do if we are going to rescue the earth, nature, and human civilization. It is obvious that we have made less progress toward these objectives in recent years than we did even a decade ago (Ruckelshaus, 1989). More species are on the endangered or extinct list with each passing year. Nature is being altered at an alarming rate by human consumption, and plastics, other waste, and pollutants are overtaking fish in our oceans. Environmental change poses a danger to the ability of the planet to support both humans and natural systems. Fundamentally, we are mismanaging our interaction with the natural world. Since we are all only the property of nature, it is our responsibility to safeguard the environment from harm (Bera et al., 2022). Overall, there is little question that strengthened environmental legislation will be crucial in protecting people and society from the environmental problems that we have caused.

You should keep in mind that there is not a "Planet B" in the entire cosmos, unless you fervently believe in Elon Musk's ambition to make Mars another livable planet.

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