Chapter 4
Air Quality Monitoring Using Geospatial Technology and Field Sensors

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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 ≤ 10 μm (PM_{10}) and ≤ 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,
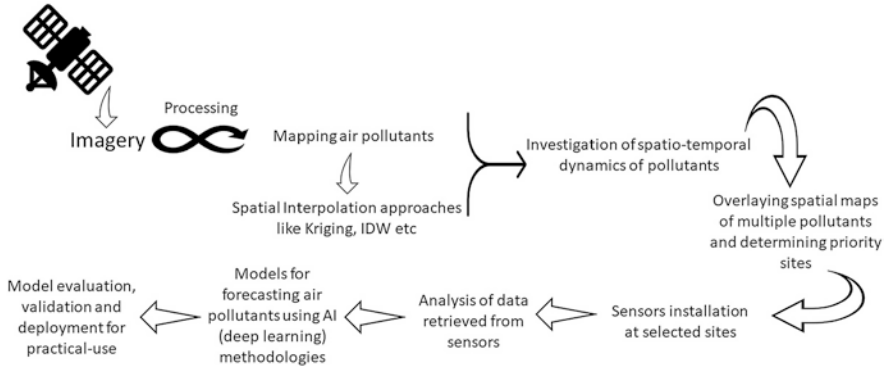
Fig. 4.1 Overview of the geospatial methodology used for air quality monitoring

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
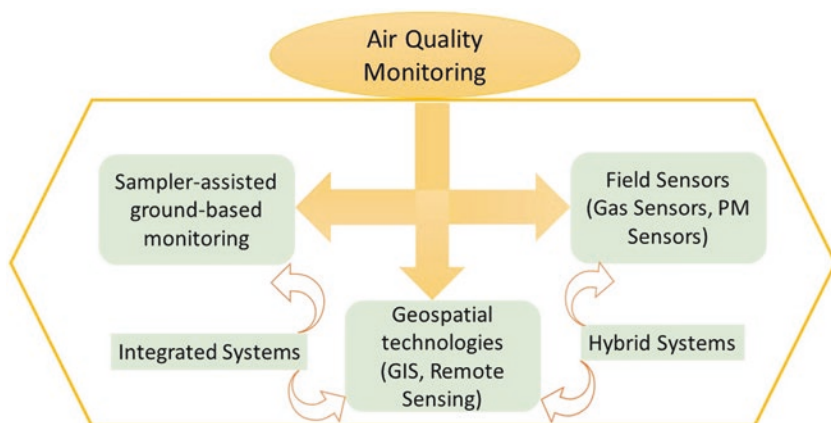
Fig. 4.2 Framework of categorisation of air quality monitoring approaches

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 ($\mu g/m^3$) 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.
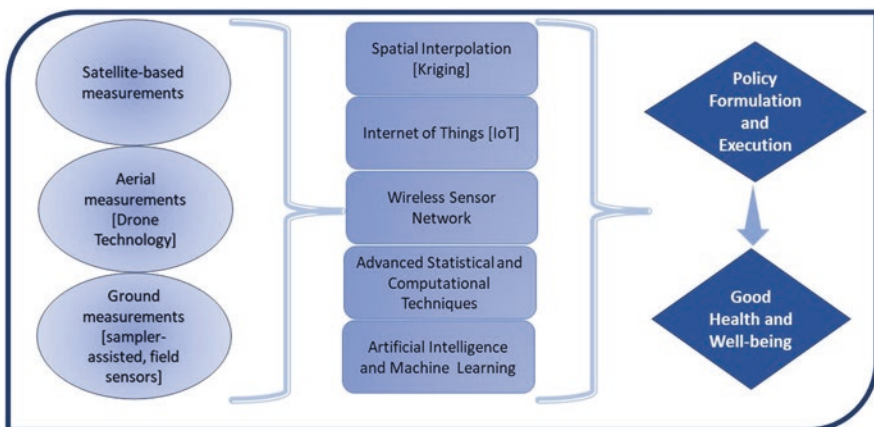

Fig. 4.3 Framework for an integrated system of air quality monitoring

(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.

Conflict of Interest The authors confirm that there are no apparent financial conflicts of interest or personal affiliations that may have potentially impacted the work presented in this chapter.

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