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Unveiling the Surge: Exploring Elevated Air Pollution Amidst the COVID-19 Era (2019–2020) through Spatial Dynamics and Temporal Analysis in Delhi

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Abstract This comprehensive study delves into the complex issue of air pollution in Delhi, with a specific focus on the levels of $PM_{2.5}$, PM_{10}, NO_2, and O_3 during 2019 and 2020 across all four seasons. By analyzing primary data and employing advanced GIS techniques, the research not only quantifies pollution levels before and during the COVID-19 pandemic but also identifies high-risk areas and establishes a clear link between pollution and public health. The study reveals that 2019 witnessed more severe pollution levels compared to 2020, with $PM_{2.5}$ and PM_{10} consistently exceeding WHO guidelines. Notably, PM_{10} levels breached Air Quality Index (AQI) standards, particularly during the winter season when it peaked at 67.99 μg/m^3 and increased post-monsoon due to crop burning. Surprisingly, summer 2019 exhibited $PM_{2.5}$ levels surpassing those of winter, underscoring the impact of reduced vehicle emissions during the summer months, while winter pollution levels remained relatively stable. The COVID-19 lockdowns in 2020 led to a substantial reduction in summer AQI by up to 58.00%, emphasizing the role of human activities in air quality. However, the study also indicates that monsoon AQI varied across different areas, with some experiencing higher emissions. Winter and post-monsoon AQI fluctuated by up to 24%, reinforcing the importance of continuous monitoring and source control measures. This research highlights the crucial role of Geographic Information Systems (GIS) in data analysis and informed decision-making for mitigating air pollution in Delhi. Its findings provide valuable insights for policymakers, offering guidance on promoting sustainability, public health, and a cleaner environment. In summary, the

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integration of GIS-driven pollution mapping aids in understanding and addressing the complex issue of air quality, ultimately contributing to a healthier and more environmentally friendly Delhi.

Keywords Lockdowns · Air Quality · GIS · COVID-19 · Health · Temporal and Spatial Variability · Delhi

1 Introduction

Air pollution stands as a formidable global challenge with far-reaching repercussions for health, the environment, and economies, as underscored by researchers (Kumar et al., 2013; Singh et al., 2020). Notably, certain Indian cities, like Delhi, grapple with soaring pollutant levels, accentuating the urgency of the issue (Kumar et al., 2015a, b). Among the diverse pollutants, fine particulate matter and nitrogen dioxide (NO_2) have emerged with well-defined health impacts Cobbold et al. (2022). Emissions into the atmosphere translate into human exposure via inhalation, ingestion, and skin contact, ultimately accumulating within the body (Ahmadipour et al., 2019). Shockingly, World Health Organization (WHO) data reveal that air pollution led to 7 million deaths in 2012. WHO studies in 124 cities in 2014 exposed elevated levels of microscopic air pollutants. Both PM_{10} and $PM_{2.5}$, fine particulate matter, consistently breached WHO air quality standards across these cities. Alarmingly, $PM_{2.5}$ was linked to 4.2 million premature deaths globally in 2016 (Ghude et al., 2016; Lelieveld et al., 2015; Selvadass et al., 2022; WHO, 2016). Atmospheric inhalable particulate matter amplifies health risks (Pagano et al., 1996; Yin et al., 2021, 2022). Meanwhile, models such as Land Use Regression (LUR) have unveiled connections between spatial distribution and temporal fluctuations, with LUR models explaining up to 60% of $PM_{2.5}$ variation (Xu et al., 2022). Cobbold's cross-sectional study in 2022 gauged perceptions of air quality and long-term exposure, revealing an improved perception of air quality in 2020 compared to 2019, albeit concerns surged in 2020. Beyond particulates, pollutants like SO_x, NO_x, CO, Volatile organic compounds, and polycyclic aromatic hydrocarbons, collectively referred to as the global burden of disease, exact their toll (Blessy et al., 2023; Clifford et al., 2016; Hansen et al., 2009; Sass et al., 2017). WHO assessments underscore the connection between air pollution and a host of ailments including cardiovascular diseases, heart disease, stroke, chronic obstructive pulmonary disease, and lung cancer. Global trends in industrialization, transportation, and other anthropogenic activities have fueled air quality deterioration, disproportionately impacting vulnerable communities (Ban et al., 2023; Chen et al., 2023; Kumar et al., 2022; Patz et al., 2007). With escalating vehicle numbers, metropolitan areas are witnessing escalating air pollution, warranting comprehensive exploration and intervention strategies (Zhou et al., 2022; Gautam & Hens, 2022; Gautam et al., 2021a, b, c). The dry season, marked by anthropogenic emissions, emerges as a critical pollution period (Zhou et al., 2022; Li et al., 2023).

In light of heightened awareness post-COVID-19, it's evident that air quality was a neglected concern. However, individuals residing in areas with elevated pollution face heightened COVID-19 risks, magnifying the urgency of air quality improvements. Delhi's rapid degradation reflects the pressing nature of the issue, driven by factors like industrialization, domestic combustion, and agricultural burning (Gurjar et al., 2016; Tiwari & Colls, 2010; Li et al., 2020; Gautam, 2020a, b). Notable pollutants such as PM, NO_x, CO, SO_2, and O_3 often surpass National Ambient Air Quality Standards (Sharma et al., 2013). A recent study found that the brief COVID-19 lockdown in India led to notable air quality improvements, with PM10 and NO2 decreasing by 40–45% and 27–35%, respectively. However, O3 levels increased by 12–25% (Dubey & Rasool, 2023). The study of AQI is very important for understanding the dynamics, emission and forecast of pollutant, Pradhan and Panigrahi (2023) evaluates the effectiveness of four statistical and twelve machine learning models for Delhi's AQI forecasting. Results show that MLP and ARIMA models outperform others.

Impressively, geoinformation systems play a pivotal role in monitoring temporal variations and spatial distribution of air pollutants, forming the foundation for informed interventions (Nagpure et al., 2015). In this context, this paper aims to unravel the temporal nuances of pollutants and underscore their impacts, all through the lens of Geographic Information System (GIS) technology.

2 Methodology

2.1 Sampling Sites (Study Area)

Our study centers on Delhi, a bustling metropolis inhabited by over 17 million residents. Encompassing an area of approximately 42.7 square kilometers (16.5 square miles) and is situated at an elevation of 216 m (Chattopadhay et al., 2014). Delhi's climate oscillates between a scorching hot semi-arid climate (Köppen BSh) transitioning into a crisp dry-winter humid subtropical climate (Köppen Cwa). This climatic oscillation entails significant fluctuations between summer and winter, characterized by varying temperatures and precipitation patterns. The mercury scales up to a scorching 46 °C (115°F) during summer and plunges to approximately 0 °C (32°F) in the winter months (Hari et al., 2021). Following the classification by the Indian Meteorological Department (IMD), New Delhi experiences four distinct seasons: winter (January to March), pre-monsoon or summer (April to June), monsoon (July to September), and post-monsoon (October to December). The study area, vividly delineated in Fig. 1, falls within this intricate seasonal rhythm. For meticulous geo-referencing of maps, administrative boundary maps of Delhi were employed. Coordinates were scrupulously collected from Google Earth, ensuring precise alignment and representation within the study framework. More details of the topographical and hydrological features of Delhi and the surrounding area have been studied by Joshi et al. (2021).

2.2 Data

The analysis hinges on publicly accessible data sourced from the official online portal of the Central Pollution Control Board (CPCB), specifically the Central Control Room for air quality management across India (https://app.cpcbccr.com/). In this pursuit, we systematically examined the temporal shifts in the average air quality levels during the summer, winter, monsoon,

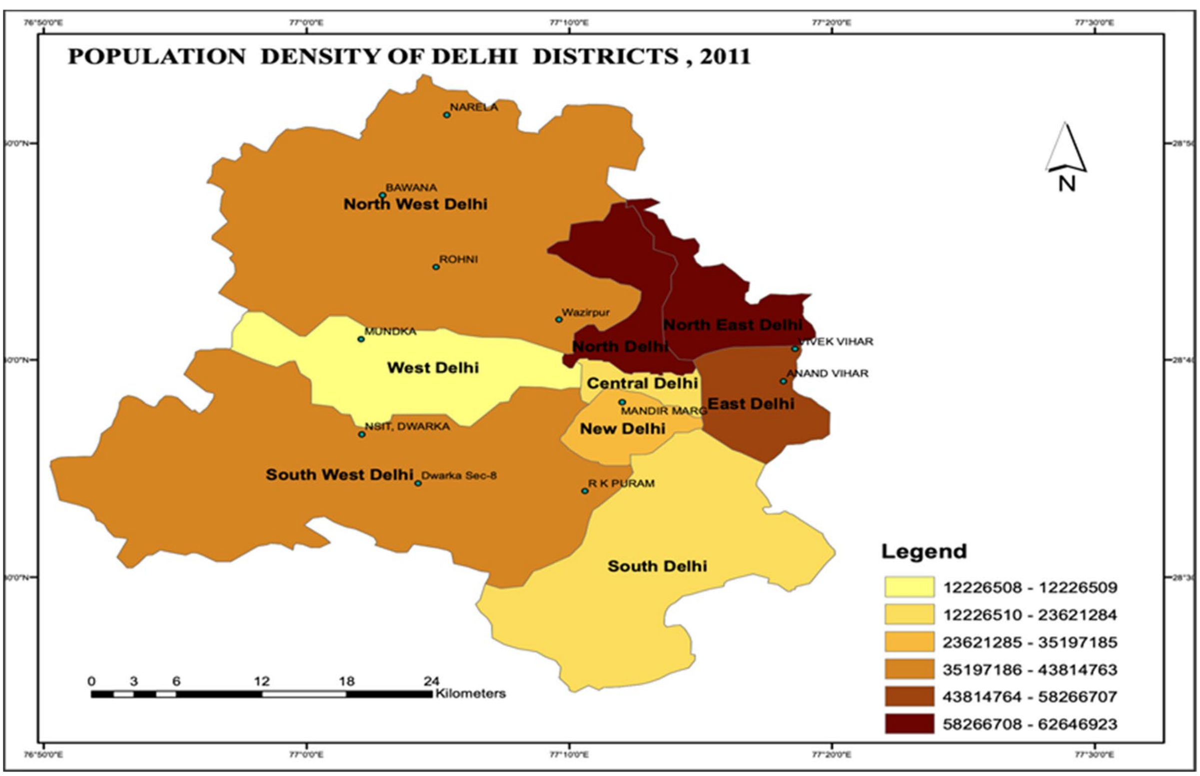


Fig. 1 Population density maps of the study area to facilitate GIS-based assessment of air pollution risks in proximity to industrial areas and the identification of relevant environmental factors

and post-monsoon seasons of both year 2019 and 2020. This investigation involved aggregating daily data from 11 air quality stations within the city to derive monthly average concentrations for each of the mentioned periods. The process is exemplified in Fig. 1 for clarity.

2.3 Methodology for Spatial Interpolation

This study employed both spatial and non-spatial data sources, including satellite imagery from platforms such as Google Earth and Google Maps, alongside the open-source GIS software QGIS. The integration of survey data with GIS layers was a crucial step in the analytical process, which further involved utilizing geoprocessing tools and conducting geostatistical analyses. Particularly, the Inverse Distance Weighted (IDW) tools played a pivotal role, as illustrated in Fig. 2, facilitating the interpolation of spatial data for accurate representation and analysis.

2.3.1 Inverse Distance Weighted (IDW)

The process of IDW interpolation involves determining cell values by blending a set of sample points using linear weighting. The weighting factor is inversely proportional to the distance, essentially reflecting the surface being interpolated from a variable dependent on location. In this study, we incorporate conditional factors, including distance and population density. The IDW tool, as implemented in ArcGIS, adheres to the principle that proximity plays a significant role, with closer points exerting a more substantial influence on the interpolated value compared to distant ones. This technique calculates weighted averages based on the reciprocal of the distance between the sample points and the location under consideration. IDW proves particularly valuable in scenarios involving point data, as often

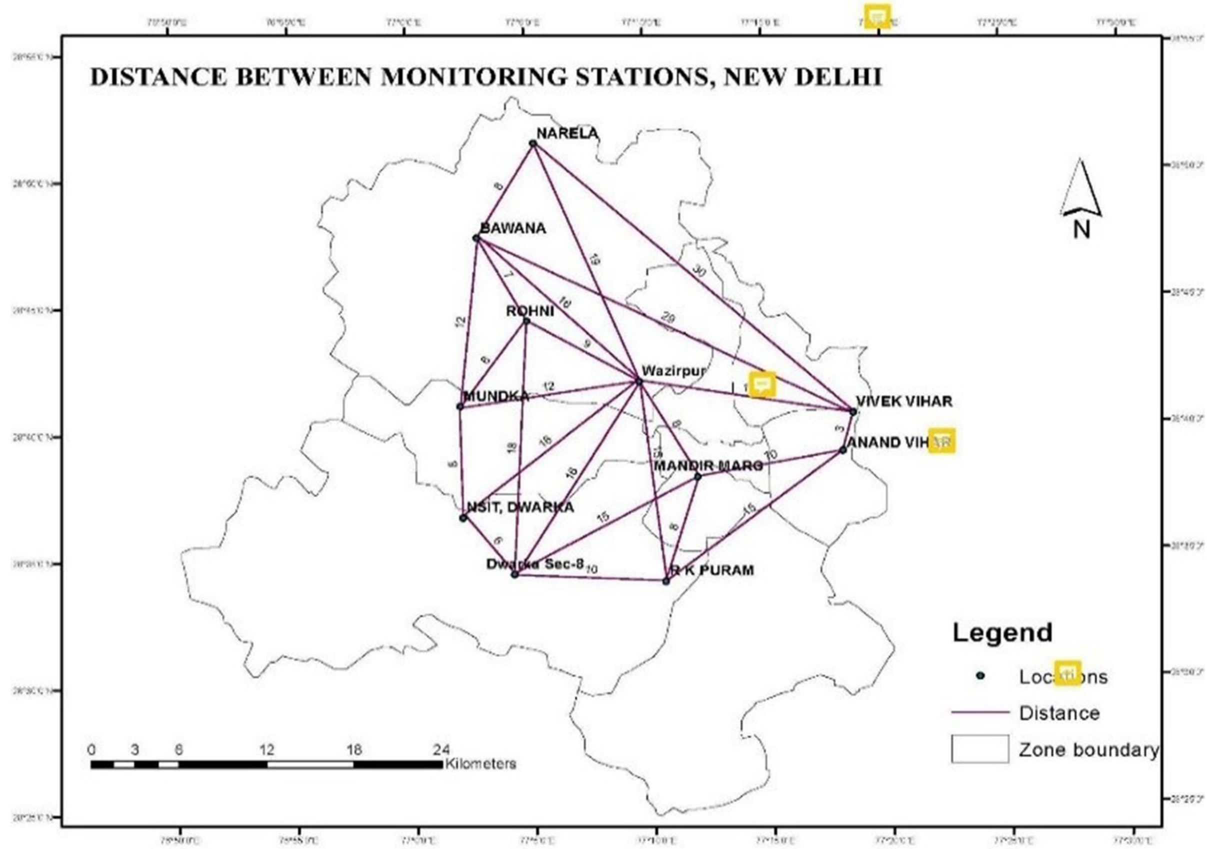


Fig. 2 Geo-referencing of monitoring stations, distances, and zone boundaries of monitoring stations over Delhi

encountered in measurements collected from air quality monitoring stations (Fig. 3).

IDW remains widely acknowledged as one of the most prevalent and suitable interpolation techniques for deciphering the spatial distribution of pollutants (Peng & Zou, 2012). This method facilitates the prediction of values at unmeasured locations by referencing the values of the surrounding predicted location (Childs, 2004). It operates on two fundamental premises: firstly, the impact of an unknown value at a particular point increases in proportion to the proximity of control points, with closer points wielding greater influence than distant ones. Secondly, the extent of influence is inversely proportional to the distance between points. Leveraging interpolated maps, we embarked on the depiction of spatial patterns for all pollutants, incorporating the IDW methodology. This approach serves as a cornerstone for unveiling the intricate spatial distribution of pollutants and contributes significantly to the overall methodology. The representation of the air quality GIS map in different color patterns is shown as per its air quality index according to Table 1, given below.

3 Results and Discussion

Utilizing the IDW tool, interpolated maps were generated by amalgamating PM_{10}, $PM_{2.5}$, NO_2, O_3, and Meteorological data from the years 2019 and 2020. These maps elucidated the spatial distribution and concentrations of pollutants across the study area, offering a visual depiction of regions with varying degrees of pollution levels. This visualization effectively pinpointed potential hotspots and areas warranting heightened attention. The impact stemming from these interpolated maps was multifaceted. Primarily, they served as invaluable

Fig. 3 Illustration of Inverse Distance Weighted (IDW) interpolation process

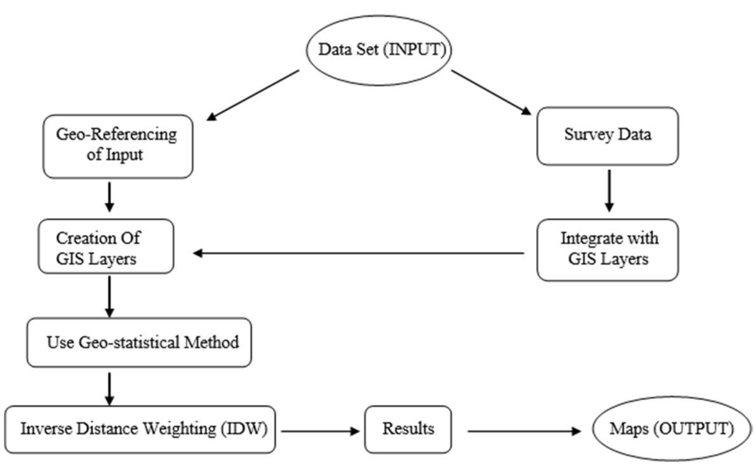


Table 1 Classification of Air Quality Index (AQI) (Akolkar. (2016)

Color coding	AQI range index	O_3 avg (8 h)	CO (8 h avg)	NO_2 (ppm)	PM_{10} (µg/m3	$PM_{2.5}$ (µg/mg
Good	0–100	0–50	0–1.7	0–42	0–100	0–60
Moderate	101–200	51–98	1.8–10.3	43–94	101–150	61–90
Poor	201–300	99–118	10.4–14.7	95–295	151–350	91–210
Very poor	301–400	119–392	14.8–30.2	296–667	351–420	211–252
Hazardous	401-Above	393-Above	30.3-Above	668-Above	421- Above	253-Above

resources for environmental agencies, policymakers, and researchers, facilitating the identification of zones characterized by heightened pollutant levels. This, in turn, assisted in prioritizing pollution control measures and strategic interventions tailored to the specific areas in need. The insights derived from these maps were instrumental in devising targeted strategies aimed at curbing emissions of PM_{10}, $PM_{2.5}$, NO_x, and O_3, thereby mitigating their adverse health and environmental consequences. Secondarily, the interpolated maps played a pivotal role in augmenting public awareness about the pollution issue. The visual representations presented in these maps were comprehensible and impactful, making the problem more accessible to the general populace. By providing a tangible and easy-to-grasp illustration of the pollution scenario, the maps played a crucial role in fostering informed discussions and public discourse on pollution-related matters.

3.1 Interpretation of Interpolated Maps of PM_{10} in 2019 and its Impact

The comprehensive examination carried out on PM_{10} levels across 11 designated study stations unveiled a series of significant insights (Refer to Fig. 4). Notably, PM_{10} exhibited a more pronounced influence during the winter season compared to other periods. The annual average of PM_{10} concentrations exceeded the prescribed standard at all 11 study stations, which encompassed Mundka, Wazirpur, Dwarka Sector-8, Narela, Bawana, Rohini, Netaji Subhas Institute of Technology (NSIT) Dwarka, Mandir Marg, R K Puram, Vivek Vihar, and East Delhi-Anand Vihar. Specifically, the air quality at Mundka, Wazirpur, Anand Vihar, and Dwarka Sector-8 was deemed very poor, indicative of a pressing concern. This study identified biomass burning as a pivotal factor influencing air pollution during the spring and winter seasons, while coal combustion emerged as a dominant

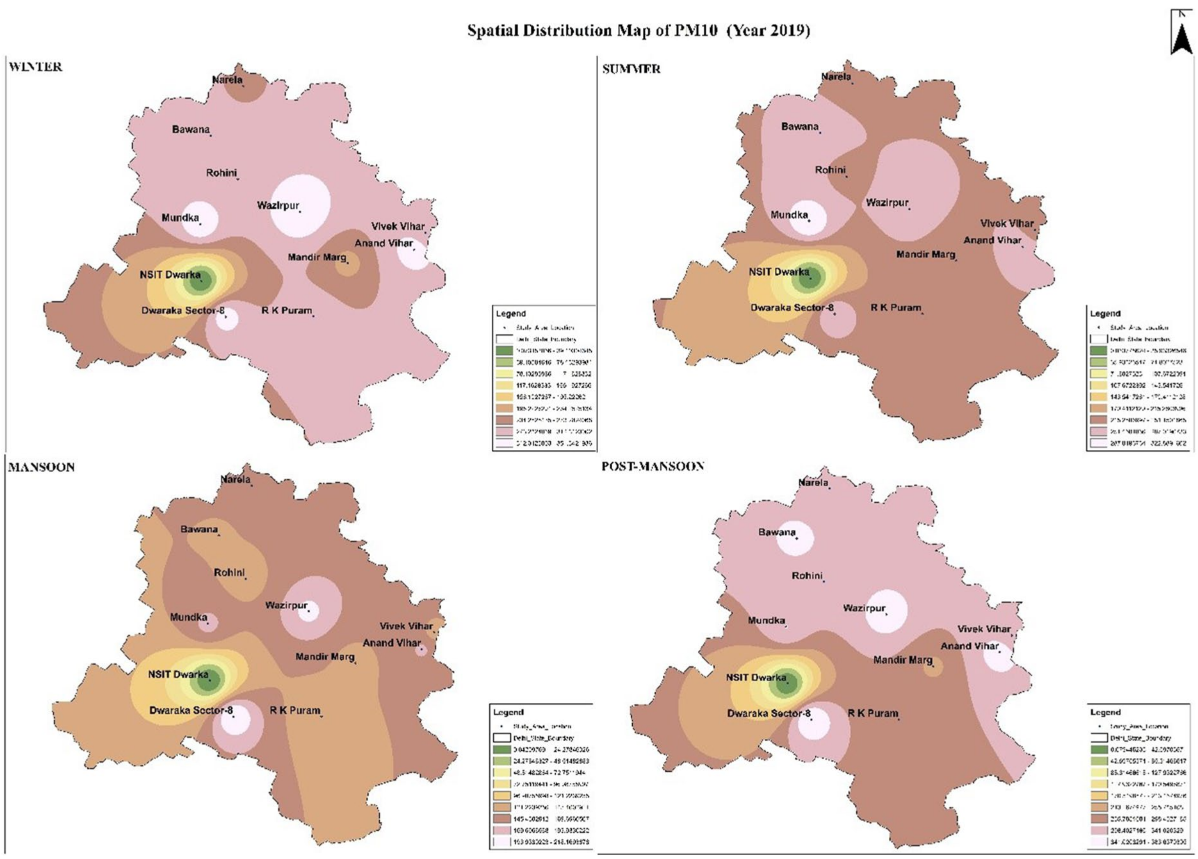


Fig. 4 Spatial variation of PM_{10} over Delhi during the year 2019

contributor during the winter months. The concentration of PM_{10} showcased seasonal fluctuations, spanning from 39–351 μg/m^3 during winter, 35–322 μg/m^3 in summer, 24–218 μg/m^3 in the monsoon, and 42–383 μg/m^3 in the post-monsoon period. Notably, the most alarming pollution levels were recorded during winter and post-monsoon seasons, aggravated by the burning of crop stubble in Punjab and Haryana. Significantly, Anand Vihar, Mundka, Wazirpur, and Dwarka Sector-8 emerged as stations harboring the most hazardous pollution category, surpassing hazardous levels by reaching up to 383 μg/m^3 in the post-monsoon season. Collectively, this study casts a spotlight on the severity of PM_{10} pollution levels, particularly during the winter and post-monsoon seasons. The crucial roles of biomass burning and coal combustion as substantial contributors underscore the urgency of implementing stringent pollution control measures, particularly within the regions grappling with the highest pollution levels. This proactive approach is paramount in safeguarding public health and enhancing the overall air quality scenario.

3.2 Interpretation of Interpolated Maps of PM_{10} in 2020 and its Impact

In the year 2020, an in-depth examination was conducted to assess the dispersion of PM_{10} (particulate matter with a diameter of 10 μm or less) (Refer to Fig. 5). The findings underscored elevated PM_{10} concentrations during the post-monsoon and winter seasons. Particularly noteworthy were the hotspots of Bawana, Rohini, and Mundka during the summer, whereas Dwarka Sector 8 emerged as a hotspot during the winter period. The study further unveiled the range of seasonal minimum and maximum average PM_{10} values. In the winter season, the range was 35–322 μg/m^3, in summer it spanned from 18–165 μg/m^3, in monsoon it hovered between 20–128 μg/m^3, and post-monsoon levels escalated to

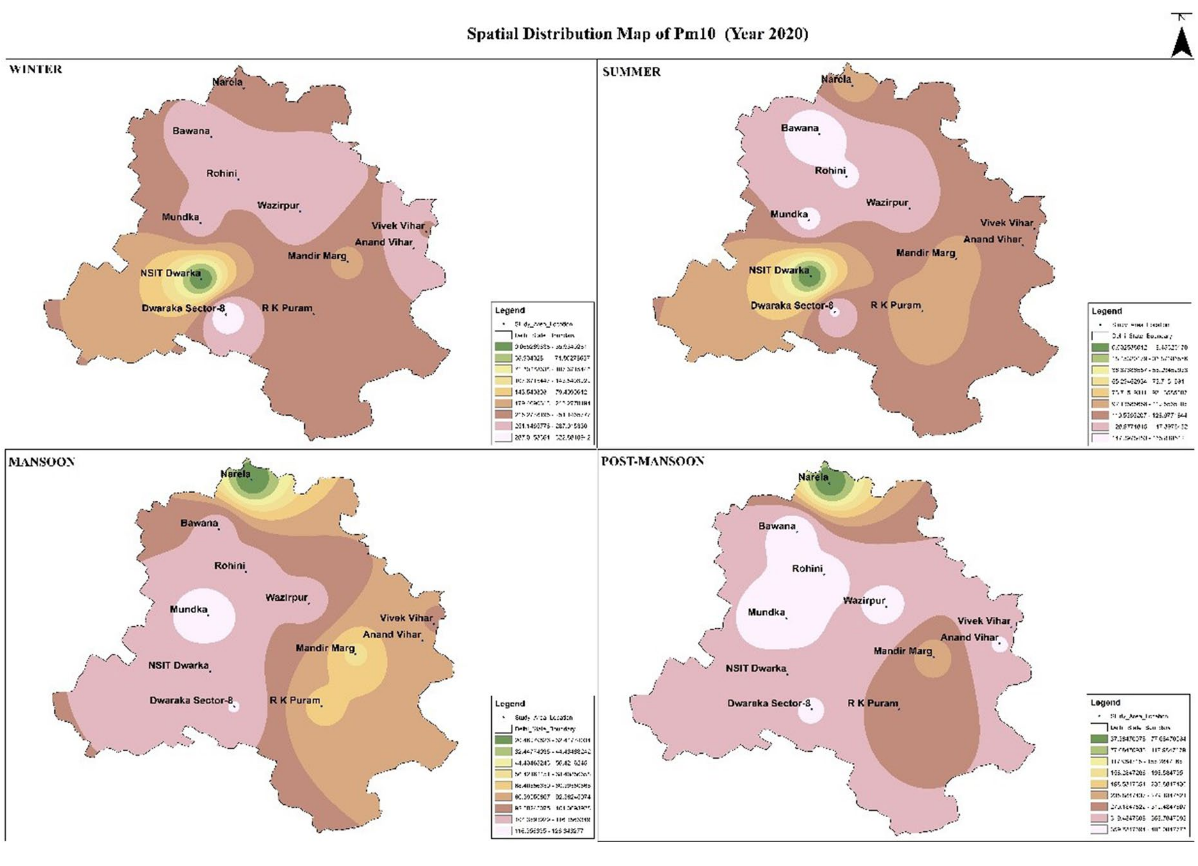


Fig. 5 Spatial variation of PM_{10} over Delhi during the year 2020

as high as 400 μg/m^3. Concentrations surpassing the normal range underscore an escalated risk of health conditions, including lung cancer and cardiovascular mortality. Additionally, PM_{10} exacerbates asthma and triggers respiratory ailments due to its capacity to lodge within the upper respiratory tract and even reach the lung alveoli. The composition of PM_{10} is diverse, as it can assimilate and transmit various pollutants. While pinpointing a singular component as the primary catalyst for PM effects remains challenging, factors such as particle size, surface area, quantity, and composition collectively contribute to determining their health implications. In essence, this comprehensive study casts a spotlight on the disconcerting distribution patterns and concentration levels of PM_{10} in 2020. The findings accentuate the potential health hazards linked with exposure to heightened levels of particulate matter, reinforcing the criticality of addressing this issue for public well-being.

3.3 Interpretation and Interpolation Map of $PM_{2.5}$ in 2019 and its Effect

The interpolation maps focusing on $PM_{2.5}$ pollution during the summer of 2019 unveiled heightened $PM_{2.5}$ levels in comparison to the winter months, illustrated in Fig. 6. Notably, the most pronounced zones of concern in terms of $PM_{2.5}$ pollution were identified in southwest Delhi and west Delhi. These regions showcased elevated $PM_{2.5}$ concentrations, signifying an impending threat to both human health and the environment. This discovery strongly underscores the urgency of deploying focused pollution control strategies and timely interventions within these areas. Such measures are essential to counteract the detrimental effects of $PM_{2.5}$ pollution during the summer season, safeguarding the well-being of both the populace and the ecological balance.

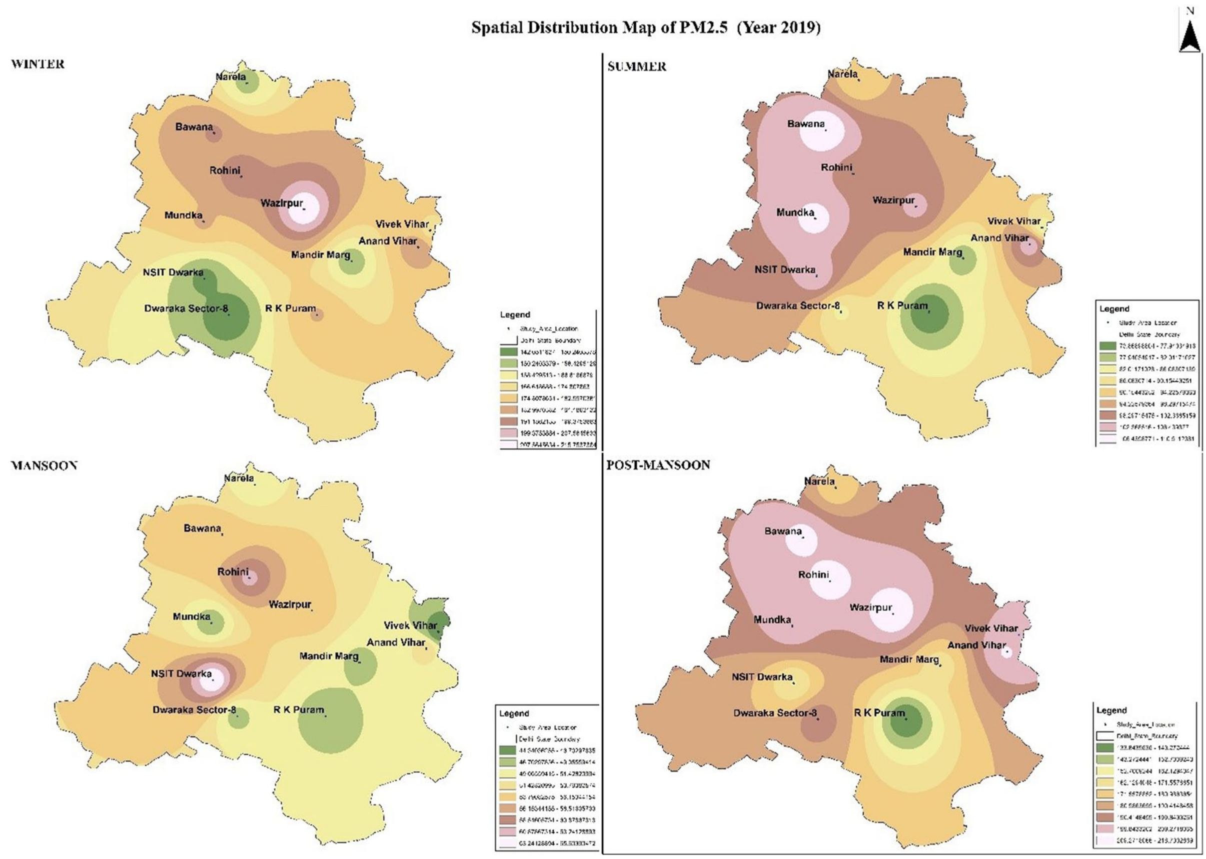


Fig. 6 Spatial variation of $PM_{2.5}$ over Delhi during the year 2019

3.4 Interpretation and Interpolation Analysis of $PM_{2.5}$ in 2020 and Its Implications

A comparative analysis of $PM_{2.5}$ concentrations between the summer and winter seasons illuminated stark distinctions (Refer to Fig. 7). During the summer, $PM_{2.5}$ levels spanned a range of 22 to 73 µg/m^3, whereas, in winter, this range escalated to a higher bracket of 113 to 178 µg/m^3. This variation can be primarily attributed to the volume of on-road vehicles in operation. The discrepancy in pollution levels during these seasons can be linked to reduced vehicle emissions during the summer, resulting in improved air quality. Conversely, heightened pollution during winter months can likely be attributed to increased vehicle usage or other contributing factors.

These findings significantly underscore the significant impact of vehicular emissions on $PM_{2.5}$ pollution. They underscore the urgency of adopting targeted strategies to regulate and diminish vehicle-related pollution, particularly during the winter season, when the pollution levels tend to be more pronounced.

3.5 Interpolation of NO_2 and Its Implications in 2019

The comprehensive study carried out in Delhi discerned that NO_2 concentration played a pivotal role in driving air quality deterioration. Through spatial analysis, it was unveiled that North and East Delhi experienced the most alarming levels of NO_2 pollution, solidifying their status as the most significantly impacted areas in terms of this pollutant. These findings underscore the urgency of deploying focused strategies to curtail NO_2 emissions and counteract their detrimental impact on air quality across these regions. A concentrated approach to monitor

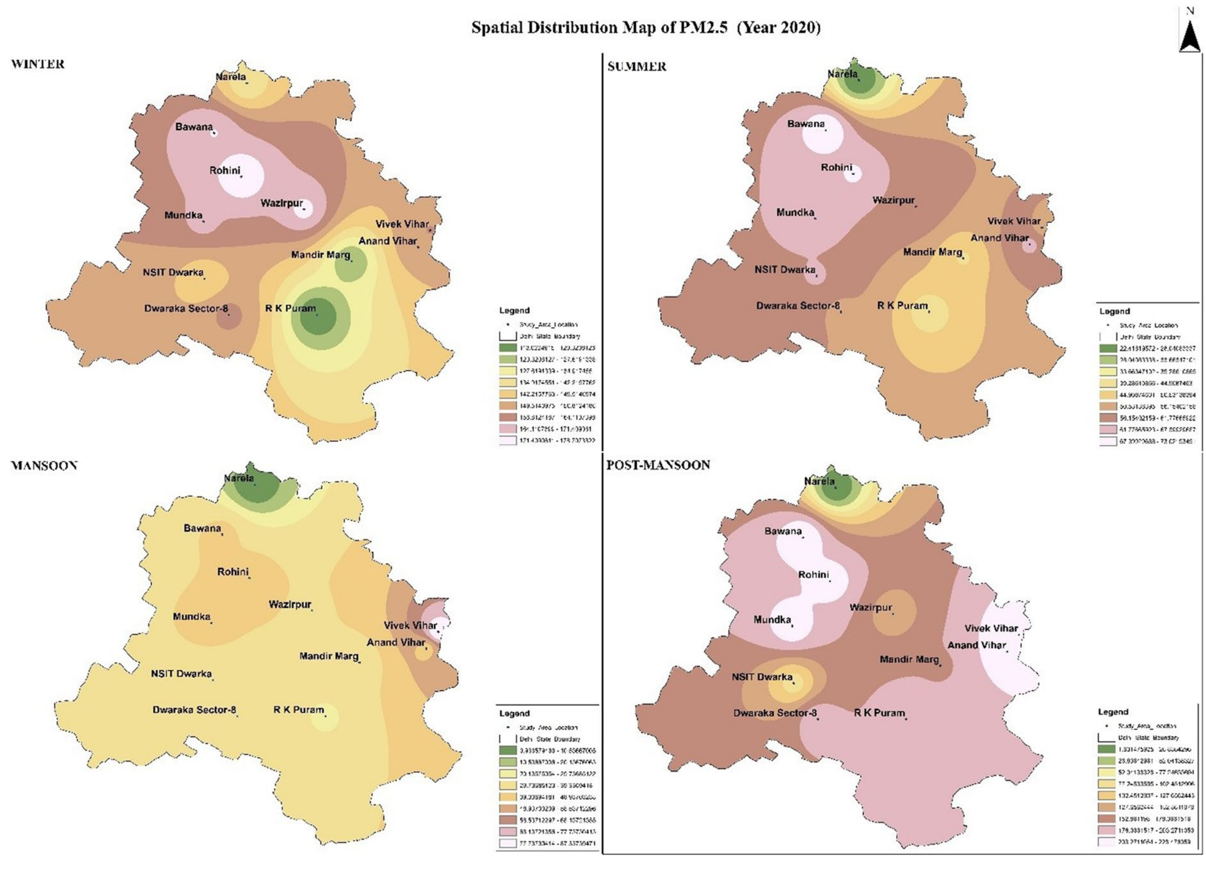


Fig. 7 Spatial variation of $PM_{2.5}$ over Delhi during the year 2020

and control sources contributing to NO_2 pollution assumes paramount importance in enhancing the overall air quality scenario in Delhi. (Refer to Fig. 8 for visual representation).

3.6 Interpolation of NO_2 and Its Implications in 2020

The investigation identified NO_2 concentration as the primary pollutant responsible for the degradation of air quality in Delhi. The spatial distribution highlights North and East Delhi as the most heavily affected zones in terms of NO_2 pollution during the year 2020. (Refer to Fig. 9 for visual representation).

3.7 Interpolation of Ozone (O_3) in 2019 and Its Implications

The spatial analysis uncovered Bawana, Rohini, and Narela as primary hotspots bearing the brunt of ozone pollution during the period from 2019. The concentration of ozone in these areas implies potential health risks, particularly for individuals with heightened sensitivity to air pollutants. (Refer to Fig. 10 for visualization).

3.8 Interpolation of Ozone (O_3) in 2020 and Its Implications

The investigation unveiled the most severe pollution levels during the summer season, followed by the post-monsoon and winter periods. Notably, locations including Anand Vihar, Bawana, Narela, Mundka, Dwarka Sector-8, and Vivek Vihar emerged as hotspots, displaying deteriorating air quality trends with ozone concentration. This finding underscores a direct correlation between ozone levels and pollutants such as PM_{10}, $PM_{2.5}$, and NO_2 (Fig. 11).

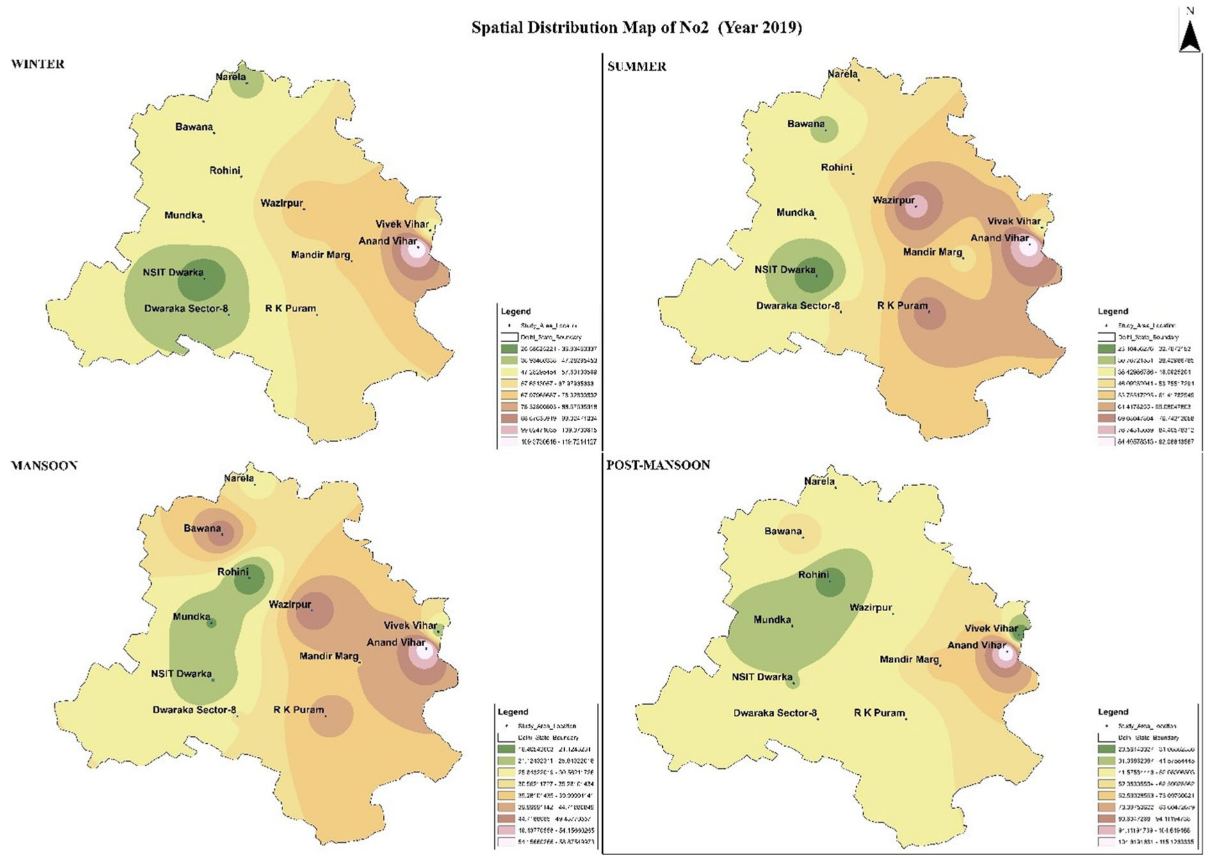


Fig. 8 Spatial variation of NO_2 distribution over Delhi during the year 2019

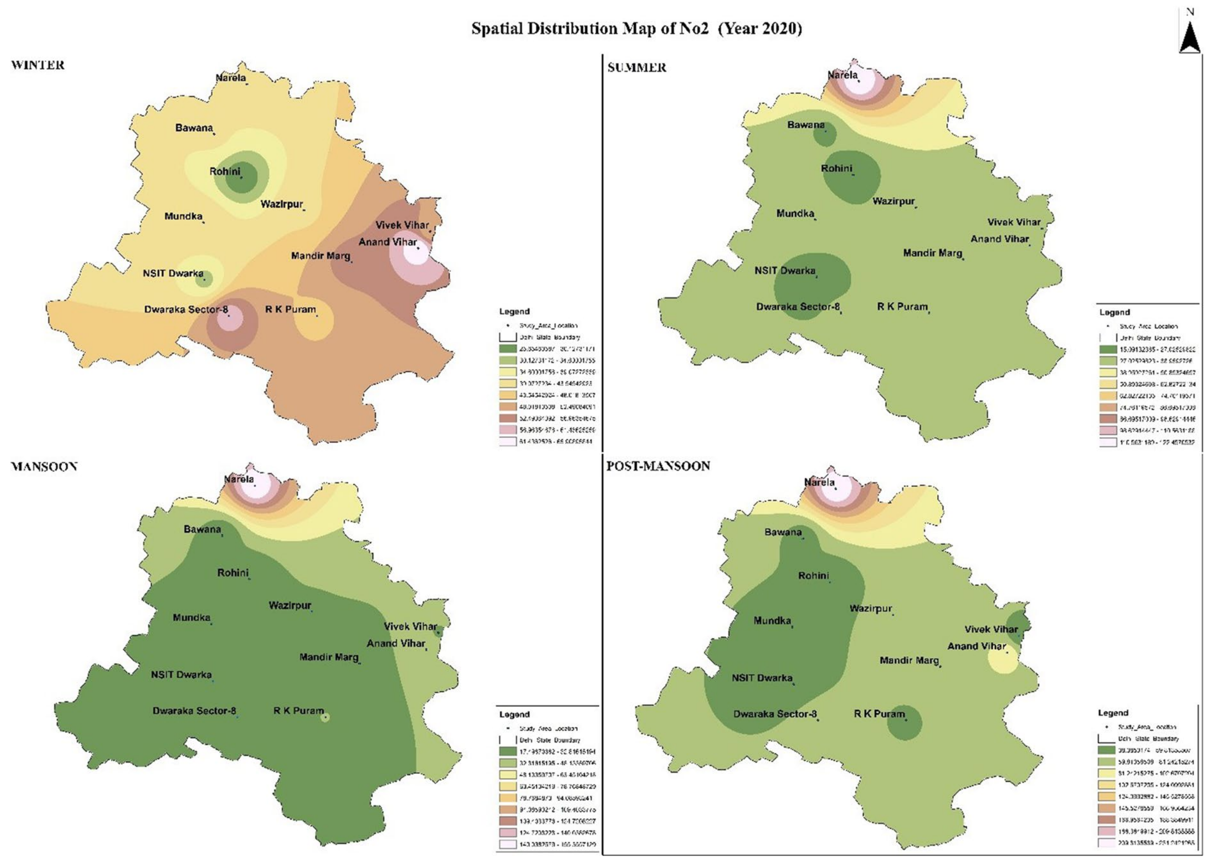


Fig. 9 Spatial variation of NO_2 over Delhi year during 2020

3.9 Interpolation Maps for Meteorological Parameters (AT, WS, WH, SR, BP, RH) in 2020 and Their Influence on Ongoing Pollution Trends

In the year 2020, interpolation maps were generated to visualize a spectrum of crucial meteorological parameters, encompassing ambient temperature (AT), wind speed (WS), wind direction (WH), solar radiation (SR), barometric pressure (BP), and relative humidity (RH). This comprehensive analysis pinpointed the significant contribution of these meteorological factors to the precarious air quality conditions prevalent in East, West, and North Delhi regions. Among these, PM_{10}, $PM_{2.5}$, and NO_x concentrations emerged as the pivotal pollutants driving the deterioration of the overall ambient air quality in the city. Furthermore, the study discerned that meteorological parameters including AT, WH, BP, and RH play a discernible role in influencing the city's air quality degradation. This intricate interplay between meteorological conditions and air pollution underscores the complexity of the situation in Delhi. A profound grasp of these interrelationships is pivotal in devising efficacious air quality management strategies. This study accentuates the critical need to holistically consider both pollutant emissions and meteorological dynamics, thereby holistically addressing the multifaceted challenge of enhancing air quality within Delhi. (Refer to Fig. 12 for visual representation).

3.10 Seasonal Fluctuations of Analyzed Pollutants in 2019 and 2020

This study extensively scrutinized the monthly fluctuations of diverse pollutants across eleven stations in Delhi, utilizing data sourced from the Central Pollution Control Board (CPCB) spanning from January 2019 to December 2020. During the winter

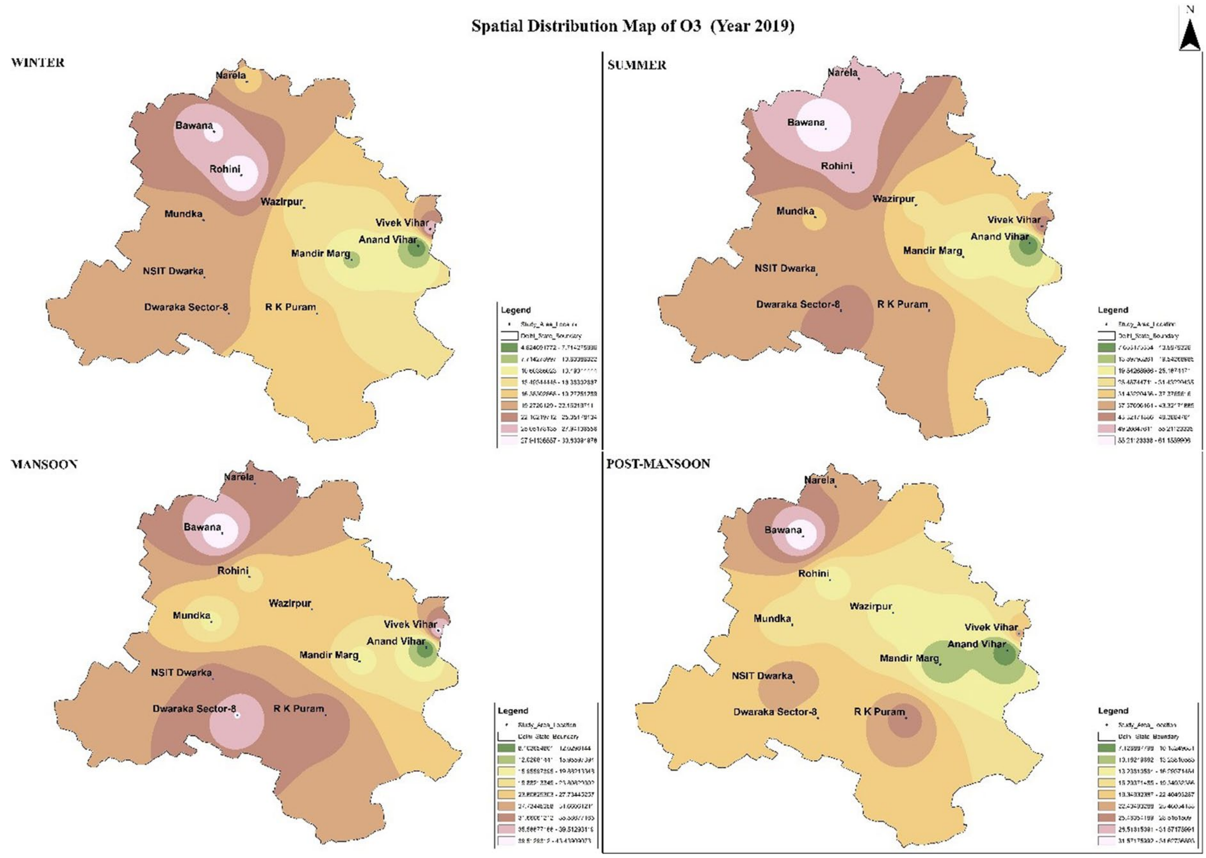


Fig. 10 Spatial Interpolation Map Illustrating Ozone (O_3) Distribution in the Year 2019

season, PM_{10} concentrations in Delhi ranged from 18.86 µg/m^3 to 67.99 µg/m^3, with the highest levels at Mundka (341.06 µg/m^3) and Wazipur (286.92 µg/m^3) and the lowest at Mandir Marg (222.30 µg/m^3). After the lockdown, a substantial reduction occurred, ranging from 94.64 µg/m^3 to 153 µg/m^3, attributed to decreased transport and industrial activities. Anand Vihar experienced the most significant change at 153.80 µg/m^3, compared to 94.64 µg/m^3 in Rohini. During the monsoon season, PM_{10} levels ranged from 33.45 µg/m^3 to 112.13 µg/m^3, with Dwarka Sector-8 showing pronounced changes due to settling particles (Fig. 13). In the post-monsoon season, minor PM_{10} increases were noted in Narela and Dwarka Sector-8, possibly due to relaxed COVID-19 policies. This underscores the effectiveness of lockdown measures in reducing PM_{10} concentrations, especially in highly polluted areas like Anand Vihar, emphasizing the need for ongoing monitoring and sustainable practices (Gautam et al., 2021a).

The study observed a slight reduction in $PM_{2.5}$ during winter 2020, but lockdown and summer monsoon had a more significant impact in reducing $PM_{2.5}$ during summer and monsoon seasons. Over Dwarka Sector-8 and Narela, $PM_{2.5}$ levels decreased by 30.32 µg/m^3 to 68.06 µg/m^3 compared to the previous year (Fig. 14). However, relaxation of COVID-19 policies and increased industrial activities led to $PM_{2.5}$ levels exceeding limits in R K Puram, Vivek Vihar, Bawana, and Mundka (Pal et al., 2022). The outcomes divulged distinctive trajectories in pollutant concentrations over discrete temporal segments (Gautam et al., 2021a, b, c; Kumari & Toshniwal, 2020; Mahato et al., 2020; Srivastava et al., 2020). Notably, the period from March to September 2020 witnessed pronounced escalations in pollutants like PM_{10} and $PM_{2.5}$ (Kerimray et al., 2020; Sethi & Mittal, 2020),

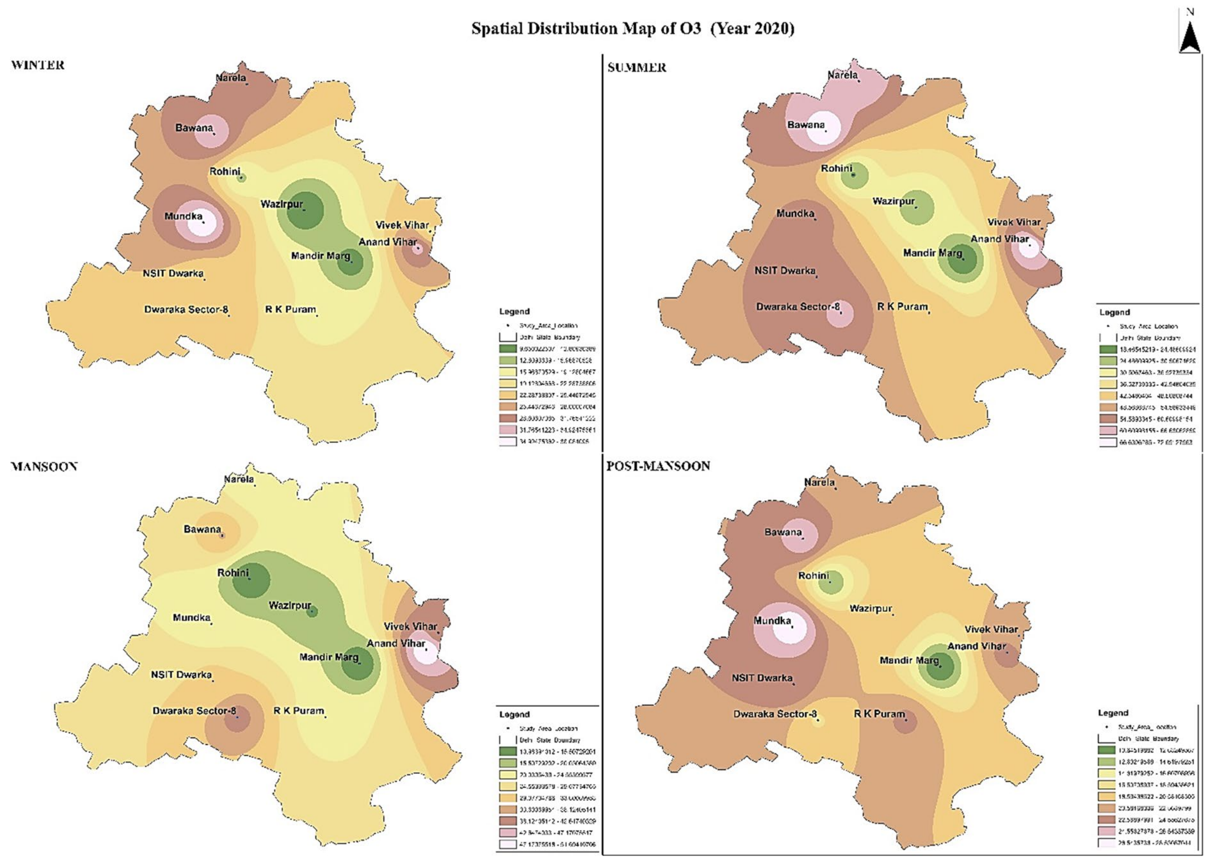


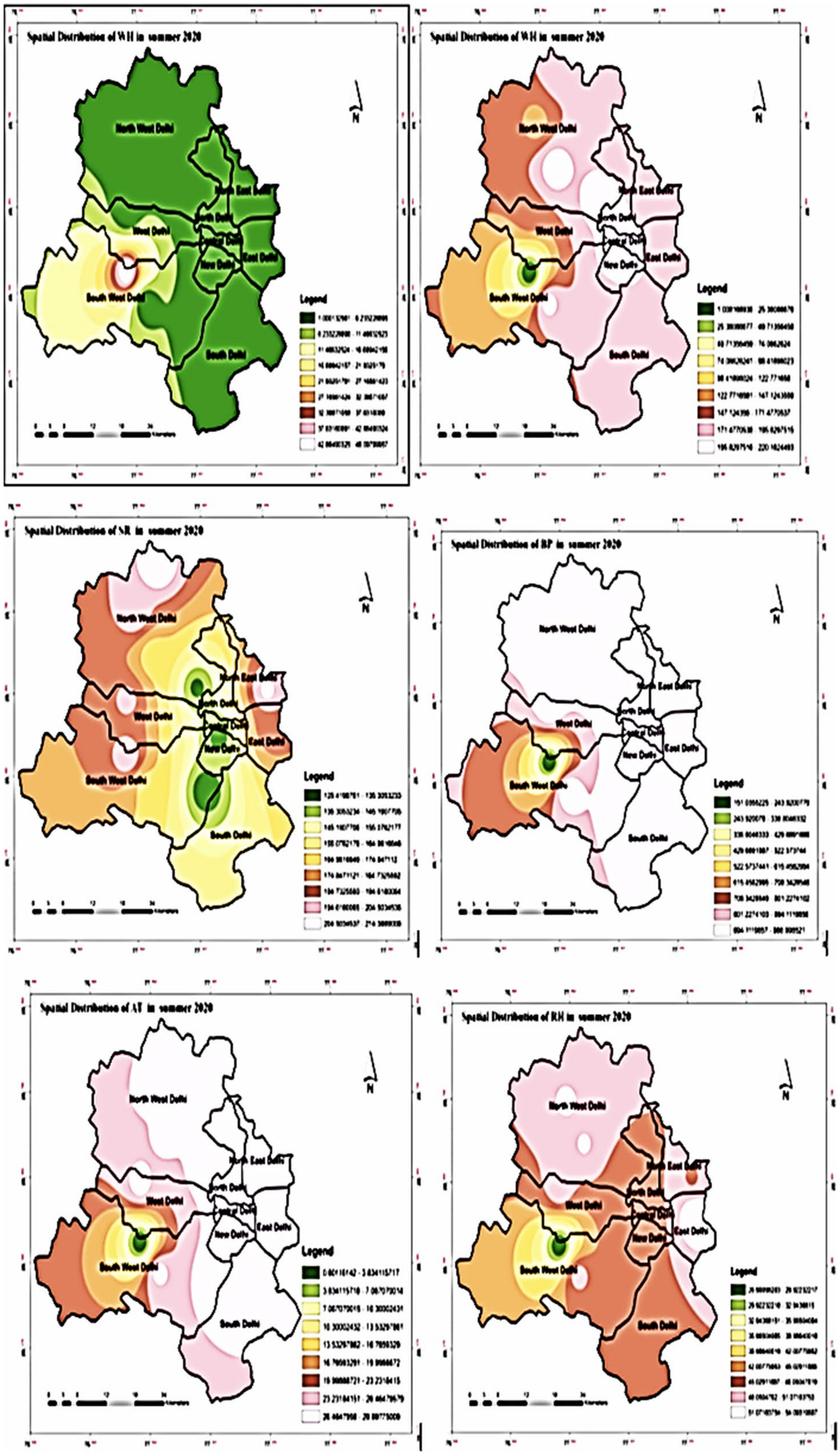
Fig. 11 Spatial Interpolation map depicting ozone (O_3) distribution in the year 2020

followed by relatively minor variations thereafter. The intervening lockdown exerted a favorable influence, contributing to diminished concentrations of PM_{10} and $PM_{2.5}$ in locales such as Wazirpur.

In the winter season, the study reveals a notable reduction in NO_2 concentrations in 2019, nearly halving in some areas. However, in 2020, locations like Dwarka Sec-8 and NSIT Dwarka showed higher NO_2 levels compared to 2019. During this period, NO_2 levels ranged from 23.09 μg/m^3 to 92.19 μg/m^3 in 2019, while in 2020, they varied from 20.12 μg/m^3 to 122.5 μg/m^3. A similar reduction trend was observed during the summer season in 2020, with only a 75.59 μg/m^3 increase compared to 2019. In the monsoon season, a reduction in NO_2 was reported, except in areas like Vivek Vihar, Rohini, and Narela, which had higher levels in 2020. Post-monsoon, NO_2 levels were relatively higher in 2020 compared to 2019. Specifically, Anand Vihar, Bawana, and NSIT Dwarka had slight reductions in NO_2 concentrations in comparison to the previous year (Fig. 15).

Regarding O_3 levels, there was a reduction in certain locations like Wazirpur, Vivek Vihar, and Rohini, indicating positive impacts from air pollution control efforts. However, O_3 remained dominant in other areas during winter, with levels ranging from 0.53 μg/m^3 to 35.05 μg/m^3. During the summer monsoon season, there was a significant reduction in O_3 levels (7.32 μg/m^3 to 67.62 μg/m^3), possibly due to increased rainfall and favorable meteorological conditions for pollutant dispersion (Fig. 16).

Interestingly, O_3 levels during the monsoon season showed low variation, suggesting a relatively stable impact of human activities on air quality at this time. In the post-monsoon season of 2020, O_3 levels dominated compared to the same period in 2019. Several factors, including changes in weather patterns, human activities, or


Spatial Distribution of WH in summer 2020
North West Delhi
North East Delhi
North Delhi
West Delhi
Central Delhi
East Delhi
New Delhi
South West Delhi
South Delhi
Legend
Spatial Distribution of WH in summer 2020
Legend
Spatial Distribution of SR in summer 2020
Legend
Spatial Distribution of BP in summer 2020
Legend
Spatial Distribution of AT in summer 2020
Legend
Spatial Distribution of RH in summer 2020
Legend

◂**Fig. 12** Monthly Temporal Variations of Solar Radiation (SR), Barometric Pressure (BP), Ambient Temperature (AT), Relative Humidity (RH), and their corresponding impacts across all study stations

environmental influences, could contribute to this shift. This underscores the importance of ongoing monitoring and analysis of air quality data to comprehensively understand the complex interplay of factors affecting air quality and its implications for environmental and public health.

Simultaneously, O_3 concentrations underwent a considerable downturn in 2020, while NO_2 levels demonstrated subtle fluctuations amidst the lockdown. Stations like Vivek Vihar, Rohini, R.K. Puram, and Mundka manifested analogous pollutant patterns encompassing PM_{10}, $PM_{2.5}$, and NO_2. In contrast, O_3 prominently manifested in Mundka relative to 2019. Stations including Bhawana, Mandir Marg, NSIT, Narela, and Dwarka echoed comparable trends post-lockdown, revealing augmented PM_{10} and $PM_{2.5}$ concentrations likely linked to biomass burning activities (Gadhavi & Jayaraman, 2010; Prabhu et al., 2020; Shaik et al., 2019).

Elevated pollutant concentrations during January and February could be attributed to the shallow boundary layer effect, causing pollutant accumulation near the Earth's surface (Badarinath et al., 2009; Budakoti & Singh, 2021; Nair et al., 2007). These findings underscore the intricate dynamics of pollutant variations across diverse localities within Delhi, underscoring the imperative of comprehending localized influences and activities contributing to air pollution. Implementing tailored strategies for controlling and mitigating pollution sources, especially during heightened pollution episodes, emerges as critical for enhancing regional air quality.

Analysis of seasonal pollutant trends in Delhi revealed declining $PM_{2.5}$ and PM_{10} levels in winter, summer, and monsoon, with notable variation in the 2020 post-monsoon period. NO_2 followed a similar pattern but increased post-monsoon in 2020. Ozone formation benefited from reduced emissions in summer. Targeted air quality strategies and ongoing monitoring are vital for Delhi's air quality and public health.

3.11 Evaluation of Air Quality Index (AQI) Impact on Public Health

The evaluation of combined pollutant effects and the resulting AQI shifts in Delhi between 2019 and 2020 yielded invaluable insights. The study unveiled noteworthy AQI alterations in specific locations during this period. A standout was NSIT, exhibiting a substantial 44.1% AQI increase. Similarly, Wazirpur, Narela, and Mandir Marg saw significant AQI shifts, with rises of 34.2%, 36.1%, and 19.2%, respectively. On the other hand, stations like Anand Vihar, Rohini, Mundka, and Dwarka Sector 8 displayed relatively modest AQI changes below 15%. However, it's pertinent to observe that certain spots such as Vivek Vihar and Bawana depicted elevated pollutant mass concentrations, attributing to higher AQI values than in 2019. This could potentially be linked to COVID-19 pandemic-induced manufacturing of essential goods like Personal Protective Equipment (PPE) kits, medicines, and masks.

These findings underscore the intricate interplay between pollutant levels, AQI shifts, and factors including industrial activities and local conditions. The study accentuates the necessity of continual air quality monitoring and assessment, along with the implementation of robust pollution control measures, particularly in locales experiencing notable AQI fluctuations.

Addressing pollution sources and activities contributing to heightened pollutant concentrations emerges as a pivotal strategy for enhancing air quality and protecting public health in Delhi. (See Fig. 17a-b for visual representation).

3.12 Correlation Analysis

To analyze the relationship between different parameters used in the study, we calculated the correlation matrix using r software (Hmisc Package). The correlation matrix provided us with seasonal correlation as well as an overall correlation in different colors (Black: Annual correlation, Red: Monsoon, Olive Green: Post-monsoon, Sky blue: Summer, and Purple: Winter).

We found that PM_{10} showed a significant correlation with NO_2 (r = -0.72), $PM_{2.5}$ (r = 0.90), solar radiation (r = -0.32), and temperature (r = -0.51).

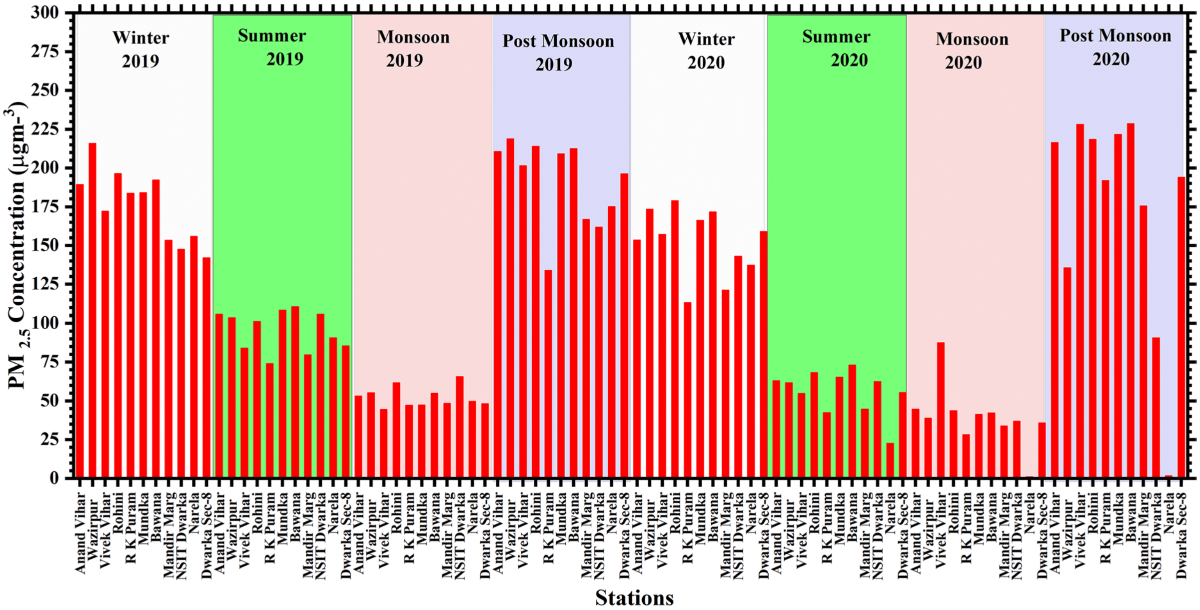


Fig. 13 Monthly variations of $PM_{2.5}$ across all stations in Delhi during 2019 and 2020

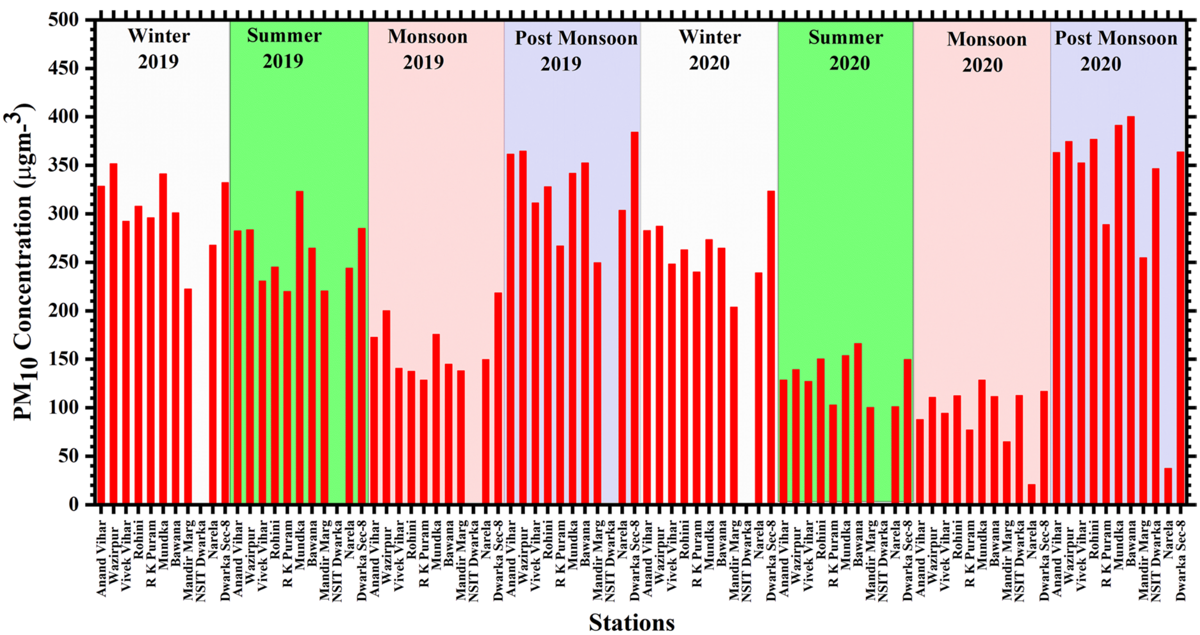


Fig. 14 Monthly variations of PM_{10} across all monitoring stations in Delhi during 2019 and 2020

On the other hand, NO_2 had a significant correlation with O_3 (r = -0.44-winter), $PM_{2.5}$ (-0.63-post monsoon), and wind speed (r = -0.28). The O_3 parameter showed a significant correlation with solar radiation (0.26) in summers and was negatively correlated with relative humidity.

Additionally, $PM_{2.5}$ was found to be negatively correlated with temperature (r = -0.52), wind speed

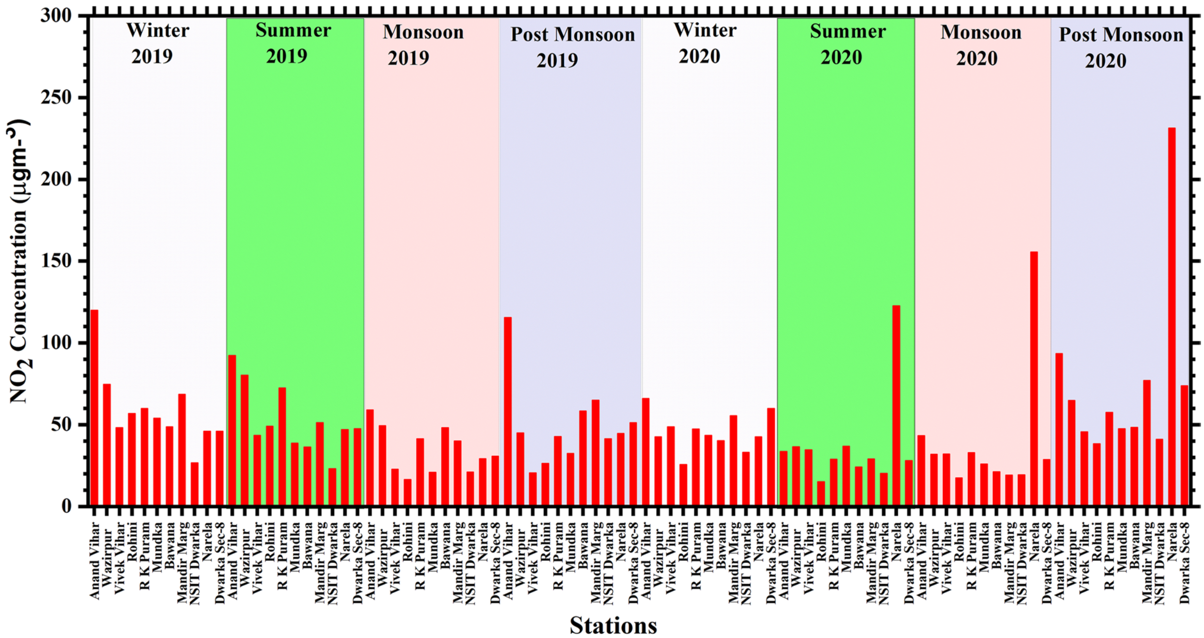


Fig. 15 Monthly Variations of NO_2 Pollutant over the monitoring stations in Delhi During 2019 and 2020

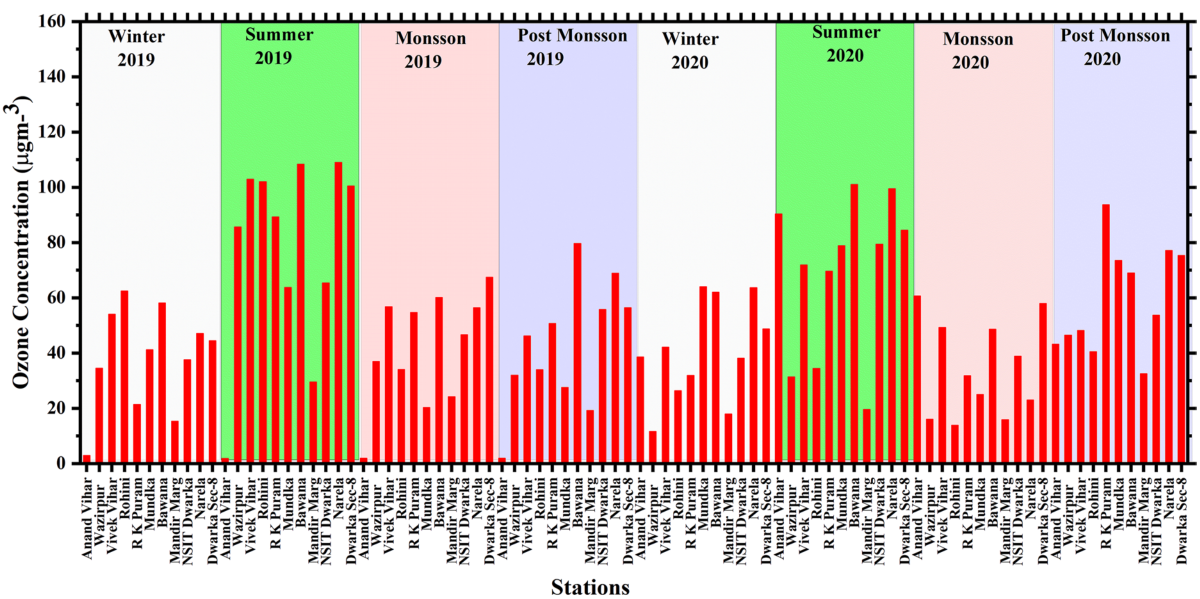


Fig. 16 Monthly Fluctuations of Ozone (O_3) Pollutant over 11 selected monitoring stations in Delhi during 2019 and 2020

(r = -0.71 & -0.72-winter & post-monsoon), and solar radiation (r = -0.49). Furthermore, the high correlation between $PM_{2.5}$ and PM_{10} indicated that their sources were common. These findings provide insights into the interdependence of various parameters affecting air quality and can help in devising effective strategies for mitigating air pollution (See Fig. 17a–b for visual representation).

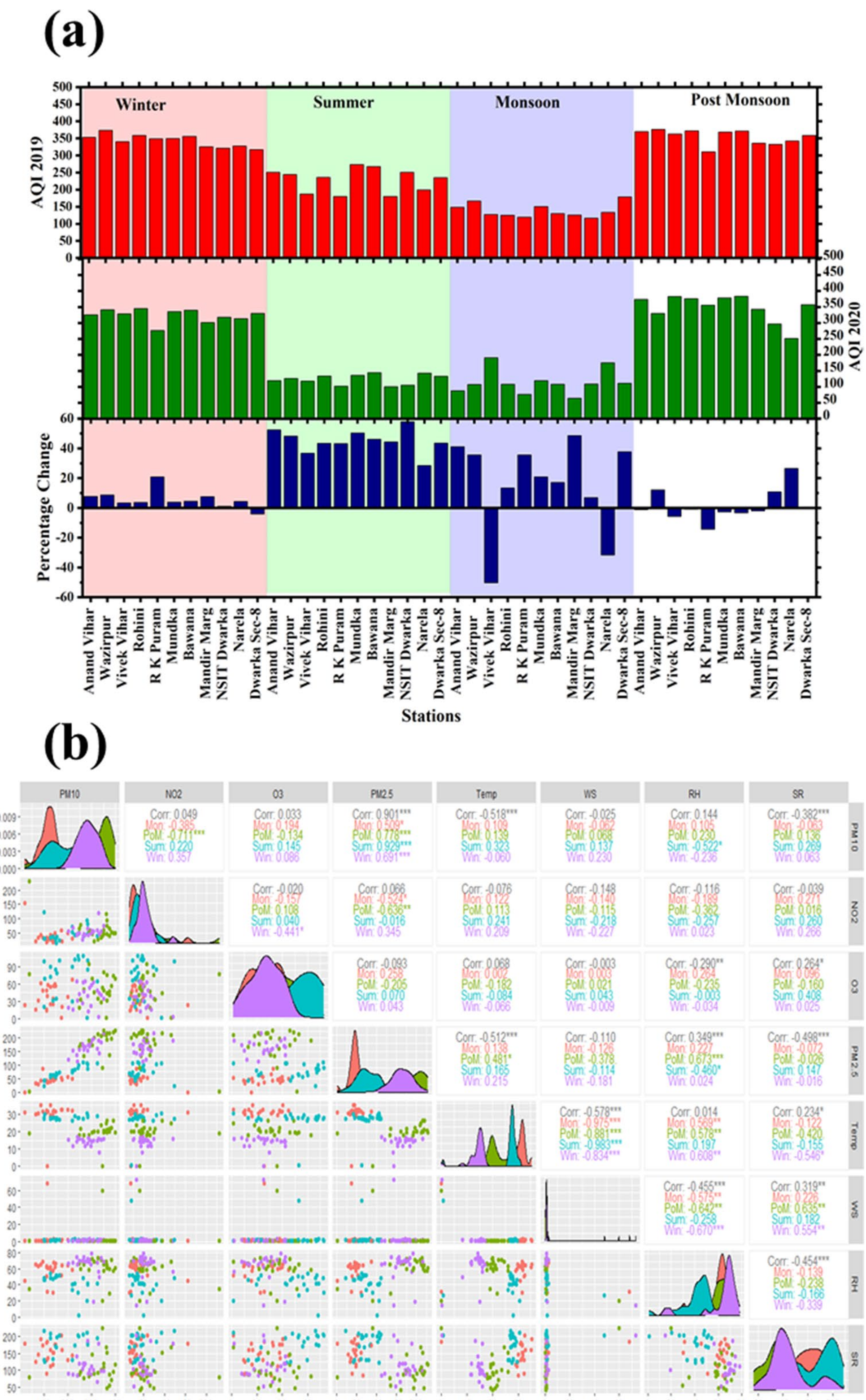


Fig. 17 **a** –**b** AQI and correlation matrix over Delhi in 2019 and 2020

4 Conclusion

This study underscores the pivotal role of Geographic Information Systems (GIS) in pollution mapping, encompassing data collection, analysis, visualization, and decision-making. GIS offers multifaceted advantages across diverse domains. Concerning Delhi's air quality, PM_{10} levels frequently exceeded AQI standards, reaching a peak of 67.99 μg/m^3 during winter. The situation worsened in winter and post-monsoon due to nearby crop burning. Surprisingly, summer 2019 witnessed even higher $PM_{2.5}$ pollution levels than in winter, with southwest Delhi recording values as high as 73 μg/m^3, and west Delhi peaking at 178 μg/m^3. Reduced on-road vehicles were key in lowering summer pollution, while winter pollution remained largely unaffected. The AQI trend typically decreased from winter to monsoon but abruptly increased post-monsoon. In 2020, the lockdown led to a significant decrease in summer AQI, with reductions as high as 58.00% in NIST Dwarka, 52.49% in Anand Vihar, and 50.27% in Mundka. Monsoon AQI percentages ranged from 6.98% in NSIT Dwarka to 48.85% in Mandir Marg. However, Vivek Vihar (50.31%) and Narela (31.12%) showed higher emissions compared to 2019, attributed to PPE kit production and transportation activities.

Winter and post-monsoon periods exhibited up to a 24% change in AQI, emphasizing the need for continuous monitoring and action to address pollution sources and enhance air quality in Delhi. Policymakers can leverage these findings to promote sustainable practices for public health and the environment. In essence, GIS-powered pollution mapping is crucial for a comprehensive understanding, strategic action, and collaborative efforts toward a cleaner and healthier environment. This study's insights into Delhi's air quality reinforce the urgency of addressing pollution sources and taking informed actions to enhance air quality and promote community and environmental well-being.

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Declarations

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