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RESEARCH ARTICLE

Mapping the Spatiotemporal Variability of Particulate Matter Pollution in Delhi: Insights from Land Use Regression Modelling

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Abstract
This study investigates the spatiotemporal dynamics of pollutant concentrations in Delhi through the utilization of land use regression models. Analysis of data for year 2019 from 38 monitoring stations reveal elevated PM_{10} and $PM_{2.5}$ levels, peaking in winter ([PM_{10}: 306.90 ± 53.76 μg/m^3], [PM2.5: 185.52 ± 31.59 μg/m^3]) and dropping in monsoon ([PM_{10}: 107.77 ± 31.19 μg/m^3], [$PM_{2.5}$: 40.86 ± μg/m^3]), surpassing national standards ([PM_{10}: 60 μg/m^3], [$PM_{2.5}$: 40 μg/m^3]). Spatial distribution analysis indicates higher concentrations in the north and northwest regions, attributed to dense habitation, industrial zones, and vehicular traffic. Analyzing particulate pollutants data for year alongside urban land use/cover features and socioeconomic variables, the study reveals a robust relationship between particulate concentrations and urban attributes, explaining 37–of $PM_{2.5}$ and 38–62% of PM_{10} concentration variations. The models demonstrate good accuracy, with low RMSE values ($PM_{2.5}$: 9.55, PM_{10}: 27.49), underscoring the impact of urban landscape and surface conditions on air quality distribution. Understanding this link offers insights for better urban planning strategies that integrate air quality considerations, crucial for effective policy frameworks addressing pollution in urban environments.

Keywords Land use regression · PM_{10} · $PM_{2.5}$ · Delhi · Urban environment · Modelling

Introduction

Urbanization is an essential component in the industrialization and economic growth of a country. It can change the distribution of population, lifestyle as well as the ecological environment of an area (Shang et al., 2018). However, in developing countries, rapid urbanization and uncontrolled expansion have become elements of concern as they put stress on the existing natural resources and cause environmental degradation by affecting environmental processes at micro and macro scales.

Urban expansion due to urbanization results in a significant change in land use and land cover as well as encroachment of already limited green cover and agricultural land. As a result, several environmental degradations can occur including rising Land Surface Temperature (LST), Urban Heat Island (UHI) affect. Moreover, air quality gets directly or indirectly influenced by the built environment and urban form through the distribution of land use and land cover (Clark et al., 2011). The increasing air pollution levels, primarily due to particulates and gases, have been identified as a major concern in urban areas (Ganguly et al., 2021; Singh et al., 2021). Poor air quality due to the rise in air pollution levels can generally be attributed to anthropogenic generated emissions like vehicular, industrial, construction as well as domestic burning, in addition to emissions tha released naturally (Ganguly et al., 2019; Hama et al., 2020). These sources release particulate matter (PM_{10}, $PM_{2.5}$), gaseous pollutants like oxides of nitrogen and Sulphur, carbon monoxide, ozone, and heavy metals (Guttikunda et al.,

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2014). It has been well-established that synoptic patterns and meteorological parameters can drive and modulate the concentrations of these pollutants (Zhang et al., 2015). It is believed that there has been a close association between air pollution and urban landscape and long-term air quality can be improved by proper land use planning and management (Hien et al., 2020).

Due to heterogeneity in sources of air pollutants, remote sensing and GIS-based statistical modeling are being provided as a solution to the conventional fixed monitoring stations which are expensive and inadequate to capture the

of the influential research conducted across various regions worldwide. A study by (Huang et al., 2017) used Land Use Regression (LUR) to investigate the relationship of different variables (e.g., land use type, vehicular & industrial emissions, geographical coordinates, meteorology, topography, and population density) with air pollutants (i.e., $PM_{2.5}$, SO_2, NO_2, and O_3). Similarly, research conducted in the US by (McCarty & Kaza, 2015) explored the association between urban spatial structure and different air pollutants using the Ordinary Least Square (OLS) regression method. Lu et al. (2020) developed land use regression models for O_3, N large spatial variations. Land Use Regression (LUR) modeling combines air pollution monitoring data from specific locations with GIS-derived predictor variables to develop stochastic models. These models enable the estimation of pollutant concentrations at sites where direct monitoring data is unavailable (Hoek et al., 2011; Mikeš et al., 2023). LUR models are characterized by their robustness, requiring fewer data inputs compared to dispersion models. They are often preferred in epidemiological studies, particularly those constrained by limited resources for exposure modelling, over dispersion model approaches (or other models based on mathematical models of physical processes). This preference arises from their relative cost-effectiveness, computational efficiency, and lower demand for extensive data and expertise in complex physical and chemical processes (Beelen et al., 2013; Mölter & Lindley, 2021). LUR has gained widespread adoption due to its capacity to elucidate and predict spatial heterogeneities in air pollution levels.

Since its inception, LUR modelling has rapidly evolved and expanded from its original form, initially employing multiple linear regressions with averaged data from routine stations or passive sampling. Initially focused on capturing long-term spatial air pollution variations, it faced limitations in capturing local-scale spatial patterns with high temporal resolution (Beelen et al., 2009; Vienneau et al., 2010). In recent years, LUR approaches have been refined to model a broader range of air pollutants spatiotemporally. Modern LUR models employ multi-source observations (such as data from fixed monitoring stations or mobile monitors or satellites or a combination of them) and advanced statistical techniques to estimate spatial and temporal variations of various pollutants, catering to both long-term and short-term exposure studies (Ma et al., 2024).

LUR methodologies have primarily proven effective in modelling the annual mean levels of NO_2, NO_x, SO_2, PM_{10}, $PM_{2.5}$, O_3 and VOCs (Gilbert et al., 2005; Hatzopoulou et al., 2017; Li et al., 2021; Zhang et al., 2018). The utilization of LUR models for predicting air pollutant levels is prevalent across various regions worldwide, with particular emphasis on Europe, the US, and China. A comprehensive table (Table 1) has been assembled to synthesize the literature on Land Use Regression models highlighting some

and NO and elucidated the intricate spatiotemporal dynamics of air pollution.

LUR models have shown efficacy in developed regions with robust data sources and high spatial resolutions. On the contrary, there is a paucity of research, investigating the effectiveness of land use regression models in the context of developing countries. In the context of India, the application of Land Use Regression (LUR) models has been limited, with the earliest known study conducted by (Saraswat et al., 2013) focusing on fine, ultrafine, and black carbon particulate matter. However, this study had notable limitations, including equipment constraints, sampling from only one LUR site at a time in addition to a fixed-location site, and a limited number of predictor variables. Another study, (Sanchez et al., 2018) delved into the application of LUR models in a peri-urban setting near Hyderabad, India, shedding light on the dearth of knowledge regarding the effectiveness of LUR models in less urbanized areas within low-/middle-income countries (LMICs). The development and hence, applicability of reliable land use-based regression (LUR) models particularly in developing nations remains restricted due to insufficient and inaccurate predictor variable data and inadequate monitoring of air pollutants. Consequently, these models may yield inaccuracies, impacting the evaluation of public exposure to air pollution (Pervez et al., 2021).

This paper aims to extensively utilize remote sen and Geographic Information Systems (GIS) techniques extensively to assess ambient air quality in Delhi, a highly polluted urban area in India. The research focuses on constructing Land Use Regression (LUR) models to scrutinize the yearly and seasonal fluctuations of particulate pollutants in the city. A unique facet of this investigation involves an in-depth analysis of the relationships between air pollutants and diverse land use-land cover variables, encompassing road length, building density, population distribution, and meteorological parameters. This meticulous examination not only elucidates the intricate nexus between land use patterns and air quality but also paves the way for a nuanced understanding of pollution mechanisms. The study's emphasis on unraveling these associations serves as a foundation for proposing targeted mitigation

Table 1 Some prominent land use regression studies

References	Area	Pollutant(s)	LUR model equation	Model accuracy (R^2)
Chalermpong et al. (2021)	Bangkok, Thailand	$PM_{2.5}$	− 4.57e + 2 − 0.55 * **Humidity** + 0.569 * **Pressure** − 1.45 * **Temperature** + 0.0118 * **Cumulative Number of Hotspots** − 6.48 * **Windspeed** − 6.20E−4 * **Urban Green Space within 300 m** + 4.07 * **Number of Buddhist Temples** − 1.69E−4 * **Residential area within 100 m** + 1.92E−2 * **Fire Radiative Power** + 3.06E−6 * **Area of transport terminal** + 4.15 * **Distance to nearest road**	0.32
Eeftens et al. (2016)	Switzerland	$PM_{2.5}$	− 13.2 + 1.81 * **PM2.5_2010 (dispersion model estimates)** + 0.0478 * **Length of Major roads within 25 m**—0.000000521 * **Urban green within 5000 m** + 0.0000515 * **Traffic load of major roads**	0.57
		PM_{10}	− 19.2 + 2.02 * **PM10_2010 (dispersion model estimates)** + 0.0707 * **Length of Major roads within 25 m**—0.00000092 * **Urban green within 5000 m**	0.63
Jones et al. (2020)	Southern California, US	UFP	7.74338 + 2.761089 * **Inverse distance to LAX airport** + 0.01834 * **NO2 estimate for 2010 at year 2000 census block-level** + 0.03491 * **Percent of 1KM buffer that is airport** + 0.00eight7 * **Sum of A1 road length within 50 M buffer** + 0.004705449* **Percent of 5000 M buffer classified as highly developed** + 0.10298 * **Traffic intensity from passenger vehicles in 1KM buffer** − 3.3755* **Percent of 5000 M buffer classified as deciduous forest** − 0.3454 * **Percent of 1000 M buffer classified as cultivated crops** − 0.0801485 * **Percent of 5000 M buffer classified as mixed forest** + 0.001980555 * **Percent of 50 M buffer classified as developed, medium intensity** + 0.00588122 * **Percent of 100 M buffer classified as developed, open space** + 0.00307249 * **Percent of 50 M buffer classified as highly developed**	0.66
		$PM_{2.5}$	− 1.714 + 0.37251 * **Vehicles miles travelled for passen-**	0.47

			ger cars + 0.00024061 * **Housing unit density within 5000 m** + 0.018289032 * **percent of 5000 M buffer classified as developed, low intensity** + 0.02109 * **NO2 estimate for 2010 at year 2000 census block-level** − 0.1615035 * **Forest within 5000 m** + 0.00012780 * **Length of major roads within 1000 m** + 0.00122303 * **percent of 50 M buffer classified as highly developed**	
		BC	4.70754 + 0.05269 * **NO2 estimate for 2010 at year 2000 census block-level** + 0.09068 * **traffic intensity from passenger vehicles in 1KM buffer** + 1.55328726 * **inverse distance to LAX airport** + 0.010466185 * **percent of 5000M buffer classified as developed, low intensity** + 0.00907* **sum of A1 road length within 50M buffer** − 0.1911475 * **percent of 500M buffer classified as cultivated crops** − 3.5168 * **percent of 5000M buffer classified as deciduous forest** + 0.01483 * **percent of 1KM buffer that is airport** + 0.00089133 * **sum of A3 road length within 100M buffer**	0.38
Meng et al. (2016)	Shanghai, China	PM_{10}	65.90 + 0.374 * **Distance to Coast** + 5.34E−3 * **Industrial Emissions (in tons)**—1.30 * **Urban green area within 1000 m** + 4.78E−2 * **Total Road length within 5000 m**	0.8

Table 1 (continued)

References	Area	Pollutant(s)	LUR model equation	Model accuracy (R^2)
Miri et al. (2019)	Sabzevar, Iran	PM_1	33.52 + 2.12E− 02 * **Distance to religion/cultural land use** + 2.66E− 03 * **Industrial area within 500**m − 1.29E−04 * **Educational land use area within 500m**	0.68
		$PM_{2.5}$	41.70 + 3.28E− 03 * **Industrial area within 500 m** + 2.30E−02* **Distance to religion/cultural land use**—0.62***Maximum height of building within 200 m**	0.71
		PM_{10}	53.39 + 1.77E—03* **Other land use area within 100 m** + 4.05E− 02 * **Distance to religion/cultural land use** − 4.14E− 03* **Distance to bus** terminal—9.52E− 03* **Distance to urban facility land use**	0.75
Saraswat et al. (2013)	Delhi, India	ln ($PM_{2.5}$)	0.01 + 0.98 * **Log of mean hourly 10th percentile concentrations from the rooftop site** + 1.5E−3 * **Population within 5000 m**	0.73
Shi et al. (2020)	Liaoning, China	$PM_{2.5}$	53.54 + 1.72E−3 * **Average building floor area within 300 m** + 17.31 * **Building coverage ratio within 100 m** -32.11 * Water **body within 3000 m**—0.55 * **Average building height within 50 m**	0.61
Tularam et al. (2021)	Durban, South Africa	PM_{10}	− 25 + 0.52 * **Dispersion Model** + 4.3E−6 * **Urban Area within 2000 m** + 1.8E−6 * **Industrial area within 2000 m** + 6.6E−4 * **Population within 1000 m**	0.85
Wan Azmi et al. (2024)	Peninsular Malaysia	PM_{10}	44.942 + 1.687E−6 * **Industry within 5000 m** + 3.74e−4 * **Residential area within 5000 m** -2.757e−6 * **Infrastructural within 5000 m**—7.943e−8 * **Forest area within 5000 m**	0.58
Wong et al. (2021)	Taiwan	$PM_{2.5}$	− 16 + 5.86 * **Winter** + 3.06 * **SO2_Kriging** + 0.55 * **O3_Kriging** + 0.9 * **NO2_Kriging**− 0.0002 * **Distance to nearest airport**− 0.003 * **Forest within 5000 m** + 0.01 * **Farm land within 4000 m**	0.58
Li et al. (2015)	Changsha Area, China	NO_2	25.9 + 8.868E−3 * **Length of major roads within 1300m buffer** + 6.987E−6 * **Residential area within 1200 m** + 1.188E−5 * **Area of land for public facilities within 1200 m buffer**—2.729E−6 * **Urban green space within 1200m**	0.51
		PM_{10}	39 + 1.544 * **Length of major roads within 900 m buffer** + 1.779E−5 * **Residential area within 1200 m** + 5.318E−5 * **Area of public facilities within 300 m**	0.48
Li et al. (2024)	Hong Kong	$PM_{2.5}$	24.3 + 8.73E−04* **Light duty vehicles within 500 m** − 2.60E−06 * **Urban green space within 4000 m** + 3.84E−05 * **Residential area within 300 m**	0.84

The bold terms represent the independent variables used in the equation for creating the Land Use Regression model, where the pollutant levels are the dependent variable. To put it simply, in the regression equation y = ax + by = ax + b, the "x" factors are the ones highlighted in bold

strategies, offering innovative avenues for controlling and ameliorating air pollution in urban settings akin to Delhi. The objectives of this study are as follows:

- Utilize the LUR modeling to explore the relation between particulate pollutants and land use variables, including road length, building density, population distribution, and meteorological parameters.

- Investigate the spatio-temporal variability of particulate pollutants in Delhi, examining annual and seasonal fluctuations and identifying potential trends.

Study Area

Delhi (28°34′N and 77°12′E) is the capital of India. Delhi is the second most populous city in the country with a

population of 16.8 million as per the 2011 census and an average growth rate of 1.92%. The climate of the city is semi-arid and subtropical type, with the western and northwestern directions being the dominant wind directions and the annual mean wind speed ranging between 0.9 and 2 m/s (Masood & Ahmad, 2020). The annual mean temperature of the city has been observed to be 31.5 °C, with a maximum temperature of 45 °C noted in the summer months of March to June. Temperature significantly falls in the winter months of December and January, during which stagnant meteorology favors trapping of emissions and thus, produces high pollutant concentrations (Rai et al., 2020). The city receives most of its rainfall during the monsoon, generally from July to September.

Delhi, has been experiencing significant changes in land cover and land use due to accelerated economic development. (World Air Quality Report: Region & City PM2.5 Ranking, 2021) reported Delhi to be the most polluted capital in the world based on the average annual $PM_{2.5}$ concentrations for the fourth consecutive year. In a research investigation carried out by (Ganguly et al., 2021) in major metropolitan cities of India, Delhi exhibited the most severe air pollution primarily due to the prevalence of PM_{10} particles. The crucial sources that have significantly deteriorated the air quality of the city are vehicular emissions, biomass burning, power plants, industrial waste, and the construction sector (Hama et al., 2020; Jain et al., 2020). Moreover, being a landlocked area, geographic location, and local meteorology contribute significantly to aggravating the air pollution situation in Delhi (Kumar et al., 2015). Therefore, with the air quality of the area being severely polluted, developing an effective policy framework and advanced pollution control and preventive strategies necessary.

Methodology

Figure 1 shows the flowchart of the methodology which included the procuring of air quality datasets and remote sensing and GIS based predictor variables which were used in developing the land use regression models. Further subparts of this section include the detailed information of the data used and the process followed.

Air Pollution Data

Daily concentrations of particulate pollutants: $PM_{2.5}$ and PM_{10} were obtained from the online repository of the Central Pollution Control Board (CPCB) for the 38 monitoring stations in Delhi (Fig. 2). The data were procured for one

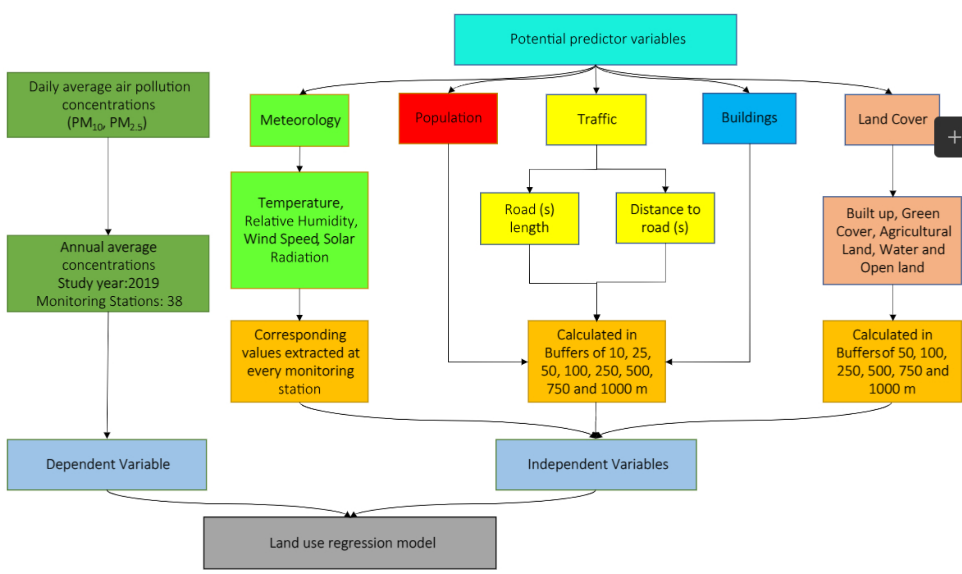

Fig. 1 Flowchart of LUR development

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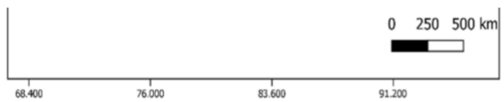

Fig. 2 Map of Delhi along with the locations of installed air quality monitoring stations

year from 1st January to 31st December 2019. This period was chosen as a focal point for several reasons. In 2019, the National Clean Air Programme was ratified, aiming to reduce particulate concentrations by 20–30% by 2024, placing special emphasis on the necessity for enhanced ambient and emissions monitoring, as well as more source apportionment studies to bolster clean air action plans (NCAP, 2019). Moreover, post 2018 period witnessed significant improvements in monitoring and data quality, rendering it more suitable for developing reliable land use regression models (Guttikunda et al., 2023). These models rely on a robust dataset derived from an increased number of representative monitoring stations (Lu et al., 2020; Ma et al., 2024).

The monitoring stations are regulated and maintained by CPCB, the Delhi Pollution Control Committee (DPCC), and the Indian Meteorological Department (IMD), and they conduct the measurements according to the (Guidelines for the Measurement of Ambient Air Pollutants, 2013) set by CPCB. The methods used for the measurement of pollutants considered for analysis

Table 2 Methods of measurement of different air pollutants considered for the study

Pollutant	Method of measurement
Particulate matter (size less than 10 µm) PM_{10} µg/m^3	Gravimetric
	TOEM
	Beta attenuation
Particulate matter (size less than 2.5 µm) $PM_{2.5}$ µg/m^3	Gravimetric
	TOEM
	Beta attenuation

are mentioned in Table 2. Furthermore, the air quality monitors are calibrated regularly by the mentioned authorities in conformity with the operating instructi of equipment, ensuring data quality (Hama et al., 20 Additionally, data irregularities were checked for no data values, zero or negative values, and outliers and were

removed for quality assurance and better interpretation of the data.

Predictor Variables

The selection of suitable potential indicators and buffer sizes is important with respect to land use regression modeling as the spatial pattern of pollutant concentration is source specific and varies for different constituents. This may lead to various degrees of exposure misclassification which risk the utility of models (Aguilera et al., 2015). The optimal buffer size selection balances spatial variability and model precision (Chalermpong et al., 2021; Liu et al., 2021). Ideally, buffer dimensions should be selected while taking into consideration recognized dispersion trends. For example, several monitoring studies have indicated that the influence of a main road on the levels of traffic-related air pollutants decreases exponentially as the distance from the road increases (Baldwin et al., 2015; Batterman et al., 2014). directions for predictor variables in LUR modelling helps build more reliable, interpretable, and generalizable models, ultimately advancing our understanding of the relationships between land use and environmental outcomes (Wu et al., 2017). For example, increased road length is expected to be positively associated with air pollution, therefore, a positive direction of effect is assigned to the "road length" variable in the LUR model, reflecting the anticipated relationship with air pollution levels. The potential predictors that were selected have been used frequently in previous studies (Beelen et al., 2013; Chalermpong et al., 2021; Eeftens et al., 2016; Jones et al., 2020; Z. Li et al., 2021, 2024). Each category was further divided into several categories. Follow previous studies, circular buffers were incorporated around each monitoring site at radii ranging from 10 to 1000 m to capture the effect of the predictor variable on the particulate pollutants. However, noncircular variables such as distance to the nearest road from monitoring stations and meteorological parameters were also included.

Therefore, considering the influence of various elements on the generation, diffusion, and distribution of particulates in urban areas, different predictor variables were selected for our study, including land cover, road length, building area, population, and meteorological parameters. The selected predictor variables have been highlighted in Table 3 along with the pre-defined direction of their effect. Setting a priori

Land Cover

Land cover studies encompass a range of features that offer valuable insights into the composition, spatial distribution, and dynamics of landscapes (Pal & Ziaul, 2017). These features help understand landscape composition, dynamics, and

Table 3 Predictor variables with priori direction

Predictor variable	Buffer	Total variables	Variable affect
Total road length	10, 25, 50, 100, 250, 500, 750, 1000	8	+
Type I roads: primary roads	10, 25, 50, 100, 250, 500, 750, 1000	8	+
Type II roads	10, 25, 50, 100, 250, 500, 750, 1000	8	+
Type III roads	10, 25, 50, 100, 250, 500, 750, 1000	8	+
Distance to the nearest road		1	–
Distance to the nearest road Type I		1	–
Distance to the nearest road Type II		1	–
Distance to the nearest road Type III		1	–
Built-up*	50, 100, 250, 500, 750, 1000	6	+
Green area*	50, 100, 250, 500, 750, 1000	6	–
Agriculture area*	50, 100, 250, 500, 750, 1000	6	±
Open spaces*	50, 100, 250, 500, 750, 1000	6	±
Water*	50, 100, 250, 500, 750, 1000	6	–
Building area	10, 25, 50, 100, 250, 500, 750, 1000	8	+
Population	100, 250, 500, 750, 1000	5	+
Temperature		1	–
Wind speed		1	-
Wind direction		1	-
Relative humidity		1	-
Solar radiation		1	+
Total		84	

*Variables obtained from land cover classification of Landsat-8

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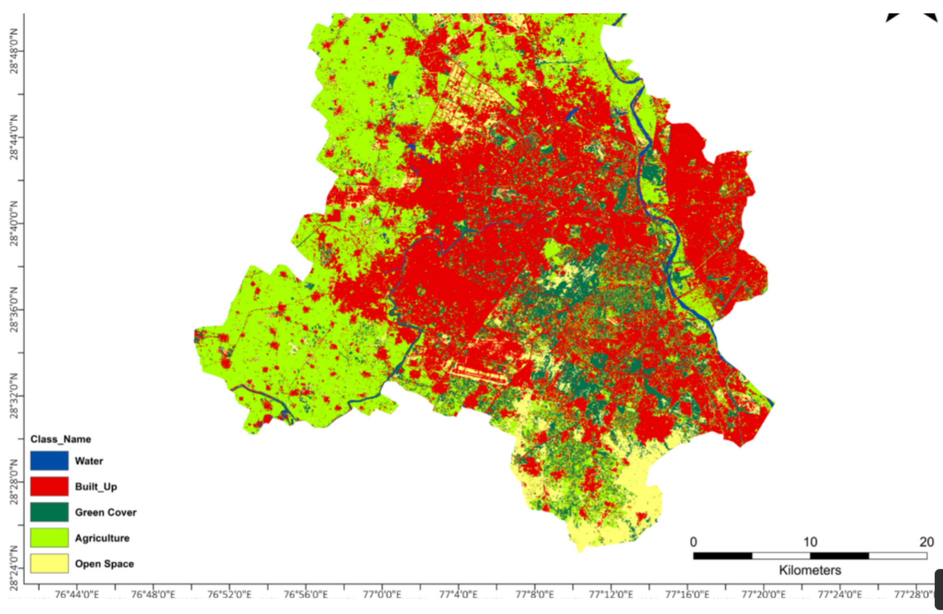

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Fig. 3 Land use cover distribution of Delhi

their impacts on ecosystems and human activities. One key aspect involves land cover classification which can provide a fundamental understanding of the landscape's composition (Latif & Kamsan, 2018).

of the land cover classification that we have performed. This assessment helps in further evaluating the suitability of the map for the intended use (Naikoo et al., 2020). The overall accuracy of the classified image with Google earth pro

The Landsat-8 satellite for Delhi city was obtained from the USGS Earth Explorer online repository (https://earthexplorer.usgs.gov/) for 2019. Image pre-processing included layer stacking of raster bands and mosaicking them using the shapefile of the Delhi state boundary to extract the area of interest (AOI). Land cover classification of the Landsat-8 image of Delhi city was performed using the maximum likelihood approach, which is a type of supervised classification as displayed in Fig. 3. Based on the National Remote Sensing Centre (NRSC) level-1 classification (NRSC, 2014), Delhi was characterized into five major land cover classes: built-up, agriculture, green cover, open space and water bodies.

Furthermore, post-classification accuracy analysis was conducted to assess the precision and quality of the classified map. It provides information regarding the effectiveness as a reference dataset was 91.50% and the Kappa statistics value was determined to be 0.894. According to the earlier studies, classified image and reference data can be considered compatible when the value of the Kappa coefficient is greater than, or equal to 0.75 (Kamali Maskooni et al., 2021; Wondrade et al., 2014).

Table 4 Area and percentage of land cover categories

Land cover class	Total area	Percentage area
Water	15.64	1.06
Built-up	722.85	48.92
Green cover	157.06	10.63
Agriculture	469.14	31.75
Open space	112.84	7.64

Supervised classification results (Table 4) reveal that most land is covered by built-up (48.92%), followed by agriculture (31.75%), green cover (10.63%), open space (7.64%), and water (1.06%). Figure 3 shows that a higher concentration of impervious cover, i.e., built-up that includes urban settlements and roads, exists near the center, toward the east and in the southeastern part of the city. Agriculture is largely concentrated toward the northern, western, and southwestern parts of the city. It is also practiced along the banks of the Yamuna River. The majority of green cover is located toward the southern part of the city center.

Traffic Variables

The road network of Delhi was downloaded from Open Street Maps and classified as follows: Type I roads include expressways and national highways, Type II roads include state highways and major district roads, and Type III roads encompass all other roads, including residential roads. To capture the effect of traffic on particulates, the length of roads (in total and various categories) was calculated in buffers ranging from 10 to 1000m. Additionally, to account for variations in proximity, the Euclidean distance from the monitoring station to the nearest road was calculated for total road lengths and different road types. In the absence of precise traffic volume data, the road network serves as a valuable proxy, offering insights into potential traffic intensity patterns (Azmi et al., 2023).

Other Variables

Meteorological data, namely wind speed, wind direction, temperature, relative humidity, and solar radiation were available at the CPCB online repository for 2019. Population data were procured from WorldPop (https://www.worldpop.org), which is available at 100m. Building footprints data was procured through the Mapflow plugin in QGIS software, which is an open-source software used for scientific analysis and visualization of remote sensing and GIS data.

Land-Use Regression Model Development and Validation

Land-use regression models were developed for the particulate pollutants in the study area for 2019. A supervised stepwise approach was used to select variables which explained the maximum variability (R^2) and ultimately develop the linear regression model. The predictor that explained the highest adjusted R^2 was selected in the model if it conformed to the a priori direction and had a p-value less than 0.10. Subsequently, remaining predictors were added if they satisfied the conditions of being in a priori direction, having a p-value less than 0.10, and improving the value of adjusted R^2 by at least 1%. The resultant models were examined for collinearity in which variables with a variance inflation factor (VIF) > 3 were eliminated and (removed when p-value > 0.10), and the model was re-run.

Ultimately, the LUR models were cross-validated using Leave One Out Cross Validation (LOOCV) using the scikit-learn library in Python. The scikit-learn library is an open-source library and is considered an efficient tool for predictive data analysis (https://scikit-learn.org). We used root-mean-squared error (RMSE) to evaluate and compare the predicted and measured concentrations (Araki et al., 2018).

Results

Spatio-Temporal Variability of Particulate Pollutants

Table 5 shows the average concentrations of particulates PM_{10} and $PM_{2.5}$ for annual and seasonal variations. The annual mean concentrations of both PM_{10} and $PM_{2.5}$ exceeded the National Ambient Air Quality Standards (NAAQS) limits in India. PM_{10} stood at 217.49 µg/m^3, surpassing the NAAQS limit of 100 µg/m^3, while $PM_{2.5}$ at 108.66 µg/m^3 is well above the NAAQS limit of 60 µg/m^3. This highlights that particulate pollution pose a significant risk to public health and the environment throughout the year. Furthermore, air quality fluctuated throughout the year, with winter presenting the most significant challenge. Both PM_{10} (306.90 µg/m^3) and $PM_{2.5}$ (185.52 µg/m^3) concentrations demonstrated substantial increases during winter, significantly exceeding the NAAQS limits. Summer offered slight relief, yet concentrations remained high, with PM_{10} at 219.53 µg/m^3 and $PM_{2.5}$ at 79.60 µg/m^3. However, the monsoon season marked a notable improvement, with particulate matter levels dropping substantially—PM_{10} decreased to 107.77 µg/m^3, and PM2.5 dropped to 40.86 µg/m^3. Following the monsoon, particulate pollution resurged during the post-monsoon season, with PM_{10} concentrations increasing to 279.74 µg/m^3 and $PM_{2.5}$ concentrations rising to 163.56 µg/m^3. While local sources such as vehicular emissions and dust

Table 5 Descriptive statistics of particulate pollutants

	PM_{10} (µg/m^3)		$PM_{2.5}$ (µg/m^3)	
	Mean	SD	Mean	SD
Annual	217.49	38.34	108.66	13.74
Winter	306.90	53.76	185.52	31.59
Summer	219.53	41.38	79.60	14.85
Monsoon	107.77	31.19	40.86	7.35
Post-monsoon	279.74	46.18	163.56	19.76

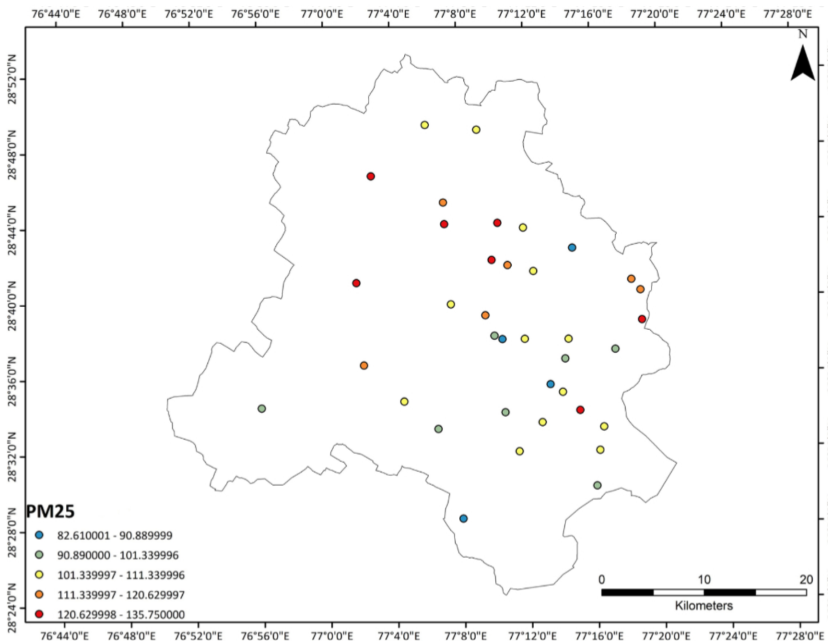

Fig. 4 Annual mean concentrations of $PM_{2.5}$ monitored at monitoring stations in Delhi

resuspension from roads, construction, and soil contribute significantly, regional sources, particularly those located in the Indo-Gangetic plain, also impact the city's air quality. These sources are often dominated by open agricultural residue burnings, which are common in pre-monsoon (April) and post-monsoon (October & November) for clearing agricultural fields for the next crop (Tobler et al., 2020). Moreover, dust storms elevate particulate concentrations during the summer months (Ganguly et al., 2021).

The spatial distribution of annual concentrations of particulates has been presented in Fig. 4- PM2.5 and Fig. 5-PM10. Maximum concentrations of particulates were relatively higher in the north and northwestern regions of the city which comprises of monitoring stations like Alipur, Narela, Bawana, Jahangirpuri and Wazirpur. The high pollutant concentrations could be attributed to dense inhabitation, the presence of industrialized zones, and heavy traffic in those areas (Hama et al., 2020; Shankar & Gadi, 2022). The southern areas of the city comprising of areas like Dr. Karni Singh Shooting Range and Aya Nagar exhibit relatively lower concentrations of particulates. This could be attributed to the presence of dense Aravalli Forests surrounding these areas. The green cover and forest can act as a barrier and thereby capturing and filtering airborne pollutants through their foliage and soil, improving air quality in surrounding areas (Abhijith et al., 2017; Kumar et al., 2019). Furthermore, (Singh et al., 2022) while delineating the air quality monitoring stations of Delhi based on road network clusters and land cover, classified Dr Karni Singh Shooting Range as an urban area experiencing relatively better air quality.

LUR Modelling Results and Validation

$PM_{2.5}$ models

The Land Use Regression (LUR) models reveal intriguing insights into $PM_{2.5}$ concentrations (presented in Table 6) annually and across different seasons. Eleven different variables of all 84 variables were selected for developing $PM_{2.5}$- LUR models. In the annual model, green areas within a 750m buffer negatively impacted $PM_{2.5}$ levels, while open land within a 100m buffer had a positive association. Additionally, greater distances from road types I and II correlated with lower $PM_{2.5}$ concentrations, alongside wind speed. This comprehensive model boasted an impressive R^2 value of

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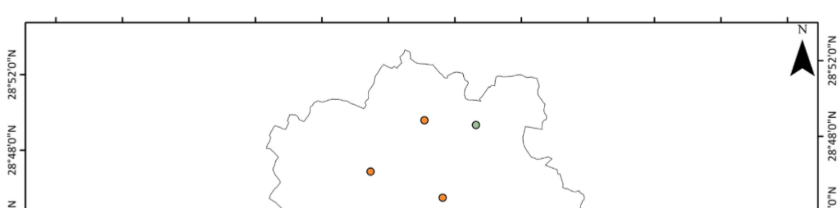

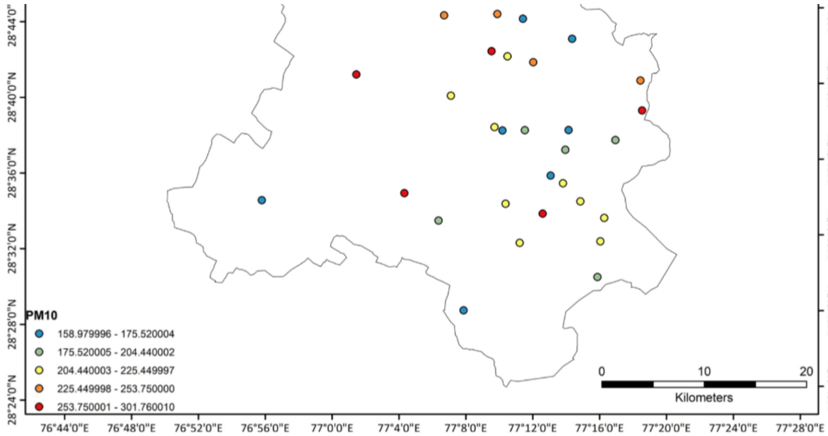

Fig. 5 Annual mean concentrations of PM_{10} monitored at monitoring stations in Delhi

Table 6 LUR models for annual and seasonal mean concentrations of $PM_{2.5}$

Models	Parameters	R^2	Adj R^2	RMSE (μg/m³)	LOOCV RMSE (μg/m³)
Annual	124.36483−0.000016 * **Green_750** + 0.0033391 * **Open_land_100**−0.00322 * **Distance to nearest road type-I (m)**—0.020544 * **Distance to nearest road type-II (m)**−4.447516 * **Wind Speed**	0.58	0.52	9.55	10.53
Winter	199.4991 + 0.0018785 * **TR_I_1000**−0.00037 * **Green_250**−0.04572* **Distance to nearest road type-II (m)**	0.39	0.33	25.72	29.80
Summer	93.77074−1.937e-5 * **Green_1000**−0.02551 * **Distance to nearest road type-II (m)**	0.44	0.41	11.38	11.71
Monsoon	28.809853 + 0.000677 * **RT_II_250** + 0.0001673 * **RT_III_1000**	0.37	0.33	6.00	5.68
Post-monsoon	135.89816 + 0.0001517 * **Built_up250** + 0.0022946 * **RT_I_250** + 0.0060557 * **Open_land_100**	0.43	0.37	15.63	16.73

The bold terms represent the independent variables used in the equation for creating the Land Use Regression model, where the pollutant levels are the dependent variable. To put it simply, in the regression equation y = ax + by = ax + b, the "x" factors are the ones highlighted in bold

0.58, signifying a robust explanation for 58% of the variance in $PM_{2.5}$ levels.

During winter, length of the type-1 road network within 1000m emerged as a significant predictor, positively influencing $PM_{2.5}$ concentrations. Conversely, green areas and distances from road type-II showed a negative association with PM2.5 levels. Despite these factors, the winter model yielded slightly a lower R^2 value of 0.39. In contrast, the summer model showcased the negative influence of green areas and distance from road type-II on $PM_{2.5}$

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concentrations, contributing to an R^2 value of 0.44. Moving to the monsoon and post-monsoon seasons, the influence of road type variables varied, yet played a pivotal role in predicting $PM_{2.5}$ concentrations. The monsoon model achieved an R^2 value of 0.37, while the post-monsoon model exhibited a higher R^2 value of 0.43.

Additionally, the models underwent validation using the leave-one-out cross-validation (LOOCV) method, ensuring their reliability in predicting $PM_{2.5}$ concentrations. Therefore, the final developed models were thoroughly evaluated yielding the RMSE values for LOOCV ranging from 5.68 to 29.80 μg/m³. These results affirm the robustness and reliability of the models in accurately predicting $PM_{2.5}$ concentrations across different seasons. Furthermore, these findings underscore the significance of season-specific variables in shaping spatial–temporal variations in $PM_{2.5}$ concentrations, providing valuable insights for targeted pollution mitigation strategies.

PM_{10} Models

Similarly, the Land Use Regression (LUR) models were employed to explain the spatiotemporal variability of PM_{10} in Delhi. The variables significant to the different models for PM_{10} are listed in Table 7. In the annual model, the presence of built-up areas within a 1000 m buffer, road type III within a 25 m buffer, and building density within a 10 m 100 m buffer, and building density within a 10m buffer were positively correlated with PM_{10} levels. However, a negative correlation was observed between green areas within a 250 m buffer and PM_{10} concentrations. Similarly, greater distances from road type-II were associated with lower PM_{10} concentrations. The winter model showcased a robust R^2 value of 0.62. In contrast, the summer model unveiled a positive association between variables road type III within a 10m buffer as well as building density within a 1000 m buffer and PM_{10} levels. Conversely, a negative association was identified between distances from road type-II and PM_{10} concentrations. The summer model yielded an R^2 value of 0.39. Transitioning to the monsoon and post-monsoon seasons, built-up areas within a 750 m buffer were positively correlated with PM_{10} concentrations. Conversely, greater distances from road type-II and road type-III were associated with lower PM10 levels. The monsoon model displayed an R^2 value of 0.38, while the post-monsoon model achieved an R^2 value of 0.46.

To ensure the reliability of these models, leave-one-out cross-validation (LOOCV) was conducted, resulting in RMSE values ranging from 25.94 to 41.75 μg/m³. These findings underscore the significance of considering season-specific variables in comprehending spatial–temporal variations in PM_{10} concentrations, thereby offering valuable insights for targeted pollution management strategies.

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within a 25 m buffer, and building density within a 10 m buffer exhibited positive associations with PM_{10} levels. Conversely, greater distances from road type-II were linked to decreased PM_{10} concentrations. This comprehensive model demonstrated a noteworthy R^2 value of 0.55, signifying that 55% of the variation in PM_{10} concentrations was elucidated by the included variables.

During winter, built-up areas within a 500 m buffer, road type III within a 10 m buffer, agricultural areas within a

Discussion

This study has produced some important findings and outcomes. To our knowledge, there exist negligible studies that have employed land-use based regression modeling to understand the spatiotemporal variations of particulate concentrations in India and particularly in Delhi. Saraswat et al.

Table 7 LUR models for annual and seasonal mean concentrations of PM10

Models	Parameters	R^2	Adj R^2	RMSE (μg/m³)	LOOCV RMSE (μg/m³)
Annual	140.57726 + 2.9576e−5 * **Built_up1000** + 0.1177387 * **RT_III_25** + 0.1244303 * **Building_10** − 0.055587 * **Distance to nearest road type-II (m)**	0.55	0.49	27.49	35.03
Winter	270.5553 + 0.0001086 * **Built_up_500** + 0.1920989 * **RT_III_10** − 0.000526* **Green_250** + 0.0054113 * **Agri_100** − 0.091397 * **Distance to nearest road type-II (m)**	0.62	0.56	35.78	41.75
Summer	203.23755 + 0.2537419 * **RT_III_10** + 3.7128e−5 * **Building_1000** − 0.066635 * **Distance to nearest road type-II (m)**	0.39	0.32	34.02	38.99
Monsoon	88.939215 + 3.5979e−5 * **Built_up_750** − 0.042824 * **Distance to nearest road type-II (m)** − 0.287041 * **Distance to nearest road type-III (m)**	0.38	0.31	25.94	29.82
Post-monsoon	308.52701 + 0.221655 * **RT_III_10** − 0.000642 * **Green_250** − 0.066772 * **Distance to nearest road type-II (m)**	0.46	0.41	35.56	40.12

The bold terms represent the independent variables used in the equation for creating the Land Use Regression model, where the pollutant levels are the dependent variable. To put it simply, in the regression equation y = ax + by = ax + b, the "x" factors are the ones highlighted in bold

(2013) have attempted to develop the LUR models for $PM_{2.5}$, ultrafine particles, and black carbon in Delhi. However, the LUR models used the observations measured for very short and discontinuous durations and only 14 indicators were used to establish the relationship. Moreover, the study states that the models developed were relevant only from February through May. In fact, for India, authors were able to find just two studies conducted by (Nori-Sarma et al., 2020; Sanchez et al., 2018) in areas of Mysore and a peri-urban area of Hyderabad. Both studies mentioned in the former statement have highlighted the inadequacy of the spatial covariate data which is one of the major impediments in spatial interpolation modeling in developing countries along with the sparse monitoring network. Thus, in order to address the inadequacies uncovered in the literature, this study has examined the viability of land use regression modeling in an urban area of India that is characterized by heterogeneous sources of pollution. Thus, we generated land use models based on the 38 fixed air quality monitoring stations and 84 GIS based predictors to understand the spatiotemporal variability of PM_{10} and $PM_{2.5}$ air pollutants.

Delhi is one of the most polluted cities in the world, and substantial spatial–temporal variations exist in the levels of air pollutants. This can be attributed partially to the geography of the area and partially to human-induced anthropogenic activities, including the disorganized urban development and uncontrolled industrialization. Therefore, our study attempted to investigate the applicability of a land use regression modeling approach using built-up environment indicators and socioeconomic variables coupled with meteorological factors to reproduce the variations of particulate concentrations over a wide geographical area of Delhi. Thus, with the available dataset of GIS predictors and meteorological parameters, our models can be used to predict particulate concentrations in areas where air pollution monitoring is not performed. This helps in understanding the spatial heterogeneity of the particulate pollutants and further, contributes to identifying the existing as well as predicting the future air pollution hotspots of the city. It has been well established by studies conducted mostly in Europe and America that land use regression models help investigate the exposure of air pollution to public health (Cordioli et al., 2017; Wilton et al., 2010).

This study developed LUR models for annual and seasonal concentrations of particulate pollutants (PM_{10} and respectively indicating that our models have the capability of reasonably explaining a large fraction of spatial variability of particulate pollutants based on the data available from fixed monitoring sites. The predictor variables that explained variability of $PM_{2.5}$ included green cover, open land, distance to the nearest road from the monitoring station, and wind speed being the only meteorological factor involved. The variation in annual mean concentrations of PM_{10} could be explained by the overall built-up area, road network length, building area, and distance to the nearest road. The results agree with previous studies that have attempted to establish a link between urban built environment variables and particulate pollution. Chen et al. (2018) developed a LUR model for $PM_{2.5}$ using industrial land, road length, population density, and wind speed as final variables, which explained the 52% variation in annual $PM_{2.5}$ concentrations in China. Our results are also consistent with those observed for Beijing, which is considered the sister city of Delhi. Wu et al. (2015) achieved an R^2 value of 0.52 for annual mean concentrations of $PM_{2.5}$ in Beijing collected at 35 monitoring sites. A study by (Li et al., 2024) utilized the LUR model in the city of Hong Kong to explore the spatiotemporal variability of particulate concentrations. Their study identified key indicators in the annual LUR model for Hong Kong, which included the area of urban green space, the number of light-duty vehicles, and the area of residential land. Interestingly, these findings closely parallel our own results regarding $PM_{2.5}$ concentrations (Table 6), wherein distance to road networks serving as a proxy for traffic variables and green space are included as indicators in the annual model.

Further, it can be observed from Table 5 that seas[onal] variations have a strong influence on particulate concentrations in Delhi. The lowest levels of air pollution were observed during the monsoon, whereas the highest concentrations were noted for the winter season. These observations are in line with the previous studies that reported higher particulate concentrations during cold periods than warm seasons (Ganguly et al., 2019; Hama et al., 2020). Stable weather combined with increased biogenic emissions due to biomass burning, domestic fuel combustion, and vehicular emissions during the winter affect air quality. Low temperatures and shallow boundary conditions inhibit the dispersion of air, leading to a rise in the level of pollutants during the winter (Shankar & Gadi, 2022). Thus, to capture this spatiosonal concentrations of particulate pollutants ($PM_{2.5}$ and PM_{10}) based on 38 air quality monitoring stations in Delhi, India, in 2019. We combined built environment, socioeconomic and meteorological variables to develop these models. The LUR models established to capture the variability of annual and seasonal mean concentrations of particulates performed reasonably well, ranging from 0.35 to 0.58 for $PM_{2.5}$ and from 0.38 to 0.62 for PM_{10}. The R^2 values of annual $PM_{2.5}$ and PM_{10} LUR models were 0.58 and 0.55,

temporal seasonal variability, we produced LUR models for the study area. Four models developed for seasonal concentrations of $PM_{2.5}$ could explain variations ranging from 35 to 44%. While, PM_{10} -LUR seasonal models had R^2 values of 0.38–0.62, the highest value achieved for the winter. In a study by (Li et al., 2015), seasonal LUR models were developed for PM_{10}, elucidating 32 to 51% of the variation in the urban area of Changsha, China. Key variables in their models comprised the length of major roads, residential area, and

land area designated for public facilities. Likewise, our seasonal models (Table 7) incorporated traffic-related variables such as road type and distance to roads, alongside additional factors including building area and green cover.

In formulating the LUR models, various potential predictor variables linked to emission sources (such as traffic-related, socio-economic, and built environment factors) and dispersion conditions (including meteorological parameters) were considered. Notably, traffic-related variables such as road lengths and distances from roads to air quality monitoring stations emerged as the final selected variables in all developed LUR models for both $PM_{2.5}$ and PM_{10}. This underscores the significance of traffic as a major contributor to particulate pollution in Delhi. Moreover, it has been established in source–apportionment studies (Jalan & Dholakia, 2019; TERI, 2018) conducted in the past that the transport sector is one of the significant contributors to particulate pollution in Delhi. Furthermore, an increase in overall built-up, including the building area seems to cause a rise in air pollution due to particulate pollution. A greater number of buildings attributes to highly intensive anthropogenic activities thereby, increasing the particulate concentration (Shi et al., 2020).

Another important outcome of this study could be understanding the impact of agricultural cover and open land on particulate concentrations in the study area. It is unclear from the literature studies that have conducted LUR on particulate pollutants and employed agricultural cover and open land area in their models. The authors could not provide any a priori direction for either of the predictor variables. For example, (Cai et al., 2020; Zhang et al., 2021) observed that agricultural land area was positively associated with particulate concentrations. While, (Chang et al., 2021) have observed negative correlations between agricultural areas with particulate pollution. Alam and McNabola, (2015) have mentioned negative associations between open spaces and particulate concentrations in the cities of Dublin and Vienna. While, (Wu et al., 2015) classified open space as bare land as a positively associated predictor of particulate pollutants. In our observations, green cover, which included forest areas and green spaces was negatively associated with particulate pollutants. In contrast, the agricultural land area was positively associated with particulate pollutants, especially in winter, which can be attributed to biomass burning in agricultural fields. Govardhan et al. (2023) highlighted the issue of stubble burning in neighboring states, Punjab and Haryana, which lead to a rapid increase in air pollution episodes in the region of Delhi-NCR. Furthermore, (Wu et al., 2015) highlighted that open spaces or bare land including construction sites can be potential sources of particulate pollution, therefore, the positive association of open spaces with particulate concentrations can be justified.

It is important to record the limitations of the study, that can help in understanding the current scenarios and improvements to be left as a scope of work for the future. One of the universal limitations of LUR models is the inaccessibility and inadequacy of the predictor variables in developing countries. This results in low prediction efficiency of the generated models, thereby explaining the smaller spatiotemporal variability (Wu et al., 2015). Furthermore, there are some point and non-point sources of pollution, including garbage burning, biomass burning alongside roads, and dust alongside roads which could not be included, but contribute greatly to the particulate emissions. Previous studies (Nori-Sarma et al., 2020; Sanchez et al., 2018) have highlighted the significance of cultural-specific or site-specific points of interest, including religious places, bus stations and petrol pumps, in predicting the particulate matter. We will observe improvements in the results as we incorporate refined and exhaustive predictor variables, including the uncharacterized sources and meteorology-related parameters. In our study, linear relationships have been assumed between the predictor variables and concentration to generate the models. Thus, the authors intend to investigate the scope of land use regression models by considering non-linear and machine learning models that might improve and explain the variability of particulate pollution with more efficiency.

Conclusion

- Investigated the adaptability of land use regression models within the context of India.
- Developed models utilizing built environment parameters, socioeconomic indicators, and meteorological variables.
- Analyzed spatial and temporal fluctuations of particulate pollutants focusing on Delhi with data from 38 fixed air quality monitoring stations.
- Incorporated 84 variables including traffic patterns, land usage data, socioeconomic indicators, and meteorological elements.
- Demonstrated models' capacity to explain 35–58% of variability in $PM_{2.5}$ concentrations and 38–62% in PM_{10} concentrations at an urban scale.
- Identified traffic density, road network lengths, and proximity to major roads as influential factors on pollutant concentrations.
- Highlighted the significance of built-up area, agricultural land, open spaces, and wind speed as crucial determinants of pollutant levels.
- Represents a pioneering endeavor in the region, offering insights into the potential of land use regression models

for understanding spatiotemporal dynamics of atmospheric pollutants.

- Provides valuable implications for the formulation of effective air pollution control strategies and informing land use and urban planning efforts.

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Data Availability Correspondence and request for materials should be addressed to Dr. Kamna Sachdeva at kamna.sachdeva@dseu.ac.in.

Declarations

Conflict of interests The authors declare no competing interests.

Consent for publication All the authors agree to the publication in this journal.

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