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The urban environment in South Asia: studying the ambient air quality in a mid-sized city in Bangladesh

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Improving the urban environment is an urgent task in the fast-growing mid-sized cities of South Asia. Ambient air pollution is worsened by unplanned urban land use and a lack of green and waterbodies, which combined cause a rapid increase in the urban heat island (UHI) effect. This study focuses on pervasive ambient air pollution in the urban environment, primarily driven by particulate matter (PM), which presents a dire public health threat. An *in-situ* investigation of 48 sites in a mid-sized but fast-growing city, Mymensingh, Bangladesh, suggested that the $PM_{2.5}$ concentration (118 $\pm$ 64 $\mu g/m^3$) is about eight times higher than the daily average suggested by WHO (15 $\mu g/m^3$). Weekdays and weekends do not show significant differences in PM generation. Geospatial analysis suggests that good air quality conditions are not found in the study area, and > 50% of people are exposed to PM_{10} in very unhealthy conditions ($\geq$151 $\mu g/m^3$). Traffic and commercial land cover generate the highest PM level. The monsoon climatic events control precipitation and are the most influential factor in diminishing PM concentrations. However, fast-growing mid-sized cities, like Mymensingh in Bangladesh and others throughout South Asia, are facing extreme ambient air pollution that severely impacts public health. Therefore, more action-oriented research initiatives are needed to formulate policies to control air pollution, considering local experiences, indigenous knowledge, logistics capabilities, cultural orientation, transparency, accountability, and strong collaboration, cooperation, and commitment among the public-private partnership.

KEYWORDS

urban land use, urban heat Island, ambient air quality, particulate matter, spatial analysis, public health risk

1 Introduction

More focus in recent years has been given to the urban climate in fast-growing mid-sized cities in South Asia, rather than focusing on mega cities as has been done in the past. Proven approaches include the integrated Land use-Mobility-Energy-Environmental approach in urban development (e.g., Sikder et al., 2018; Alipour and Dia, 2023). Poor urban land use planning leads to ambient air pollution (e.g., ozone and nitrogen oxide), which further affects urban heat islands (UHI) (e.g., Sarrat et al., 2006; Li et al., 2018; Ulpiani, 2021). In fact, urban pollution islands (UPI) and UHI are two major concerns for the urban environment that exist simultaneously (e.g., Agarwal and Tandon, 2010; Ulpiani, 2021).

The World Health Organization (WHO) has stated that nearly the entire global population (99%) is exposed to air that exceeds the WHO's permissible air pollution standards (WHO, 2021), and the highest suffering is experienced in low and middle-income countries (WHO, 2024a). Since 1987, WHO has been providing health-based air quality (AQ) guidelines (AQG) for governments and society to reduce human exposure to air pollution (WHO, 2021), which are related to Sustainable Development Goals (SDGs) targets 3.9.1, 7.1.2, and 11.6.2 (WHO, 2024b). In 2019, air pollution was the fourth leading risk factor for premature death (4.2 million) globally, with 89% occurring in low-and middle-income countries, and the greatest risk experienced in Southeast Asia and the Western Pacific Regions (HEI, 2020; WHO, 2022). These deaths were associated with air pollution-related ischemic heart disease and stroke (37%), chronic obstructive pulmonary disease (18%), acute lower respiratory infections (23%), and cancer within the respiratory tract (11%) (WHO, 2022). In addition, it has long-term effects, for example lower labor productivity and slowing plant development and agricultural productivity (Kapoor et al., 2024a).

Particulate Matter (PM) is the major component of air pollutants and is comprised of sulphate, nitrates, ammonia, sodium chloride, black carbon, mineral dust, and water particles (WHO, 2024c). The health risks associated with $PM_{2.5}$ (diameter $\leq$ 2.5 μm) and PM_{10} (diameter $\leq$ 10 μm) are well documented due to their ability to penetrate deep into the lungs and the bloodstream (WHO, 2024c). A 1% increase in exposure to $PM_{2.5}$ over WHO's AQG (5 μg/m^3 annual average and 15 μg/m^3 24-h average) can cause an approximately 12.8% increase in breathing difficulties, 12.5% increase in wet coughs, and 8.1% higher risk of lower respiratory tract infection (World Bank, 2022). The cleanest city in Bangladesh, Sylhet (Figure 1), has a $PM_{2.5}$ level ~10 times higher than the WHO's AQG (Islam et al., 2020).

In Bangladesh, 78,145–88,229 deaths in 2019 were caused by air pollution, costing the country 3.9–4.4% of GDP (World Bank, 2022). Poor ambient air pollution puts people at risk of breathing difficulties, cough, lower respiratory tract infections, depression, and other health conditions (World Bank, 2022). During 2018–2021, Bangladesh and its capital city, Dhaka (Figure 1), were ranked the most polluted country and second most polluted city in the world, respectively. Reasons for air pollution, e.g., for Dhaka city, are listed as smoke from brickfield kilns (58%), exhaust from transport vehicles (~10%), road dust (~8%), soil dust (~8%), biomass burning (~7%), sea salt (~1%), and dust from construction sites due to rapid urbanization (Begum et al., 2013). This city's air pollution rate is increasing 10% per year.

A significant number of studies have examined ambient AQ and public health in Bangladesh's major cities, including Dhaka and Chittagong (see Table 1). These cities have predominantly developed organically, though certain areas have undergone targeted, pocket-based development due to planning principles. This study aims to examine a mid-sized fast-growing city, where findings may offer significant insights for urban planners and policymakers. The major objectives of this study are (1) to estimate the population exposure under different levels of $PM_{2.5}$ and PM_{10} set by local regulatory authorities using high spatial resolution *in-situ* observation and (2) to identify possible sources of air pollution (excluding quantification). This study also explores the relationship between $PM_{2.5}$ and PM_{10} with other environmental and demographic factors and seasonal variation. An empirical case study has been conducted in a mid-sized city in Bangladesh named Mymensingh (Figure 1).

2 Urban climate, air pollution, and public health

A semi-systematic (e.g., Snyder, 2019) literature review approach was adopted and widely used to identify the research gaps and scope (Snyder, 2019; Zunder, 2021). Google Scholar, ScienceDirect, and Web of Science were used to search the documents. The keywords searched for were "particulate matter pollution," "air pollution trends," "indoor and outdoor air pollution," "impact of particulate matter on human health," "particulate matter concentration in urban areas," "sources of particulate matter pollutants," and "seasonal variation of particulate matter." Bangladesh-related peer-reviewed articles were considered for in-depth research analysis, and concepts and theories from international literature were synthesized. Backward and forward citation searching was also applied (e.g., Haddaway et al., 2022). A total of 30 documents related to ambient air pollution, PMs, potential sources, and impact on public health in Bangladesh were reviewed qualitatively, and the most recent literatures were documented in a tabular format (Table 1).

Ambient air pollution in Bangladesh is a serious issue, and thousands of people die every year from causes related to it (World Bank, 2022). However, detailed research is minimal compared to other global southern countries. Most of the research was dependent on the Department of Environment's (DoE) AQ Index (AQI) (mainly $PM_{2.5}$), although they have very few permanent monitoring stations and remotely sensed processed data with very coarse spatial resolution (DoE, 2024). Very few studies have been conducted on *in-situ* observation of air pollutants with very coarse spatial and temporal resolution.

The impact of air pollution on public health was linked to stakeholders' perceptions by using questionnaires, surveys, or interviews. One study conducted a pathological investigation using blood samples, but it has not been completed yet (Haque et al., 2024). However, the impacts of air pollutants, e.g., PM and nitrogen oxides [NOx = nitric oxide (NO) + nitrogen dioxide (NO_2)] among others (e.g., total suspended particles (TSP), potentially toxic elements (PTE), sulfur dioxide (SO_2), carbon monoxide (CO), carbon dioxide (CO_2), and ozone (O_3)), on public health are well established. Therefore, many researchers estimated the number of exposed people to the level of polluted air.

Recent studies analyzed *in-situ* observations with high spatial resolution but poor temporal resolution (Hossain et al., 2023). There is scope for detailed analysis to take advantage of high spatial

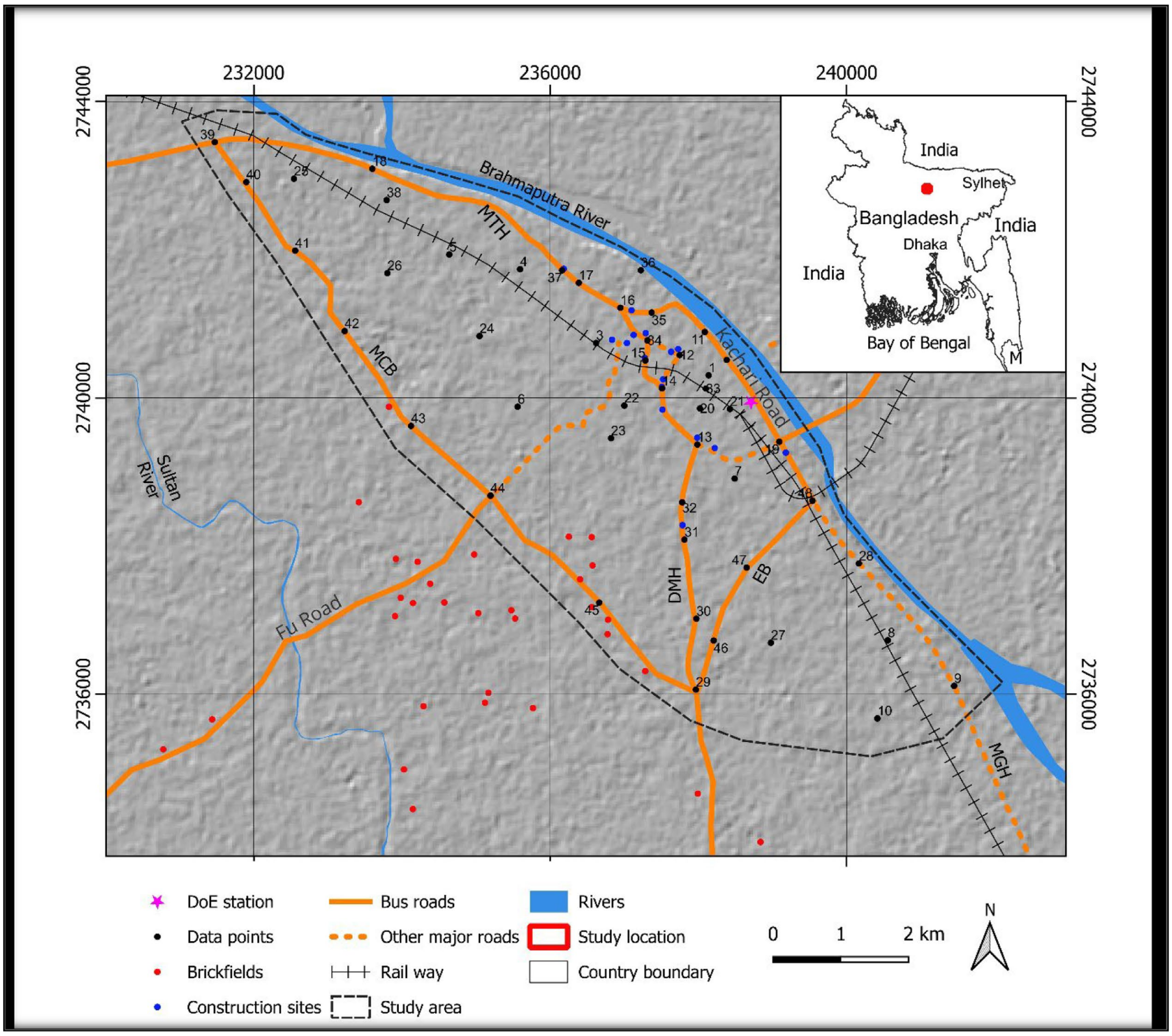

FIGURE 1
The location map of the study area—Mymensingh City Corporation. The locations of Mymensingh Tangail Highway (MTH), Mymensingh City Bypass (MCB), Dhaka Mymensingh Highway (DMH), Eastern Bypass (EB), Mymensingh Gafargaon Highway (MGH), and Myanmar (M) are also located. The hill shade map in the background is produced from 30 m resolution SRTM data (Farr et al., 2007). The unit of the grid is meters is presented in WGS 84, UTM Zone 46 N.

resolution *in-situ* observation. Analysis of the additional data with high temporal resolution from DoE (2024) might offer insights into the ongoing air pollution conditions and exposed populations. This study used those opportunities. A summary of the most recent studies is presented in Table 1.

3 Research methods

3.1 Study area

Mymensingh City Corporation (MCC), which has a total area of 5,679 ha, is a mid-sized South Asian city located in Bangladesh (Figure 1). It extends from longitude 90°19′53.18″ east to 90°27′35.48″ east and latitude 24°42′4.71″ north to 24°47′46.87″ north. The area is of low altitude (2–39 m), with a very gentle slope up to 31.5 degrees. It was a district headquartered by the British Indian government in 1787 and became a divisional headquarters in 2015. Mymensingh City was upgraded from a Municipality to a City Corporation in 2018. Being recently promoted to divisional headquarters and city corporation, a massive construction development is underway in the MCC area. It also became a hub for commercial and administrative activities. Therefore, the mass population travels from within this district and neighboring districts.

The yearly average temperature in Mymensingh is 28.73°C, ranging from 8.2°C in January to 46.12°C in May, and this temperature is about 1 % higher than the Bangladesh average. This area receives rainfall of ~70.7 mm, ranging from 1.33 mm in January to 134.34 mm in May. The average relative humidity in this area is about 67.18%, ranging from 46.47% in February to 81.95% in July (Weather and Climate, 2023).

According to Banglapedia (2023), officially there are six seasons in Bangladesh, but some seasons flow into other seasons and make others shorter. According to hotness-coldness and dryness-rainfall,

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TABLE 1 Most recent literature on air pollution and public health in Bangladesh.

Pollutants/ sampling	Key findings
$PM_{2.5}$, PM_{10}, TSP, and PTEs (literature review between 1992–2021) (Kumar et al., 2024)	• In Dhaka, the association between Pb in $PM_{2.5}$ (0.5 μg/m^3), PM_{10} (0.9 μg/m^3), and TSP (0.5 μg/m^3) were measured for a 24-h average. • The high concentration of Pb in $PM_{2.5}$ is associated with the combustion of fossil fuels, windblown dust, brickfields, various industries, uncontrolled use of Pb in paints, and fugitive emissions from battery manufacturing.
$PM_{2.5}$ (*in-situ*; eight day) (Jawaa et al., 2024)	• $PM_{2.5}$ concentrations in Dhaka measured 77–153 μg/m^3. • Soil dust with S-rich petroleum oil (65%), industrial emissions (5%), non-exhaust emissions (5%), and heavy engine oil combustion (25%) contributed to $PM_{2.5}$ generation. • Sulfur is the main trace element for burning coal and vehicle emissions.
PM_1, $PM_{2.5}$, and PM_{10} (*in-situ*; 2018–20) (Saju et al., 2023)	• High levels of PM_1 (143 ± 45 μg/m^3), $PM_{2.5}$ (302 ± 110 μg/m^3), and PM_{10} (415 ± 184 μg/m^3) were measured. • Children and the elderly were identified as particularly vulnerable to the health risks posed by PM exposure, with notable variations in risk across different urban settings and seasons.
$PM_{2.5}$, PM_{10}, NO, NO_2, SO_2, CO, and O_3 (DoE observed; 2012–19) (Khan R. H. et al., 2023)	• During the peak dry seasons, the average monthly maximum concentrations of $PM_{2.5}$ (477 μg/m^3), PM_{10} (712 μg/m^3), NO_2 (210 ppb), O_3 (132 ppb), and CO (79 ppm) were measured. • Outdoor workers faced increased risks for respiratory and cardiovascular conditions due to air pollution.
$PM_{2.5}$ (remotely sensed; 2002–20) (Hassan M. S. et al., 2022)	• $PM_{2.5}$ showed a positive correlation with land surface temperature and water vapor concentration and a negative correlation with digital elevation model (DEM), rainfall, normalized differentiate vegetation index (NDVI), and wind speed. • $PM_{2.5}$ also had a positive correlation with low-income urban and rural groups, road density, and population density.
$PM_{2.5}$ (remotely sensed; 2002–19) (Hassan M. S. et al., 2022)	• The annual average $PM_{2.5}$ concentration in Dhaka (65–67 μg/m^3), Narayanganj (62–65 μg/m^3), Gazipur (60–66 μg/m^3), Narshingdi (61–64 μg/m^3), and Munshiganj (63–67 μg/m^3) Districts was estimated. • $PM_{2.5}$ concentration increased by 42% during 2002–19. • Pregnant women and those aged over 60 years were the most sensitive to $PM_{2.5}$. • Pregnant women were the most vulnerable but had the least information about $PM_{2.5}$.
$PM_{2.5}$ (DoE observed; 2013–18) (Kulsum and Moniruzzaman, 2021)	• In Dhaka, annual average $PM_{2.5}$ was calculated to be 90 μg/m^3. • Average $PM_{2.5}$ concentration for monsoon season (32 μg/m^3), pre-monsoon season (72 μg/m^3), post-monsoon season (92 μg/m^3), and winter (171 μg/m^3) were estimated. • The relationship between $PM_{2.5}$ and NDVI is negative but non-linear.
$PM_{2.5}$ (Literature review; 2017–19) (Ashikuzzaman et al., 2021)	• $PM_{2.5}$ data revealed that winter possessed the highest concentration for three cities. • Survey respondents suggested that winter (18.0, 24.6, 18.5%) possessed the second highest position after summer (37.9, 33, 49.7%) for Dhaka, Chittagong, and Khulna, respectively. • During monsoon season, $PM_{2.5}$ concentrations were about half of the concentrations found in winter, suggested by respondents.
$PM_{2.5}$ and PM_{10} (DoE observed; 2014–19) (Islam et al., 2020)	• A weekly average AQ index was estimated to be 171 for Dhaka and 106 for Sylhet. • 23 weeks in Dhaka and 14 weeks in Sylhet were forecasted to have unhealthy or worse air quality.
$PM_{2.5}$, $PM_{10,}$ SO_2, CO and O_3 (literature review between; 2013–17) (Khuda, 2020)	• A 24-h average $PM_{2.5}$ (84 μg/m^3), PM_{10} (140 μg/m^3), and SO_2 (8.7 ppb) and a 8-h average NOx (68.2 ppb), CO (1.8 ppm), and O_3 (6.9 ppb) were calculated. • Winter (dry season) was severely polluted.
Name of the pollutants are not available (Mondol et al., 2020)	• People's perception suggests that 87.5% had a basic idea about air pollution. • 46% of people responded that air pollution has a high impact on public health.
$PM_{2.5}$ and PM_{10} sources, exposed population including seasonal variation (in this study)	• In the study area, $PM_{2.5}$ generation (118 ± 64 μg/m^3) is about eight times higher than the daily average of WHO's AQ guidelines. • More than 50% of people are exposed to PM_{10} (201–300 μg/m^3) in very unhealthy conditions. • Mixed land covers (commercial and traffic; 158 ± 99 μg/m^3 $PM_{2.5}$, 272 ± 206 μg/m^3 PM_{10}) and traffic generate the highest level of PM (118 ± 59 μg/m^3 $PM_{2.5}$ and 212 ± 128 μg/m^3 PM_{10}).

three distinct seasons are observed in this country: very hot pre-monsoon summer (March–May), rainy monsoon (June–October), and cold and dry winter (November–February).

The Brahmaputra River and the Mymensingh City Bypass bound the northeast and southwest borders of the study area. Around the Mymensingh City Bypass and south of it, 34 brickfields can be identified from Google Map (Figure 1). Heavy vehicles for both passenger and goods transportation are seen on bus roads, as illustrated in Figure 1. In addition, passengers and goods are transported by human-wheelers and battery-powered three-wheelers (rickshaws and vans).

Recently, the status of Mymensingh *Paurashava* (the local government unit in the urban area) has changed to City Corporation. Therefore, massive urbanization and urban activities have increased, leading to high air pollution. This study explores the extent of air pollution due to $PM_{2.5}$ and PM_{10} in Mymensingh City Corporation.

3.2 Data sources and analytical approach

PM ($PM_{2.5}$ and PM_{10}) data were collected from secondary sources: field campaigns conducted from 27 March to 02 April 2023 (dry season) using a portable Airveda $PM_{2.5}$ and PM_{10} AQ Monitor (Supplementary Table A1) (Airveda, 2022). The measurements were conducted in 148 sample sites (Figure 1) including commercial areas (12 sites), mixed-use areas (7 sites), residential areas (10 sites), and traffic-heavy areas (19 sites) in proximity to the possible sources of air pollutants, with three different time intervals: 7–9 a.m., 12–2 p.m., and 5–7 p.m. In Bangladesh, peak traffic hours are typically observed between 7–9 a.m. and 5–7 p.m. Conversely, 12–2 p.m. is characterized by significantly lower traffic flow (off-peak). To comprehensively capture the traffic-related pollution variability, these time intervals were included. It was a snapshot measurement where the measurement instrument was run for 5–10 min. The value was noted when it showed a relatively stable reading (excluding high measurements due to real-time source encounters). Therefore, the measured PM data represents the general state of ambient air pollution. Geographical locations were also captured in the World Geodetic System 1984 (WGS 84) coordinate system. Further, $PM_{2.5}$ (μg/m^3) concentration data between 13 February 2023 and 10 April 2024, measured at a permanent station (Figure 1) in the study area operated by DoE, was accessed from DoE (2024).

The cloud-free Sentinel 2A data were occupied from Copernicus (2024), which were processed by ESA. This data was captured on 11 April 2023, which ensures that the environmental conditions of PM data are similar to those measured in the field.

Populated and built-up area data were grid-based (raster) (Table 2). Each pixel represents the number of people living in that particular area in 2020 (for population) and the percent of built-up area in 2018 (for built-up area).

Shuttle Radar Topography Mission (SRTM) data was also grid-based, with each pixel representing elevation in meters. Meteorological data, such as precipitation (mm), temperature (°C), and relative humidity (%) at a two-meter height at the location of the DoE permanent station, were accessed from NASA (Table 2).

R software was used to analyze the descriptive statistics of PM data (Supplementary Table B1). The explorative findings are presented with graphs and box plots. This enables the visualization of the site-specific, land cover-specific, and weekdays-weekends variation of data. The 27th (Monday) to 30th (Thursday) of March and 2nd (Sunday) of April 2023 were the weekdays and the 31st of March (Friday) and 1st of April (Saturday) were the weekends in Bangladesh. The average PM concentration (μg/m^3) was also presented in a graphical and tabular format.

3.3 Computation of the exposed population to air pollution

To quantify the vulnerable population under exposed PM, a continuous surface map of PM with 30 m spatial resolution was generated using the inverse distance weighted interpolation method, where measured PM data points were used as input using QGIS (QGIS.org, 2024). The PM surface layers were classified based on a classification scheme from the DoE. The classification scheme used categories of good (0–50 μg/m^3), moderate (51–100 μg/m^3), caution (101–150 μg/m^3), unhealthy (151–200 μg/m^3), very unhealthy (201–300 μg/m^3) and extremely unhealthy (301+ μg/m^3) for both $PM_{2.5}$ and PM_{10}. These classified PM layers were used to clip the population layer to calculate the number of populations living in different conditions of pollution levels. A summarization of the population (aggregate and percentage) was estimated (Supplementary Table B2). However, for the visualization, the population layer was converted to a density map (population/ha), overlaid by contours of different pollution levels generated from classified PM layers (Figure 2).

3.4 Spatially weighted correlation analysis with environmental factors

To explore the relationship among PM, NDVI, DEM (in meter), slope (in degree), built-up area (in %), and population density (person/ha), a multivariate ordinary least squares regression (MOLSR), Pearson's product–moment correlation (PPC), and geographically weighted regression (GWR) were conducted.

The general of MOLSR is as follows in Equation 1:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n \quad (1)$$

where y is the dependent variable, β_0 *is* constant, and $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the coefficient to the independent variables $x_1, x_2, x_3, \ldots, x_n$. However, in the GWR, the locational term is considered with MOLST and the general form of GWR is as follows in Equation 2 (e.g., Hassan S. et al., 2022; Majumder et al., 2023):

$$y_i u = \beta_{0i} u + \beta_{1i} u x_{1i} + \beta_{2i} u x_{2i} + \beta_{3i} u x_{3i} + \ldots + \beta_{ni} u x_{ni} \quad (2)$$

where y is the dependent variable at location u, β_0 is constant, and $\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ are the coefficient of the dependent variables $x_1, x_2, x_3, \ldots, x_n$ at the same location u. GWR executes separately for every spatial unit i of the study area.

In MOLSR, PM ($PM_{2.5}$ and PM_{10}, separately) were considered to be dependent variables, and NDVI, DEM, slope, population density, and built-up were taken as independent variables. MOLSR was performed in four different levels: (i) exact location of PM point data,

TABLE 2 Description of used datasets in this study.

Items	Type	Data format	Spatial resolution	Spatial reference
$PM_{2.5}$, PM_{10} (Hossain et al., 2023)	Point	.txt	–	WGS 84
$PM_{2.5}$ (DoE, 2024)	Point	.txt	–	–
Sentinel 2A (Copernicus, 2024)	Raster	.jp2	10 m	WGS 84 / UTM zone 46 N
Population (Florczyk et al., 2019)	Raster	.geotiff	~79 m	World_Mollweide
Built-up area (Florczyk et al., 2019)	Raster	.geotiff	10 m	World_Mollweide
Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007)	Raster	.hgt	30 m	WGS 84
Meteorological (NASA, 2024)	Point	.csv	–	–

(ii) 100 m buffer, (iii) 250 m buffer, and (iv) 500 m buffer of PMs point data.

For MOLSR and PPC, measured values of PM were used for the exact location of PM point data. NDVI, DEM, slope, population density, and built-up data were extracted from their continuous surface layer using the Sample raster values tool of QGIS, where measured PM point data location was used as the Input layer.

NDVI was prepared following an Equation 3 using Sentinel 2A data (Table 1) applying a tool, Raster Calculator of QGIS (e.g., Islam, 2014; Islam et al., 2022b):

$$NDVI = \left(DN_{NIR} - DN_{RED}\right) / \left(DN_{NIR} + DN_{RED}\right) \tag{3}$$

where the spectral resolutions of DN_{RED} (Red) and DN_{NIR} (Near-infrared) were 0.6491–0.6801 µm and 0.7798–0.8858 µm, respectively (ESA, n.d.). The slope (in degree) of the study area was created using DEM data. The DEM and built-up (in %) data (Table 1) were used in raw format. Density data was taken from an earlier step.

However, in the case of 100 m, 250 m, and 500 m buffer zones, corresponding zones were created using measured PM data location. Then PM data for these buffer zones were generated by clipping the IDW interpolation point data (converted from IDW interpolated raster to point). Further, these PM point data were used as input to extract NDVI, DEM, slope, density, and built-up data, similar to the early steps. To perform MOLSR and PPC, R software was used and summarized in Supplementary Table B3.

Further, GWR was performed similarly to MOLSR using ArcGIS version 10.8. However, for GWR, (i) exact location of PM point data and (ii) 100 m buffer of PM point data was considered. GWR is a widely used method (Hassan M. S. et al., 2022) (Fotheringham et al., 2019; Zhou et al., 2019) to conduct such a study. Note that GWR is an extended version of MOLSR. For more details about how GWR works, see ESRI (ESRI, 2023).

3.5 Assessment of seasonal variation

$PM_{2.5}$ from 13 February 2023 and 10 April 2024 was used to examine the seasonal response. The data was processed and visualized using R in Supplementary Table B5 and box plot (Figures 3, 4). $PM_{2.5}$ concentrations were presented according to months and seasons. Further, the time series of $PM_{2.5}$, temperature, and relative humidity were presented against precipitation. The precipitation and relative humidity were downscaled, respectively, by dividing six and three for visualization, which is widely practiced in the scientific community to explore visual relationships (Islam et al., 2022a). The vertical left and right axes were presented by daily precipitation (mm) and $PM_{2.5}$ concentration (µg/m^3). Furthermore, $PM_{2.5}$ was plotted against temperature, precipitation, and relative humidity with linear regression lines.

3.6 Identification of potential PMs source

Potential sources of PMs in the study area were examined following (i) literature reviews, (ii) *in*-situ AQ monitoring, (iii) field visits, and (iv) stakeholder consultations. The literature review helped us understand potential sources of PM in urban Bangladesh. *In*-situ monitored AqQ was also used to identify potential sources and locations of PM in the study area. The locations with high PM concentrations were identified for field observations.

Field observations were then conducted to assess the local environment where high PM concentrations were identified. This involved site visits within the study area. The local environment was surveyed, with factors such as industrial activities, vehicular traffic patterns, construction sites, and other potential PM sources (compared with literature findings) taken note of. These field assessments were carried out at different times of the day to capture potential variations in PM levels and sources.

Finally, stakeholder consultations and interviews were carried out as part of a study to supplement field observations, providing valuable insights into specific PM sources. The stakeholders were selected randomly to ensure a diverse representation of perspectives. The interactions involved engaging with various individuals, including teachers, students, and residents, amongst others. The interviews were open-ended, allowing participants to discuss their experiences, concerns, and insights on PM in the study area. Note that the quantification and ranks of the air pollution sources were not recorded as they were considered to be out of the study scope. A methodological flow chart is presented in Figure 5.

4 Results

4.1 Descriptive statistics of measured PM

The PM data measurement reveals a total of 1,008 points at 48 sites on commercial, mixed, residential, and traffic land covers. Of

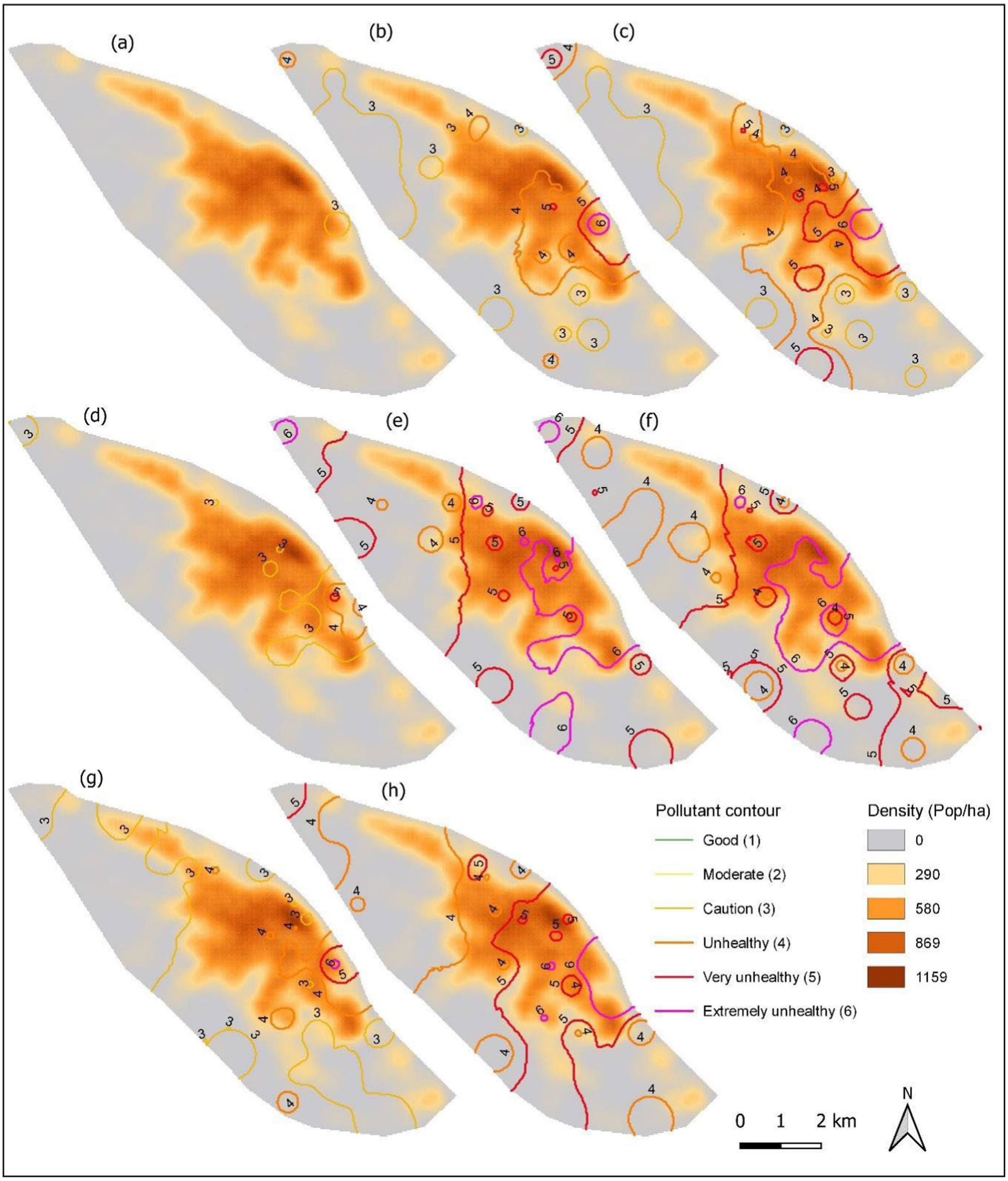

FIGURE 2
Population density overlaid by air pollution level contour, with particulars **(a)** $PM_{2.5}$ at 7–9 a.m., **(b)** $PM_{2.5}$ at 12–2 p.m., **(c)** $PM_{2.5}$ at 5–7 p.m., **(d)** PM_{10} at 7–9 a.m., **(e)** PM_{10} 12–2 p.m., **(f)** PM_{10} at 5–7 p.m., **(g)** $PM_{2.5}$ average, and **(h)** PM_{10} average.

these, 993 points of data were identified as valid since the PM_{10} concentration of the remaining 15 data points was lower than the $PM_{2.5}$ concentration, which voids the PM measurement principle. In the measured data, $PM_{2.5}$ ranges from 50 to 449 μg/m³ with a mean of 118 μg/m³, and PM_{10} ranges from 59 to 857 μg/m³ with a mean of 200 μg/m³. The minimum concentration of $PM_{2.5}$ (50 μg/m³) was measured in the morning session (7–9 a.m.) on residential land cover (id 26) on weekends and traffic land cover (id 46) on weekdays. However, the maximum $PM_{2.5}$ concentration (449 μg/m³) was on mixed land cover (id 43) on weekday evenings (Figure 1). For PM_{10}, minimum concentration (59 μg/m³) was recorded in the morning on commercial (id 2) and traffic (id 36 and 38) land covers on weekdays, however, the maximum concentration was found in the afternoon on mixed land cover (id 19) on weekdays (Figure 1).

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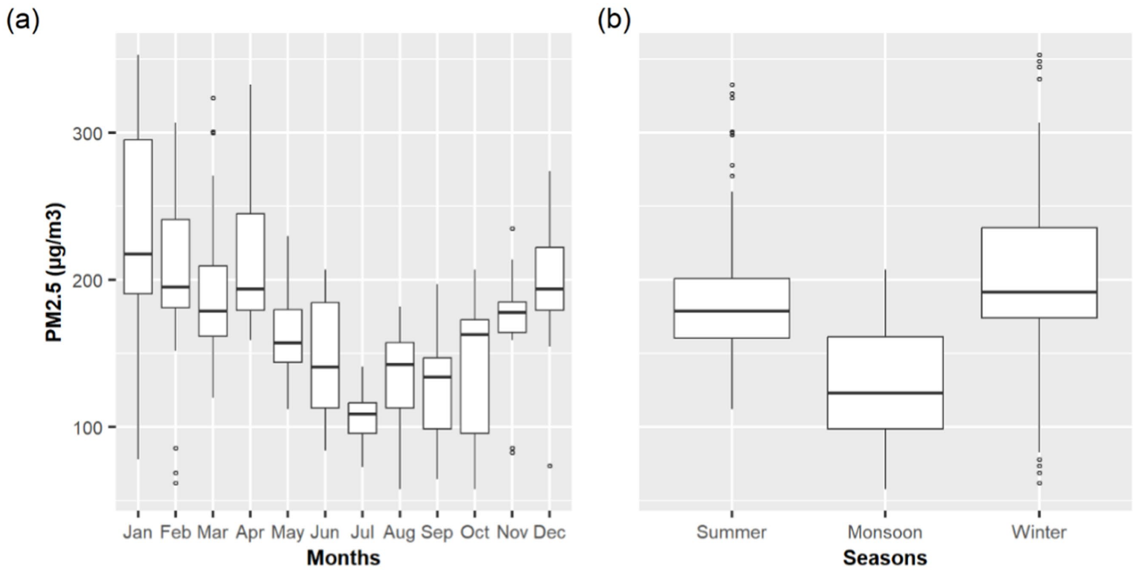

FIGURE 3
Month- **(a)** and season- **(b)** specific $PM_{2.5}$ concentration (µg/m^3) for the study area.

According to the land covers, the least (98 ± 46 µg/m^3 $PM_{2.5}$ and 156 ± 89 µg/m^3 PM_{10}) and the most (158 ± 99 µg/m^3 $PM_{2.5}$ and 272 ± 207 µg/m^3 PM_{10}) PM is generated on residential and mixed types of land covers, respectively (Supplementary Table B1; Figure 6a). Concerning the time of day, PMs levels are at their lowest in the mornings (66 ± 12 µg/m^3 $PM_{2.5}$ and 87 ± 27 µg/m^3 PM_{10}), and highest in the afternoons (259 ± 124 µg/m^3 PM_{10}) and evenings (151 ± 72 µm/m^3 $PM_{2.5}$). The box plots show that there is no significant variation in PM level between weekdays and weekends (Supplementary Table B1; Figures 6a,b).

4.2 Exposed population by air pollution

According to the DoE (DoE, 2024), good AQ levels were not found in the study area (Figure 2; Supplementary Table B2). About 43% of the population was exposed to very unhealthy PM_{10} levels, and 7% were exposed to extremely unhealthy PM_{10} levels. In the afternoon, approximately 31% of the population was exposed to unhealthy to extremely unhealthy $PM_{2.5}$ levels, and about 49% were exposed to unhealthy to extremely unhealthy PM_{10} levels. The situation worsened in the evening, with about 49% of the population exposed to unhealthy to extremely unhealthy $PM_{2.5}$ levels and approximately 98% exposed to similarly unhealthy PM_{10} levels (Supplementary Table B2). The central part of the study area experienced the highest levels of pollution (Figure 2).

4.3 Relationship between PM and environmental factors

In this study, the relationship between particulate matter (PM) and factors such as NDVI, population density, slope, DEM, and built-up % are varied across different methods (MOLSR, PPC, and GWR) and sample points (Supplementary Tables B3, B4). PM (both $PM_{2.5}$ and PM_{10}) showed a negative correlation with NDVI, slope, DEM, and built-up % and a positive correlation with population density at exact point locations (n = 48) and within a 100 m buffer (n = 1,645). In 250 m and 500 m buffer zones, PM (both $PM_{2.5}$ and PM_{10}) had a negative correlation with NDVI, DEM, and built-up % and a positive correlation with slope and population density. However, within the 250 m buffer zone, $PM_{2.5}$ had a positive correlation with built-up % (Supplementary Table B3). Both MOLSR and GWR showed the same coefficient for exact point locations (n = 48), but GWR estimated a slightly lower coefficient than MOLSR for the 100 m buffer zone (n = 1,645) (Supplementary Tables B1, B2). The appendix provides detailed statistics and significant relationships between PM and other independent variables (Supplementary Tables B3, B4).

PM's relationship with all other variables may not be a straightforward linear relationship. For example, in this study, PM's (for both $PM_{2.5}$ and PM_{10}) relationship with NDVI was more non-linear (exponential) (Residual standard error: 43.09 for $MP_{2.5}$ and 90.63 for PM_{10}) than linear (Residual standard error: 42.83 for PM2.5 and 90.63 for PM_{10}) (Figure 7).

4.4 Variability of seasonal response on $PM_{2.5}$

$PM_{2.5}$ concentration varies widely according to seasonal response (Supplementary Table B5; Figure 3). The highest and lowest concentrations were observed, respectively, in January (237 ± 72 µg/m^3) and July (107 ± 17 µg/m^3) (Figure 3a; Supplementary Table B5). During June–August, a monthly average high precipitation of 17–20 mm, relative humidity of 85–89%, and temperature of 28–29°C were found. This period is dominated by monsoon (Figure 3b), which showed a negative correlation with $PM_{2.5}$ concentration.

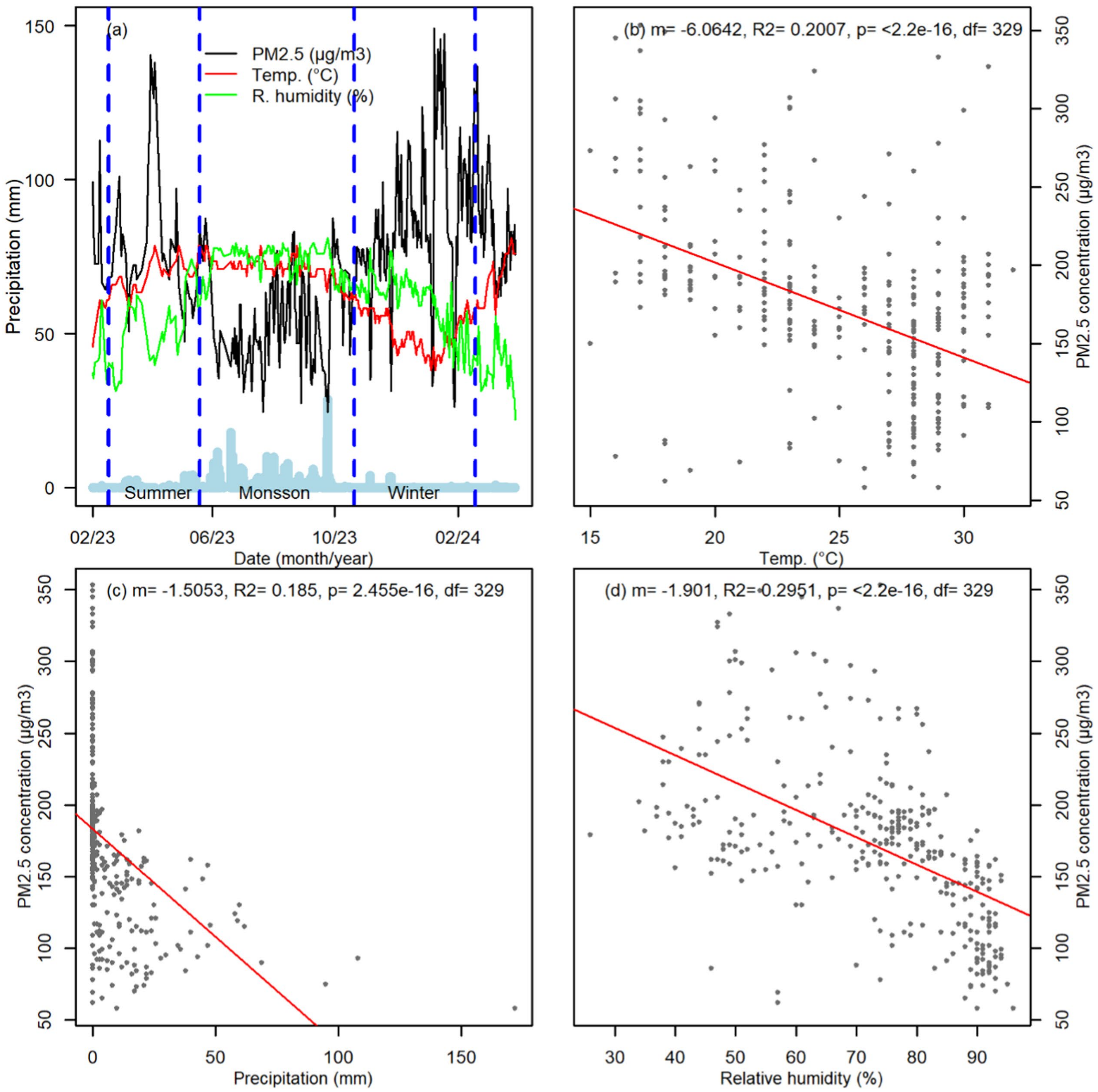

FIGURE 4
Time series of daily precipitation (mm), temperature (°C), relative humidity (%), and $PM_{2.5}$ concentration (µg/m^3) in the study area. The precipitation (light-blue histogram) is downscaled (divided by 6), and temperatures (×6) and relative humidity (×2) are upscaled for visualization **(a)**. A linear relationship (red lines) between $PM_{2.5}$ concentration and temperature **(b)**, precipitation **(c)**, and relative humidity **(d)** is also shown. Inceptor (m), residual square (R2), probability (p), and degree of freedom (df) are also shown (**b–d**).

It was noted that precipitation has the most impact on lowering $PM_{2.5}$ concentration (Figure 4c). Relative humidity also negatively impacts $PM_{2.5}$ concentration (Figure 4d). Temperature is the least impacted factor among these three, where an increase of more than 6°C temperature minimizes a one µg/m^3 $PM_{2.5}$ concentration (Figure 4b).

The DoE observed $PM_{2.5}$ concentration was 166 ± 5 µg/m^3 between 27 March and 2 April (precipitation 12 mm and relative humidity 75%). The field-measured concentration was 184 ± 6 µg/m^3 at the nearest measurement station, Id 21 (Figure 1), which is ~300 m southwest of the DoE station.

4.5 Possible sources of PM

The potential sources of PMs and their location in the study area, including brickfields, major construction sites, and other pollution sources, were identified (Figure 8). Each source plays a crucial role in contributing to the observed levels of PM. Brick kilns are significant PM generation sources (Figures 1, 8a). These kilns rely on the combustion of solid fuels such as coal or biomass during the brick-making process, releasing substantial amounts of particulate matter into the atmosphere. The emissions from brick kilns contain various fine particulates and PM, including ash and

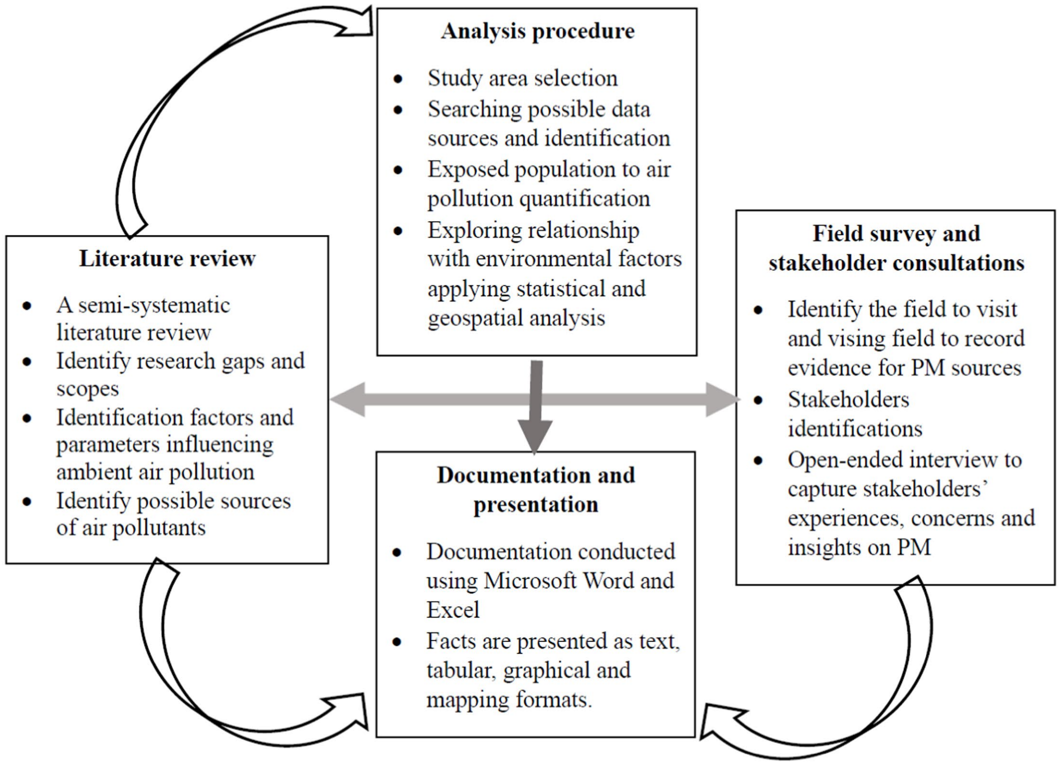

FIGURE 5
Methodological flow chart of this study.

soot. Ongoing construction and demolition activities generate significant amounts of dust, contributing to the ambient PM concentration. Areas with construction projects, such as those related to high-rise building construction along with road construction and development, serve as hotspots for PM generation due to the release of dust particles during excavation, material handling, and other construction activities. This dust is transported through wind currents by being suspended in the air. Vehicle emissions, including those from diesel and gasoline engines, were major contributors to PM in the study area due to the combustion of fossil fuels releasing particulate matter into the atmosphere. Additionally, brake and tire wear also contribute to PM emissions. The major roads in the study area (Figure 1) are packed with heavy traffic most times of the day, contributing to PM along with black carbon emissions. In commercial areas, burning wood and biomass products for cooking or heating purposes is another significant source of PM (Figure 8d). PM is emitted into the air during biomass combustion. Central Business District (CBD) areas with high population densities often experience elevated PM levels due to anthropogenic activities and urbanization processes. Dust accumulation from vehicular traffic, construction activities, and industrial operations contributes to PM in these areas. Additionally, improper waste management practices in residential and commercial areas contribute to higher PM concentrations (Figure 8f). Inadequate waste disposal and burning facilities lead to PM pollution by releasing smoke-containing PM that can travel longer distances.

The collected query-based data confirmed the consequences and issues involving PM. A college lecturer underscored the significant role of vehicles in producing PM. He said, "Vehicular emissions constitute a primary source of PM." Moreover, the increased number of private automobiles in Mymensingh city emerges as a crucial contributing factor to MP, exacerbating the environmental challenges experienced by urban areas. A graduate university student highlighted, "PM emissions originated from household activities and construction sites, attributing the responsibility to human actions." Individuals from grassroots communities provided varied responses due to a lack of in-depth understanding of the topic. Their mixed responses underscore the diverse perspectives and awareness levels within society regarding this environmental issue, highlighting the importance of inclusive education and outreach initiatives to improve public awareness and engagement. A university academic (environment) commented, "Contribution of various factors, such as outdated brick kilns, waste incineration, biomass burning, and massive transportation, highlights the multifaceted nature of PM sources."

5 Discussions

The level of $PM_{2.5}$ in Sylhet, the cleanest city in the country, is 9.7 times higher than the World Health Organization (WHO)-accepted maximum levels (5 μg/m^3 annual mean and 15 μg/m^3 24-h mean) (WHO, 2021). Similarly, in the study area, no location met the AQ standards defined by the Department of Environment (DoE, 2024). In fact, the PM levels in the study area are more than 10 times higher than the WHO-recommended levels (WHO, 2021) (Figure 6; Supplementary Table B3). Approximately 98% of the population in the

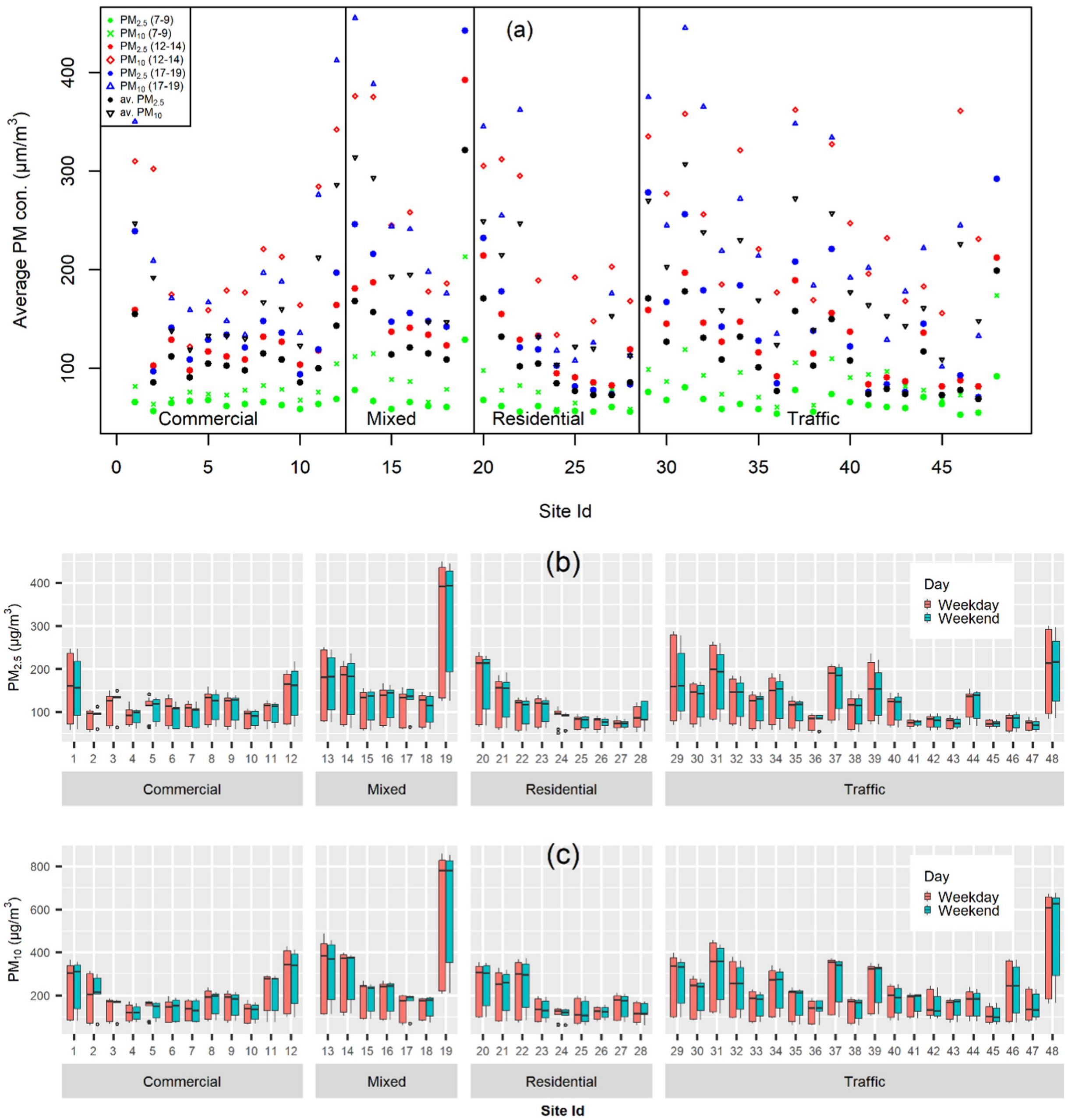

FIGURE 6
PM concentration (µg/m^3) in the study area according to land cover: average PM concentration according to the time of day **(a)**, box plot for $PM_{2.5}$ **(b)**, and PM_{10} **(c)** on weekdays and weekends.

study area experienced unhealthy to extremely unhealthy air conditions for some hours each day (Supplementary Table B3). This reflects the general state of AQ in other cities in Bangladesh (Haque et al., 2024; Hassan M. S. et al., 2022; Jawaa et al., 2024; Khan M. W. et al., 2023; Saju et al., 2023).

In general, PM has a robust relationship with environmental factors (e.g., NDVI, DEM, slope, land surface temperature), meteorological factors (e.g., precipitation, wind speed, and direction), and economic factors (e.g., GDP, income level, poverty level). These findings also correspond to the work of other researchers (Hassan M. S. et al., 2022; Kulsum and Moniruzzaman, 2021). However, due to limited resources and available data sets, only NDVI, DEM, slope, density, and built-up % were considered to explore the relationship with PM. Additionally, the study area was small and relatively flat, limiting variations in land surface temperature, wind speed, and direction. In this study, PM correlated negatively with NDVI (Supplementary Tables B3, B4), similar to other findings (Hassan M. S. et al., 2022; Kulsum and Moniruzzaman, 2021). NDVI indicates green space and the health of green infrastructure (Islam, 2014). High NDVI may suggest more generation of biogenic volatile organic compounds, contributing to O_3 generation and $PM_{2.5}$ levels depending on tree species (Cai et al., 2024). Similarly, PM showed a negative relationship with DEM and slope (Supplementary Tables B3, B4), consistent with other studies (Hassan M. S. et al., 2022), despite

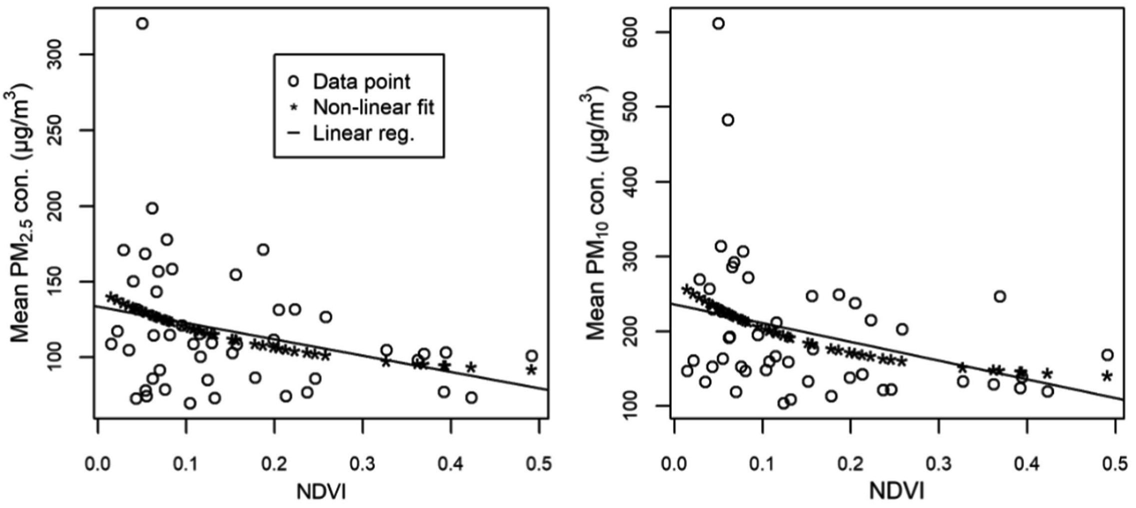

FIGURE 7
Linear and non-linear relationship between PM and NDVI.

limited variation in DEM and slope in the study area. PM is positively related to population density, which is also expected (Budde et al., 2024). Surprisingly, PM had a negative correlation with built-up % (Supplementary Tables B3, B4), contradicting other findings (Lin et al., 2013; Yuan et al., 2019; Halim et al., 2020). Typically, a higher built-up percentage indicates more urban activities and less green-blue space and green infrastructure, therefore generating more PM.

MOLSR considers a multivariable linear regression relationship, and PPC considers a one-to-one relationship. However, the relationship between a dependent and a set of independent variables may not be linear. For example, a nonlinear function may better explain PM's relationship with NDVI (Figure 3) (Kulsum and Moniruzzaman, 2021). However, GWR is an extended version of MOLSR and considers stationary and local nonstationary (geographic) values of variables (Meik and Lawing, 2017). Therefore, GWR might be the superior method to chart a relationship between a dependent and a set of independent variables since, in geography, everything is related to everything else, but near things are more connected than distant things (Tobler, 1970) and geographical variables exhibit uncontrolled variance (Goodchild, 2004). The GWR model in this study probably gave better fits between dependent (PM) and independent variables (e.g., NDVI, DEM, population density). Coefficients obtained in GWR models tended to be lower and tended more towards zero than the MOLSR model, even though it generated a slightly higher standard error (Supplementary Tables B3, B4). However, use of other statistical and geostatistical models, e.g., structural (e.g., Bose et al., 2023; Roy et al., 2023), linear mixed-effect (e.g., Sajjad Abdollahpour et al., 2024; Venter et al., 2024), or linear mixed-effect with spatial correlation models (e.g., Halla-aho and Lähdesmäki, 2020), may change the amplitude of coefficients and the direction of relationships.

In terms of seasonal variation, $PM_{2.5}$ concentration showed a negative relationship with ambient temperature (Figure 8b), consistent with other urban environments in Bangladesh (Khan R. H. et al., 2023) but contrary to findings in the USA (Jhun et al., 2015). During the summer, $PM_{2.5}$ concentration and temperature exhibited a positive relationship, while in the winter, their relationship was negative (Figure 8a). Precipitation is the strongest factor in reducing ambient $PM_{2.5}$ concentration in Bangladesh (Hassan M. S. et al., 2022) and other parts of the world (Zalakeviciute et al., 2018; Liu et al., 2020). Except for in very hot summers, the climate in Bangladesh is influenced by the monsoon, resulting in heavy rainfall and relatively high temperatures (Figure 4; Supplementary Table B5). Therefore, precipitation may have a more significant impact than temperature on controlling ambient air pollution in the study area and country. In winter, high $PM_{2.5}$ concentrations are observed at low temperatures (Figure 8b). Relative humidity is positively related to precipitation, equally affecting the reduction of ambient $PM_{2.5}$ in the study area (Figure 8d). However, relative humidity might have an inverse impact on ambient $PM_{2.5}$ in traffic environments, as found in Ecuador (Zalakeviciute et al., 2018).

Regarding PM sources, no differences were identified when comparing other urban environments in Bangladesh. Brick production, vehicular emission, biomass burning, improper waste management, and construction activities were found in the study area that have been shown to substantially increase environmental stress (Begum et al., 2013; Begum and Hopke, 2019; Kumar et al., 2024). Brick kilns are widespread in the landscape and are a significant contributor to PM generation in the study area (Figure 1). PM emissions occur due to the combustion of solid fuels during brick-making processes (Ahmad et al., 2022). Vehicular emissions are now a major source of PMs due to the increasing combustion of fossil fuels caused by high traffic volumes (Kumar et al., 2021). The burning of biomass materials (e.g., wood burning for domestic cooking and, in commercial areas, domestic and communal waste burning) releases considerable amounts of PMs into the atmosphere (Figure 8) (Johnston et al., 2019). Ongoing construction and demolition operations substantially contribute to PM concentration, particularly in areas experiencing rapid urbanization and infrastructure development (Muleski et al., 2005). Dust particles released during excavation, material handling, and other construction processes aggravate the problem of declining AQ and lead to localized pollution hotspots (Cheriyan and Choi, 2020). Moreover, Central Business District (CBD) areas, characterized by a large population density and a wide range of human activities, are hotspots for elevated PM

FIGURE 8
Existing PM sources. **(a)** Brickfield. **(b)** Construction sites. **(c)** Transport vehicles. **(d)** Burning wood in the commercial area. **(e)** CBD area with high pop. and dust. **(f)** Residential communal waste burning. Photo source: author.

concentrations (Menon and Nagendra, 2018). Dust accumulation from vehicular traffic, coupled with industrial activity, leads to elevated PM concentrations in CBD areas. Modelling might help in quantifying ambient $PM_{2.5}$ concentration with high temporal and spatial resolution (e.g., Suri et al., 2023; Kapoor et al., 2024b). However, not all PMs are locally generated. PMs can stay in the atmosphere for a long period (e.g., hours for PM_{10}, weeks for $PM_{2.5}$, and even longer for ultra-fine particles) and can travel thousands of km in dry conditions (Ali et al., 2019; Kumar et al., 2024; Pima County, 2024). The lifespan and traveling distance of PMs are highly dependent on particle size, aerodynamics (e.g., wind pressure, speed, and direction), and meteorological conditions (e.g., temperature, precipitation, and humidity). Further, climate change impacts trigger higher PM concentrations, affecting public health (Jacob and Winner, 2009; Doherty et al., 2017; Pienkosz et al., 2019).

Ambient air pollution in urban environments largely varies in relation to city size in countries around the world. Generally, urban air pollution increases in relation to city size; therefore, AQ in mid-sized cities is much better than in large cities and/or megacities in China and South Asia (e.g., in India, Pakistan) (Liu et al., 2018; Tabinda et al., 2020). On the other hand, the AQ in large cities is better in Europe, North America, and Latin America (Han et al., 2016). Therefore, the relationship between urban AQ is determined by urban function and land use rather than city size alone. Even though our case is a mid-sized city, it is one of the fastest-growing cities in South Asia. Therefore, ambient AQ should be identical to the large cities and/or megacities in the country (e.g., Jawaa et al., 2024; Kulsum and Moniruzzaman, 2021; Islam et al., 2020).

The urban areas in Bangladesh have turned into contaminated gas chambers due to severe air pollution which has increased the UHI effect, posing a significant public health risk that we are currently grappling with. However, this is common for mid-sized and fast-growing cities in South Asia, e.g., in India (Roy and Singha, 2020, 2021), Pakistan (Anwar et al., 2021), and Sri Lanka (Ileperuma, 2020). Legislatively, AQ in Bangladesh is protected and promoted by several acts, rules, and regulations by the DoE (DoE, 2024). However, the reality is that air pollution is occurring in the study area and, in general, in urban areas in Bangladesh, similar to particularly fast-growing cities in South Asia. There are big gaps in policy execution in this regard, e.g., managing traffic effectively, controlling pollution-generating backdated unfit vehicles, and instating environmentally friendly brick production (Figure 8). Poor practice in plan execution is another example, e.g., Dhaka city's green space reduced from 56% in 1989 to ~2% in 2020 (Khan M. W. et al., 2023). Many authors have suggested nature-based solutions, e.g., ensuring enough green infrastructure by promoting proper land use planning, which would have mitigate UPI (e.g., Ren et al., 2023; Wu and Chen, 2023) and UHI (e.g., Peng and Jim, 2015; Zardo et al., 2017), improve urban flood management (Jarden et al., 2016) and biodiversity and ecological services (e.g., Capotorti et al., 2019; Nakamura et al., 2020), and positively affect physical and mental health (e.g., Felappi et al., 2020; Moreira et al., 2022). However, studying such issues is out of the scope of this research. Therefore, immediate actions have to be taken to secure the interest of public health. Decisive, transparent, and accountable leadership, with strong collaboration and cooperation amongst public-private organizations and agencies, is a pre-requisite to governing the actions for controlling air pollution.

6 Conclusion

Data-driven urban public policy can help to promote a clean urban environment. This study adopted a geospatial approach to studying ambient AQ in a mid-sized Bangladeshi city. This empirical case study estimates the population's exposure to air pollution using high spatial resolution empirical *in*-situ observations to identify possible sources of air pollution and explore a relationship with other environmental and demographic factors, including seasonal variation. Findings suggested that, even though the AQ in Bangladesh cities should be protected to ensure public health, it is being polluted due to increased anthropogenic factors that in turn are facilitated by poor land use planning. Snapshot measurements in the field campaign between 27 March and 02 April 2023 confirm that

- more than 50% of people in the study area are exposed to PM_{10} in very unhealthy conditions,
- generated $PM_{2.5}$ level is about eight times higher than the daily average of WHO's AQG,
- mixed land covers (commercial and traffic) and traffic generate the highest level of PM (158 ± 99 μg/m^3 $PM_{2.5}$ and 272 ± 206 μg/m^3 PM_{10} for mixed land covers and 118 ± 59 μg/m^3 $PM_{2.5}$ and 212 ± 128 μg/m^3 PM_{10} for traffic),
- weekdays and weekends do not have a significant difference in PM generation, and
- measured $PM_{2.5}$ concentration (184 ± 6 μg/m^3) is slightly higher than what was observed by the DoE (166 ± 5 μg/m^3).

The observations and data analysis on air pollution between 13 February 2023 to 10 April 2024 suggest that

- $PM_{2.5}$ generation is the highest and lowest in January (237 ± 72 μg/m^3) and July (107 ± 17 μg/m^3), respectively,
- during monsoon season (June–October), $PM_{2.5}$ generation (130 ± 36 μg/m^3) is much lower than in summer (March–May, 184 ± 29 μg/m^3) and winter (November–February, 203 ± 57 μg/m^3) due to the effect of precipitation, and
- the effect of precipitation on $PM_{2.5}$ is greater than the effect of temperature.

Some avoidable limitations were not possible to overcome. The PM measurements were taken over seven consecutive days with three time slots each day, making it a snapshot measurement. Continuous measurements over a 2-h slot would likely provide a more representative dataset. Additionally, in-*situ* observation only reflects conditions during the dry winter season. For seasonal analysis, the study relied on observed data from a fixed station operated by the DoE.

Prevention of and protection from pollution sources is necessary. As mentioned earlier, the environment and, therefore, AQ in Bangladesh is protected by legislative acts and regulations, however, they need to be properly enforced. Many people do not know that little actions could protect from the worsening of AQ, e.g., burning residential and communal waste. Private, non-governmental, and community-based organizations could increase awareness in this regard. To control air pollution, the researchers suggested a package of activities for short-, mid-, and long-term measures (Hossain et al., 2023; Khan R. H. et al., 2023). However, many of these suggestions do not align with local experiences and knowledge, logistics capabilities, and cultural orientation. Intensive research is required for practical policy suggestions, their implications, and the realities posed by their implementation, which is out of the scope of this study.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Ethics statement

The requirement of ethical approval was waived by oral consents were taken during the interview. For the studies involving humans because it was anonymous but consents were taken from the respondents. The studies were conducted in accordance with the local legislation and institutional requirements. Written informed consent for participation was not required from the participants or the participants' legal guardians/next of kin because oral consents were taken during the interview. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

MH: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing. MI: Data curation, Formal analysis, Investigation, Methodology, Writing – original draft, Writing – review & editing, Conceptualization, Resources, Software, Supervision, Validation, Visualization. SS: Supervision, Writing – review & editing, Investigation. SH: Writing – review & editing. MAI: Writing – review & editing. MF: Writing – review & editing. MZH: Writing – review & editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frsc.2025.1497768/full#supplementary-material

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