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Land Use and the Climatic Determinants of Population Exposure to $PM_{2.5}$ in Central Bangladesh

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Abstract: The major industrial cities of Bangladesh are experiencing significant air-pollution-related problems due to the increased trend of particulate matter ($PM_{2.5}$) and other pollutants. This paper aimed to investigate and understand the relationship between $PM_{2.5}$ and land use and climatic variables to identify the riskiest areas and population groups using a geographic information system and regression analysis. The results show that about 41% of $PM_{2.5}$ concentration (μg/m^3) increased within 19 years (2002–2021) in the study area, while the highest concentration of $PM_{2.5}$ was found from 2012 to 2021. The concentrations of $PM_{2.5}$ were higher over barren lands, forests, croplands, and urban areas. From 2002–2021, the concentration increased by about 64%, 62.7%, 57%, and 55% (μg/m^3) annually over barren lands, forests, cropland, and urban regions. The highest concentration level of $PM_{2.5}$ (84 μg/m^3) among other land use classes was found in urban areas in 2021. The regression analysis shows that air pressure (hPa) ($r^2 = -0.26$), evaporation (kg m^{-2}) ($r^2 = -0.01$), humidity (kg m^{-2}) ($r^2 = -0.22$), rainfall (mm/h) ($r^2 = -0.20$), and water vapor (kg m^{-2}) ($r^2 = -0.03$) were negatively correlated with $PM_{2.5}$. On the other hand, air temperature (k) ($r^2 = 0.24$), ground heat (W m^{-2}) ($r^2 = 0.60$), and wind speed (m s^{-1}) ($r^2 = 0.34$) were positively correlated with $PM_{2.5}$. More than 60 Upazilas were included in the most polluted areas, with a total population of 11,260,162 in the high-risk/hotspot zone (1,948,029 aged 0–5, 485,407 aged 50–69). Governmental departments along with policymakers, stainable development practitioners, academicians, and others may use the main results of the paper for integrated air pollution mitigation and management in Bangladesh as well as in other geographical settings worldwide.

Keywords: $PM_{2.5}$; statistical relationship; climatic variables; land use; hotspot analysis

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1. Introduction

Ambient air pollution is one of the biggest environmental threats to public health, resulting in around 4.2 million global deaths yearly [1,2]. Rapid urbanization and swift industrialization are boosting the global economy, resulting in environmental pollutions [3,4]. Infrastructural damage to ecological balance is happening at an alarming rate because of uncontrolled air pollution worldwide, especially in South Asian and East Asian cities. Additionally, air pollution is attributed to a significant amount of economic costs in developing countries [4,5]. Furthermore, air pollution is also the fifth leading risk factor for mortality worldwide, accounting for more deaths than many better-known risk factors such as malnutrition, drug addiction, and obesity [6]. The average air quality index is very alarming in some major cities in Bangladesh [7–9]. The air pollution level in Dhaka and its suburban areas is very severe as it is ranked as the second most polluted city in the world in terms of air pollution [10–12]. Dhaka is also considered one of the most polluted cities in the world, with an 82 μg/m^3 annual average $PM_{2.5}$ concentration from a wide variety of pollution sources [13–15].

Air pollution is a major environmental and public health issue in South Asian countries due to climate change and different anthropogenic causes including rapid urbanization, industrialization, and transportation growth. Numerous studies have been conducted in the region to assess air quality, identify sources of pollution, and evaluate health impacts [16–19]. On the other hand, the main reasons for air pollution in European countries are mainly emissions from transportation (road vehicles, airplanes, and ships), industrial activities (power generation, manufacturing, and construction), agriculture (livestock, fertilizer use, and manure storage), residential heating and cooking (use of fossil fuels), and natural sources (dust and wildfires) [20–22]. Other factors that contribute to air pollution in Europe include weather conditions, topography, and the presence of pollutants in imported goods. Climate change also exacerbates air pollution by increasing the frequency and intensity of wildfires and worsening weather conditions that trap pollutants in the atmosphere [23–28].

$PM_{2.5}$ (particulate matter with an aerodynamic diameter less than 2.5 μm) is one of the major air pollutants in city areas and is a significant threat to human health and all living organisms [29,30]. It is revealed that the key reasons for this upsetting air quality in Dhaka and its adjacent areas are mainly unplanned urbanization, industrialization, and motorization. A large share (almost 58% of total $PM_{2.5}$) of Dhaka's air pollutants can be attributed to brick kilns operating in and around Dhaka, and significant contributions are also found for motor vehicles (10.4%), road dust (7.70%), fugitive Pb (7.63%), soil dust (7.57%), biomass burning (7.37%), and sea salt (1.33%) [7]. Furthermore, the fuel used by brick kilns operating in this area is mainly coal, while wood is being used as a secondary fuel; the combination of these fuel sources ultimately contributes to almost two thirds of the $PM_{2.5}$ found in the air of Dhaka [7,31,32]. However, Western countries have suggested that the level of $PM_{2.5}$ concentration should be reduced on both a daily and annual basis [33]. In contrast, developing countries like Bangladesh still emit higher levels of $PM_{2.5}$ concentration in the atmosphere. Moreover, regarding loss of human health and life, the cost in terms of capital alone every year is more than USD 1.59 billion, equivalent to BDT 134 billion [34].

Many researchers have completed research on the relationship between $PM_{2.5}$ and land use. The authors of [35] conducted a sampling-based study to determine the atmospheric $PM_{2.5}$ concentration in the Gazipur and Mymensingh districts in Bangladesh, where they found an increased level of pollutants in February 2019 because of different factors such as industrial activities, vehicular emissions, and construction. The study's main limitation was that it used a small number of sample points that did not represent the whole study area, thus leading to a lack of precision. The authors of [36] conducted a spatiotemporal analysis of $PM_{2.5}$ concentration and quantified the relationship between vegetation cover and air pollution in greater Dhaka, Bangladesh. Their results showed that the winter season experienced the highest concentration of $PM_{2.5}$, and the amount of $PM_{2.5}$ increased over time. These studies revealed that vegetation cover and $PM_{2.5}$ concentration exhibited a strong negative correlation ($r^2 = -0.75$). The lack of proper land use information and the limited number of sample points did not allow for an appropriate relationship to be obtained, which is the opposite of our paper. On the other hand, the authors of [37] concluded research that found that artificial surfaces and desert land have positive effects on $PM_{2.5}$ concentration, while forest, grassland, and barren land have negative effects on $PM_{2.5}$ concentration.

Climatic variables have an important role in assessing $PM_{2.5}$ in rural and urban areas. The authors of [38] conducted research on the relationship between $PM_{2.5}$ and seasonal meteorological factors in Dhaka, Bangladesh, where they found that rainfall and temperature had a negative association with $PM_{2.5}$. Rainfall was also negative in Dhaka [11]. Long-term $PM_{2.5}$ links with temperature, surface pressure, and relative humidity were studied by [32] in Dhaka, Bangladesh, using temporal air pollutant data from 2003 to 2019. Their results show that Pearson's correlations were significantly associated with surface pressure and relative humidity, while there was a positive correlation with surface temperature. Their key findings also revealed that vehicular emissions, road dust, soil dust, biomass burning, and industrial emissions contributed to $PM_{2.5.}$ Temperature, wind speed, and wind direction significantly predict $PM_{2.5}$ in Dhaka, Bangladesh. Ref. [39] completed research to investigate the statistical relationship between $PM_{2.5}$ and temperature, wind speed, and wind direction. Based on the literature review above, most of the studies used a limited number of sample points of $PM_{2.5}$ with a few climatic variables. In addition, most of the research used small geographic areas. As a result, the relationship between $PM_{2.5}$ with land use and several climatic variables in larger geographic areas is still unknown. To fill this knowledge gap, this paper has conducted this study using a series of multi-date $PM_{2.5}$ data, land use, and eight climatic variables in large geographic areas (6043 km^2). Finally, this paper aims to investigate the relationship between $PM_{2.5}$ and land use and climatic variables and to identify the riskiest areas and population groups using geographic information systems and statistical analyses.

2. Study Location

The study area of this research is located in the Dhaka division covering its five major industrial districts (Dhaka, Narayanganj, Munshiganj, Narshingdi, and Gazipur) of Bangladesh. The entire area lies between 23°20′00″ N and 24°20′00″ N latitudes and between 90°00′0″ E and 91°00′0″ E longitudes, which covers about 6,043 km^2 housing almost 22 million people [40] (Figure 1). Having a tropical wet and dry climate, the study area has an annual average rainfall of 1,854 mm with an annual average temperature of 25 °C. The study area was selected for some pragmatic reasons: (a) colossal population pressure, (b) massive industrial activities, (c) higher level of traffic concentration, (d) internal migration, and (e) unplanned urban activities, which are the key controlling factors for its local and regional atmospheric conditions [11,41–43]. Ref. [44] mentioned that this area has high concentrations of industrialization due to easily accessible financial resources, enormous transportation networks, location-based advantages, spatial contexts, and different management services.

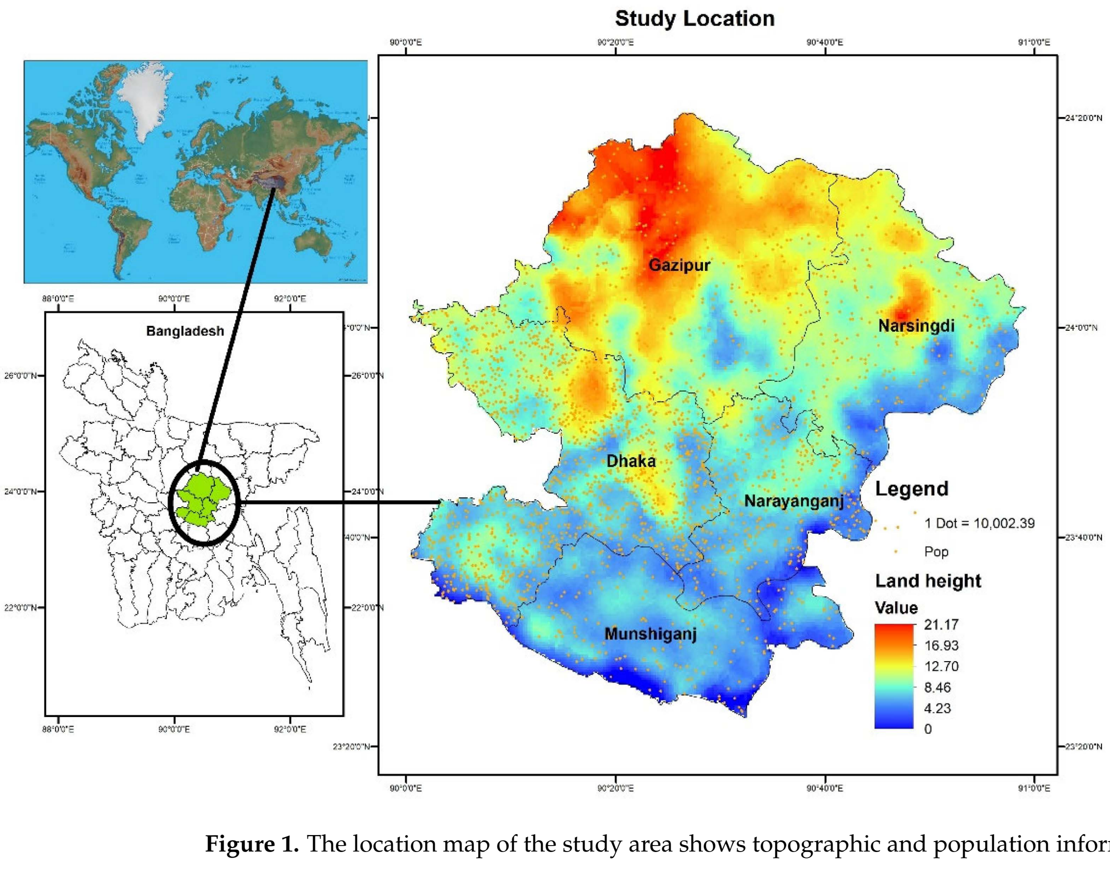

Figure 1. The location map of the study area shows topographic and population information.

3. Materials and Methods

The main methodological steps within a systematic framework which were followed (Figure 2) for completing this study are described below:

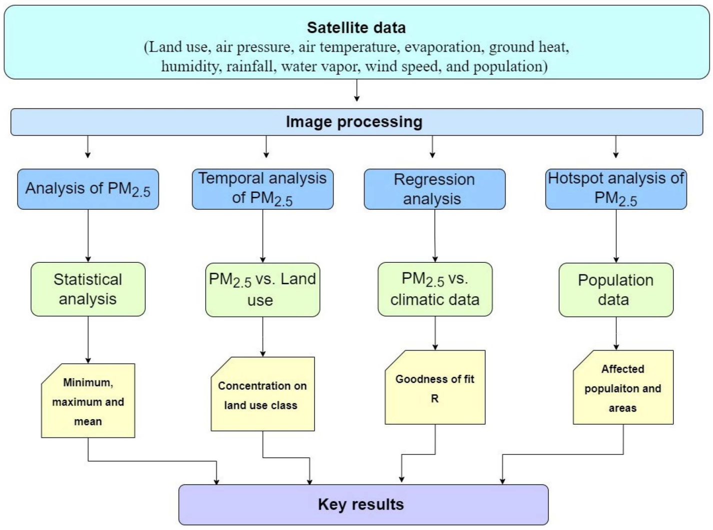

Figure 2. Major methodological steps of this research work.

For this study, the concentrations of $PM_{2.5}$ were collected between 2002 and 2021 from two sources (Table 1) and were used as the main dependent variable for analysis. Nine diverse types of independent variables collected from several satellite sensors were used in this study (Table 1). Land use, air pressure, air temperature, evaporation, ground heat, humidity, rainfall, water vapor, and wind speed were downloaded for 2021. Raster-based population data were collected from the WorldPop website with values ranging from 0 to 5, 50 to 69, and total population, were used to map the most affected people within each area [45]. The variable characteristics of both dependent and independent variables are described in Table 1.

Table 1. The variable names, sources, and the characteristics of independent and dependent variables used in the paper.

Theme	Name	Unit	Source	Time of Data Collection
Independent variables (Air pollutants)	Air Pressure	hPa	https://disc.gsfc.nasa.gov/datasets/M2TMNXSLV_5.12.4/summary	20 December 2021
	Air Temperature	k	https://disc.gsfc.nasa.gov/datasets/NCALDAS_NOAH0125_D_2.0/summary	15 December 2021
	Evaporation	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/M2TMNXLND_5.12.4/summary	20 December 2021
	Ground Heat	W m^{-2}	https://disc.gsfc.nasa.gov/datasets/NLDAS_NOAH0125_M_2.0/summary	20 December 2021
	Humidity	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/NLDAS_FORA0125_H_2.0/summary	15 December 2021
	Rainfall	mm/h	https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary	15 December 2021
	Water Vapor	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/AIRX3STM_7.0/summary	20 December 2021
	Wind Speed	m s^{-1}	https://disc.gsfc.nasa.gov/datasets/M2TMNXFLX_5.12.4/summary	20 December 2021
	Land Use	Class	http://www.globallandcover.com/	20 December 2022
Dependent variables	$PM_{2.5}$	(µg/m^3)	https://ads.atmosphere.copernicus.eu/ https://disc.gsfc.nasa.gov/datasets/M2TMNXAER_5.12.4/summary	2002–2021

3.1. Image Processing and Data Analysis

After collecting all the raster-based data, data masking, resizing, and other image-processing tasks were completed. These tasks were needed to prepare the final output of each variable for further spatial analysis [46,47]. Due to wide-ranging data values for each variable, all the values were normalized using the z-score normalization process [48]. The equation below was used to normalize the data values:

$$x_{\text{new}} = \frac{x - \mu}{\sigma} \quad (1)$$

where x_{new} = data vector after scaling, x = original data, μ = mean of the data vector, σ = standard deviation of the data vector.

3.2. $PM_{2.5}$ Analysis

The temporal analysis of $PM_{2.5}$ was completed in ArcGIS v. 10.8. The mean, minimum, and maximum values of the yearly $PM_{2.5}$ data values were also calculated and graphed in Microsoft Excel to differentiate the temporal variations of $PM_{2.5}$.

3.3. Risk Modeling Using Hotspot Area

To identify the most risk-prone areas, hotspot analysis was conducted in this study using the temporal $PM_{2.5}$ database. It is a widely used tool to analyze the most concentrated areas of $PM_{2.5}$ in air pollution research [49–52]. The main equation used for the calculation of a hotspot is below:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \overline{X} \sum_{j=1}^{n} w_{i,j}}{s\sqrt{\frac{\left[n \sum_{j=i}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \quad (2)$$

where x_j is the value of j, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the number of features, $\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}$, and $s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2}$. A Getis–Ord G_i^* produces z-scores and p-values. Areas with higher z-scores and smaller p-values signify a cluster of the hottest spots while a negative z-score and a small p-value represents the coldest areas [53].

3.4. Regression Analysis

A linear regression was used in this paper to find out the internal relationships among the different variables. A correlation analysis is the most useful tool in understanding the positive and negative relationships among the variables or factors contributing to air pollutants [50,54]:

$$y = mx + b \quad (3)$$

where y = dependent variable ($PM_{2.5}$), m = regression slope, x = independent variable, and b = constant [55].

3.5. Raster Overlay Analysis

The final risk map of $PM_{2.5}$ was overlaid with the population data to determine the spatial distribution of the most affected age groups in the study area.

4. Results

4.1. Descriptive Analysis of $PM_{2.5}$

Figure 3 highlights the minimum, maximum, and mean values of $PM_{2.5}$ pollution levels by 4-year intervals in the study area from 2002 to 2021. It is revealed that, during the 19-year period, there was an overall increase of about 41% in $PM_{2.5}$ levels in the area. The annual trends of $PM_{2.5}$ varied over time, with increases of 4.58% (μg/m^3) from 2002 to 2006, 0.82% (μg/m^3) from 2007 to 2011, 4.03% (μg/m^3) from 2012 to 2016, and 3.47%

($\mu g/m^3$) from 2017 to 2021. The minimum values of $PM_{2.5}$ increased by 55% to 78% ($\mu g/m^3$) from 2012 to 2021, while the maximum values showed significant variation from 2002 to 2021. The highest values of $PM_{2.5}$ were found from 2012 to 2021. Furthermore, the study found an upward trend in the mean values of $PM_{2.5}$ from 2007 to 2016, and these values exceeded the annual standard limit set by the World Health Organization (WHO) for $PM_{2.5}$ (15 $\mu g/m^3$) in Bangladesh. Overall, these findings suggest a concerning trend of increasing $PM_{2.5}$ pollution levels in the study area over the past two decades, with potential health implications for the local residents.

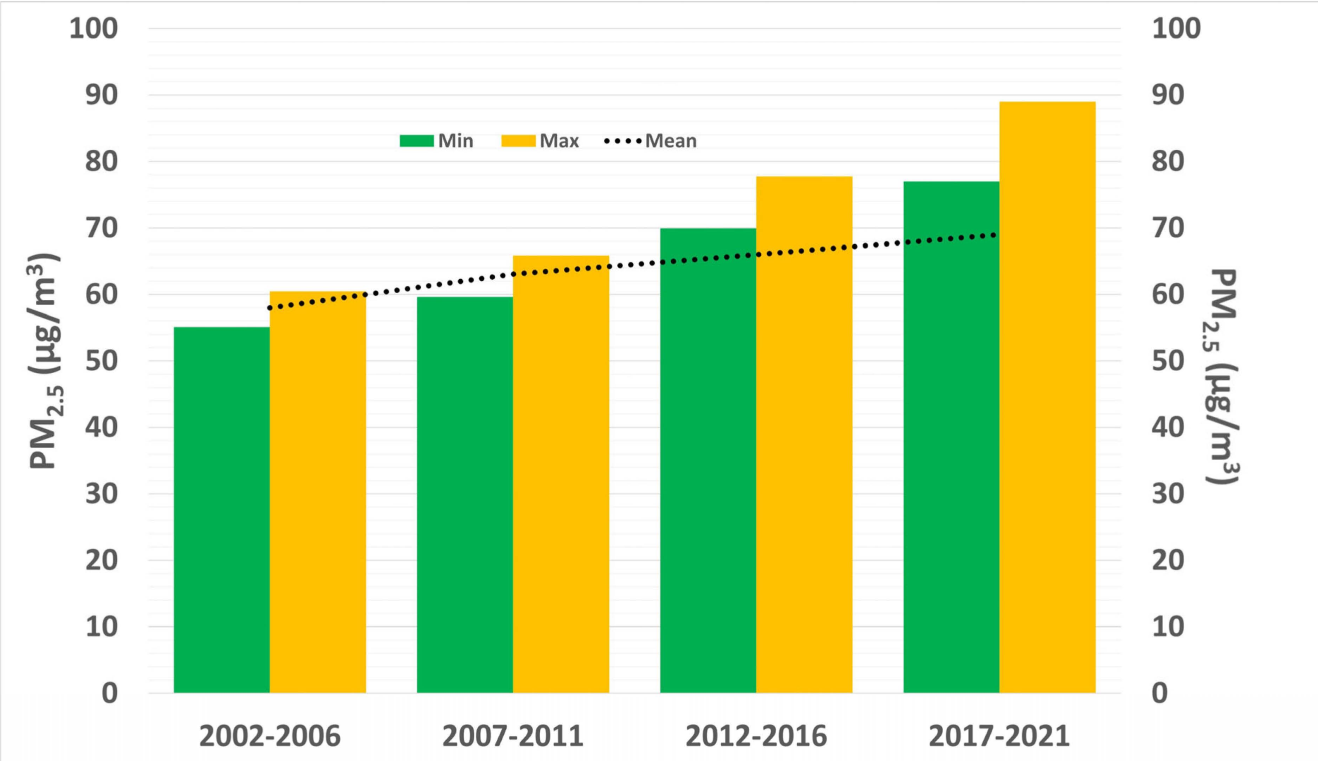

Figure 3. Temporal analysis of minimum, maximum, and mean $PM_{2.5}$ from 2002 to 2021.

4.2. Relationship between $PM_{2.5}$ and Land Use

The results presented in Figure 4 indicate that the concentration of $PM_{2.5}$ varies significantly across different land use classes in the study area. Barren lands, forests, croplands, and urban areas were found to have the highest concentrations of $PM_{2.5}$, with varying degrees of increase over the years. Barren lands, for instance, found an increase of 64% in $PM_{2.5}$ concentration ($\mu g/m^3$) from 2002 to 2021, while forest areas had an increase of 62.75%. The largest land use class in the study area, croplands, also showed a significant increase (57.70% from 2002 to 2021) in $PM_{2.5}$ concentration. Urban land, which is the dominant land use class in the study area, had an increase of 55.6% in $PM_{2.5}$ concentration ($\mu g/m^3$) over the same time period, with the highest $PM_{2.5}$ concentration level of 84 $\mu g/m^3$ found in urban areas in 2021. These findings highlight the need for targeted interventions and pollution control measures in different land use classes to reduce $PM_{2.5}$ concentration and mitigate its adverse effects on human health and the environment.

4.3. Relationship between $PM_{2.5}$ and Climatic Variables

A spatial relationship between the estimated $PM_{2.5}$ and climatic variables was conducted using a linear regression model. The regression analysis showed that air pressure (hPa) ($r^2 = -0.26$, Figure 5a) and evaporation (kg m^{-2}) ($r^2 = -0.01$, Figure 5c) were negatively correlated with $PM_{2.5}$ (Figure 5). On the other hand, air temperature (k) ($r^2 = 0.24$, Figure 5b) and ground heat (W m^{-2}) ($r^2 = 0.60$, Figure 5d) were positively correlated with

$PM_{2.5}$. It means that if air pressure is higher and evaporation is higher, these two factors may contribute to generating less $PM_{2.5}$. Alternatively, higher air temperature (k) and ground heat (W m^{-2}) may generate higher $PM_{2.5}$.

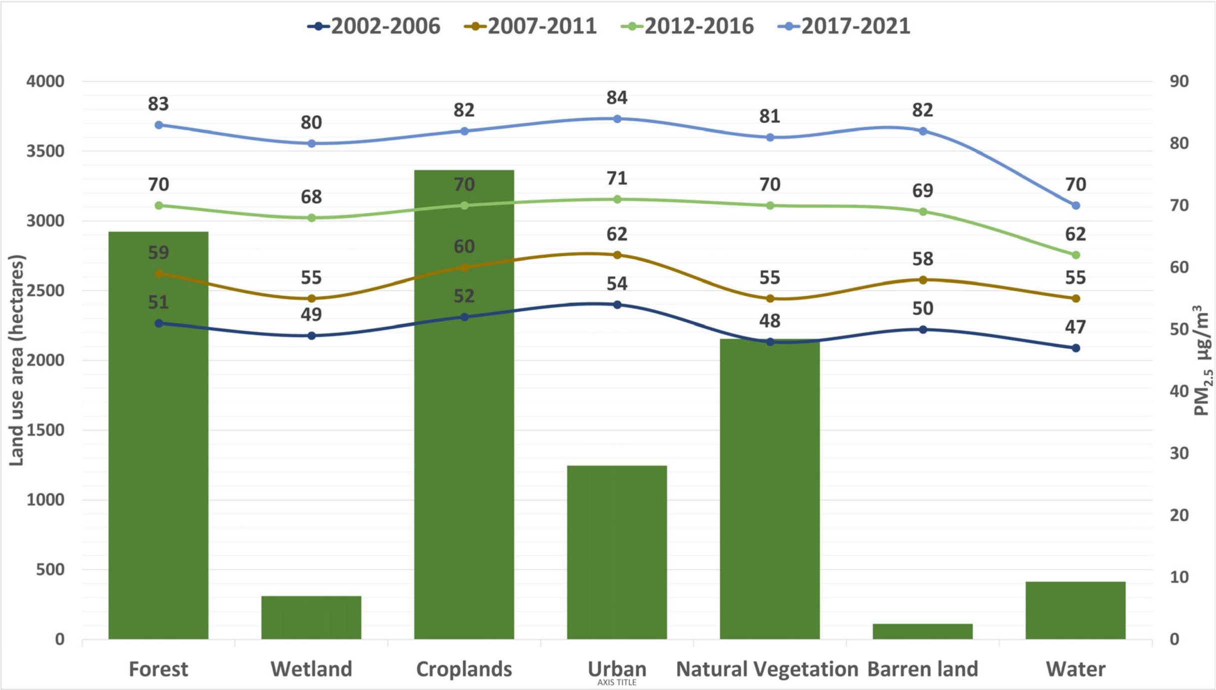

Figure 4. Relationship between temporal $PM_{2.5}$ and different land use classes.

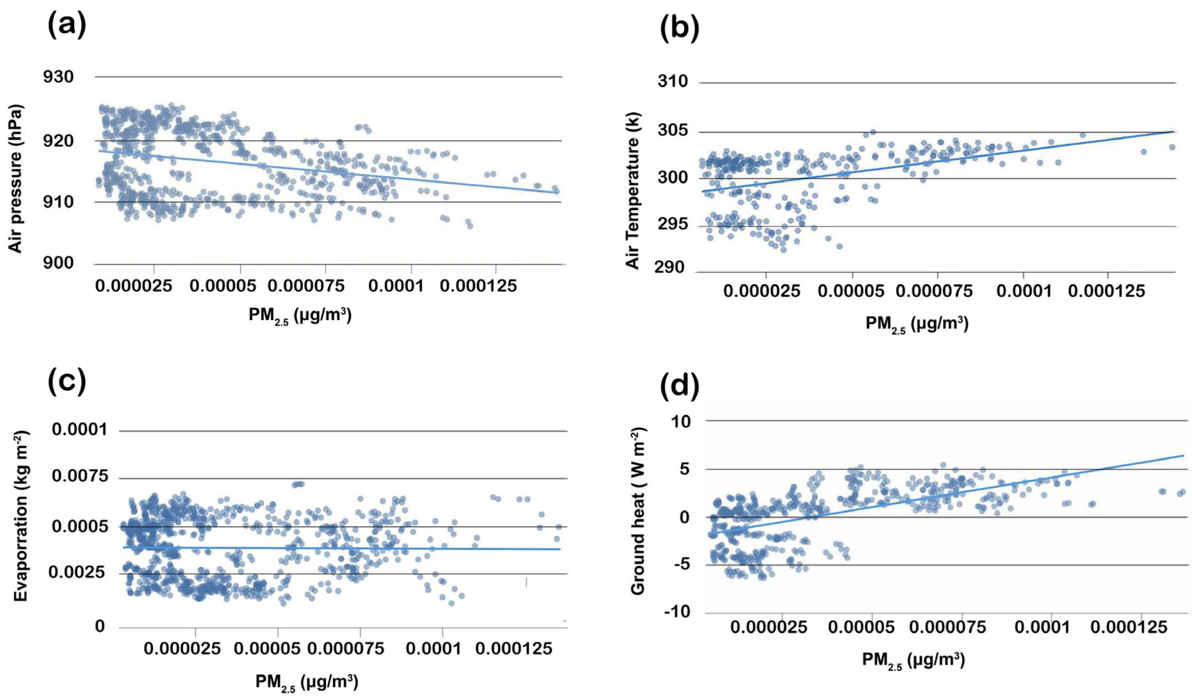

Figure 5. Regression between $PM_{2.5}$ and climatic variables, (**a**) air pressure (hPa), (**b**) air temperature (k), (**c**) evaporation (kg m^{-2}), and (**d**) ground heat (W m^{-2}).

The regression analysis (Figure 6) also revealed that humidity (kg m^{-2}) (r^2 = −0.22, Figure 6a), rainfall (mm/h) (r^2 = −0.20, Figure 6b), and water vapor (kg m^{-2}) (r^2 = −0.03, Figure 6c) were correlated negatively with $PM_{2.5}$, while wind speed (m s^{-1}) correlated positively (r^2 = 0.34, Figure 6d). It means if the humidity is high, rainfall is higher, and water vapor is higher; these factors may contribute to generating less $PM_{2.5}$. On the other hand, higher wind speed may cause higher $PM_{2.5}$.

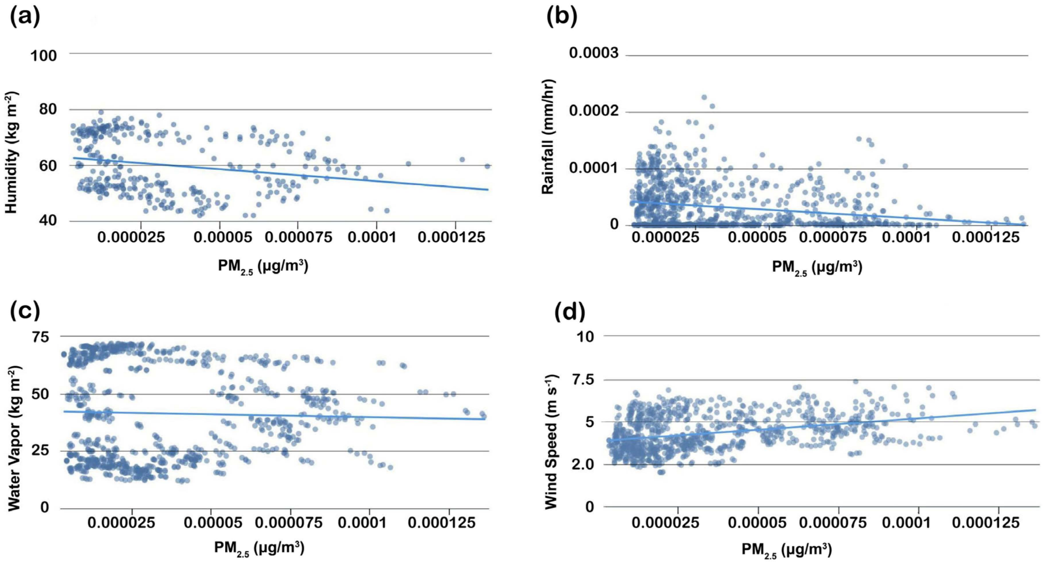

Figure 6. Regression between $PM_{2.5}$ and climatic variables, (**a**) humidity (kg m), (**b**) rainfall (mm/h), (**c**) water vapor (kg m^{-2}), and (**d**) wind speed (m s^{-1}).

4.4. Hotspot Zoning

The average annual values of $PM_{2.5}$ from 2002 to 2021 were used to identify the most pollutant and affected areas in the study area (Figure 7). From the analysis, it was observed that 60 Upazilas within five districts were the most polluted areas. The annual $PM_{2.5}$ values in Dhaka were 65 to 67 µg/m^3, while 62–65 and 60–66 µg/m^3 were the values in the Narayanganj and Gazipur districts. Similarly, Narshingdi and Munshiganj were from 61 and 64 µg/m^3. However, all of the values exceed the WHO's standard value of 15 µg/m^3. Dhaka, the central part of the study area, had more signs of air pollution than other parts of the study area. The southern parts are affected by substantial industrial and development activities, while the northern parts are concentrated slowly because of less commercial and industrial activities than other parts of the study area (Figure 7).

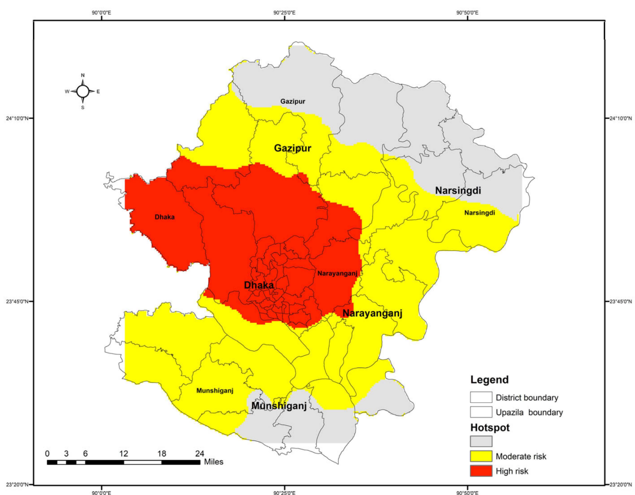

Figure 7. The average concentration of $PM_{2.5}$ from 2002 to 2021. Red is the most affected area, while gray is the significantly less-affected areas.

4.5. Affected Population Due to $PM_{2.5}$

The resultant hotspot map, created using all the mean values from 2002 to 2021, was used to demarcate the vulnerable residents in the study area. The hotspot map was analyzed with the Upazila-wise population data to estimate the vulnerable people within the 0–5 and 50–69 age groups. Table 2 shows that 19,48,029 and 485,407 populations of 0–5 and 50–69, respectively, are living in the high-hotspot area. It is also found that most of the high-hotspot areas are located in urban areas with higher population densities. In the medium-hotspot areas, 22% and 7% of the residents within 0–5 and 50–69 years old were found, respectively, while 523,128 and 181,445 populations of 0–5 and 50–69 years old were found in the low-hotspot areas.

Table 2. Spatial correlation between population and hotspot areas.

$PM_{2.5}$ (Annual)	0–5 Age	50–69 Age	Total Population
High-hotspot area (65 $\mu g/m^3$)	1,948,029	485,407	11,260,162
Medium-hotspot area (50 $\mu g/m^3$)	1,231,066	370,124	5,720,467
Low-hotspot area (45 $\mu g/m^3$)	523,128	181,445	2,343,643

5. Discussion

Estimating the spatiotemporal concentration of $PM_{2.5}$ is a critical issue for local and regional atmospheric pollution research and public health concerns. This study used a set of $PM_{2.5}$ concentration data to map the hotspot areas and analyze the statistical relationships between land use and eight climatic variables. In addition, the derived $PM_{2.5}$ data was used to explore the areas that are affecting the most number of residents. It was found that, similar to the study area, cities within had similar urbanization patterns and the average $PM_{2.5}$ value in 2021 (82 $\mu g/m^3$ in China vs. 77 $\mu g/m^3$ in Bangladesh). In Bangladesh, about 35% of the ambient $PM_{2.5}$ and 15% of the $PM_{2.5}$ are generated from brick kiln emissions and transportation systems [8,56,57]. Emissions from various kinds of poorly maintained vehicles using diesel and petrol are generating $PM_{2.5}$ pollutants in the urban areas of Bangladesh [58,59].

The concentration of $PM_{2.5}$ in the atmosphere depends on several anthropogenic factors such as transportation (vehicle movements), industrial (manufacturing plants and mining), cooking and heating activities [60], and some meteorological factors like wind speed, air relative humidity, cloud cover, and ambient temperature [3]. The results of this study revealed that the areas, i.e., Dhaka, Narayanganj, and Gazipur districts, have more anthropogenic sources like manufacturing factories, high traffic congestion, and other combustion activities, ultimately leading to these districts having relatively higher annual $PM_{2.5}$ concentrations, similar to the urban areas of India, Tanzania, and Iran [61–63]. In contrast, the other two study areas, Narshingdi and Munshiganj, have a relatively lower level of $PM_{2.5}$ concentration and can be compared to the values found in cities of European countries [64]. However, the incorporation of meteorological factors and seasonal variations could give more precise information about the concentration of $PM_{2.5}$ fluctuation instead of depending on annual average concentration, which could sometimes be misleading in describing short-term anthropogenic activities or weather conditions [65]. Several studies [66–70] found that the industrial sector is one of the major contributors to $PM_{2.5}$ emissions. In many regions, industrial activities release large amounts of pollutants, including $PM_{2.5}$, into the atmosphere. Also, urban transportation is another significant source of $PM_{2.5}$ emissions. Exhaust fumes from vehicles emit $PM_{2.5}$ particles that can contribute to the overall air pollution levels. Different agricultural activities such as burning crop residues and fertilizing fields can also contribute to $PM_{2.5}$ emissions. In addition to this, residential and commercial activities such as burning solid fuels for heating and cooking can also release $PM_{2.5}$ into the atmosphere.

Land use has an important role in changing the nature and pattern of $PM_{2.5}$. This paper has explored that the highest levels of $PM_{2.5}$ concentrations and their annual patterns has been increasing over barren lands, forests, cropland, and urban areas between 2002 and 2021 because of urbanization, huge construction sites, road networks, industrial activities, agricultural practices, traffic congestions, and impervious surfaces. The relationship between $PM_{2.5}$ and different land use patterns is complex, comprehensive, and dynamic. Van et al. [35] mentioned that vehicle emissions, brick kilns emissions, and industrial smoke are the key factors for environmental problems and public health risks, particularly $PM_{2.5}$ pollution in the Ghazipur and Mymensingh districts of Bangladesh. Yang et al. [71] also indicated that the dominant factor affecting $PM_{2.5}$ pollution was the traffic conditions found using a land use regression (LUR) model and statistical analysis to explore the effect of land use on $PM_{2.5}$ pollution in the Nanchang urban area, China. Urban areas are more vulnerable to atmospheric inversion, which may trap different air pollutants close to the ground and increase their density or concentration over time. The combination of these factors, the high population density, and their energy consumption are the vital triggering factors for influencing $PM_{2.5}$ in many ways. On the other hand, forest/vegetation can play a crucial role in producing and reducing $PM_{2.5}$ on the local atmosphere. Some specific trees or vegetation can directly absorb $PM_{2.5}$ and other particulate matter, even if they filter the air naturally by releasing clean air. Often trees and vegetation reduce wind direction which can help the circulation of $PM_{2.5}$ from one area to another. Kulsum et al. [36] mentioned that the vegetation cover and $PM_{2.5}$ concentration have a strong negative correlation ($r^2 = -0.75$). This means that the higher vegetation will reduce the level of $PM_{2.5}$ concentration in Bangladesh. This phenomenon was also observed by [72] where the forests experienced a $PM_{2.5}$ of 35–50 µg/m^3 (lower than other land cover types), likely due to the potential filtering and absorption function of the forests and vegetation. Different land uses have an impact on $PM_{2.5}$ levels in several ways. Urban areas with high levels of traffic and industrial activity can produce more $PM_{2.5}$ than rural areas [73]. Additionally, land use practices such as deforestation and farming can also contribute to rising $PM_{2.5}$ levels. For example, burning of biomass and crop residues can lead to increased levels of $PM_{2.5}$. To reduce $PM_{2.5}$ levels, land use management practices that minimize activities that produce $PM_{2.5}$ and increase vegetation cover should be implemented [74–76].

The dispersion and transportation of $PM_{2.5}$ are affected by local and regional climatic factors. The local and regional climatic factors such as air pressure, air temperature, evaporation, ground heat, humidity, rainfall, water vapor, and wind speed have a daily, monthly, and annual contribution in increasing or decreasing the $PM_{2.5}$ values. Afrin et al. [39] mentioned that wind speed (m s^{-1}) and direction did not significantly influence $PM_{2.5}$, although other wind parameters have the highest variability. However, this study found that wind speed (m s^{-1}) has a positive correlation ($r^2 = 0.34$) while air pressure (hPa) has a negative ($r^2 = -0.24$) correlation. Faisal et al. [38] found that the Pearson correlation coefficient (r) between the $PM_{2.5}$ and meteorological variables was negative with rainfall (mm/h) ($r^2 = -0.62$) and humidity (kg m^{-2}) $r^2 = (-0.82)$ but positive with wind speed (m s^{-1}) ($r^2 = 0.09$) and air temperature (k) ($r^2 = -0.73$) in Dhaka, Bangladesh. In addition, a Pearson correlation revealed a significant association among the pollutants, while a significant correlation was observed between $PM_{2.5}$ and surface temperature (k), which is similar to our paper's results. Pavel et al. [32] mentioned that surface temperature (k) is signified because of vehicular emissions, road/soil dust, biomass burning, and industrial emissions in Dhaka, Bangladesh. Tai et al. [77] also argued that meteorology parameters such as temperature, relative humidity (RH), and precipitation are important predictors for $PM_{2.5}$ variability all over the USA. Huang et al. [78] found that the annual mean and median of $PM_{2.5}$ concentrations were 88.07 µg/m^3 and 71.00 µg/m^3, respectively, from August 2013 to July 2014. $PM_{2.5}$ concentration was significantly higher in winter ($p < 0.0083$) and in the southern part of the city ($p < 0.0167$). Moreover, the day-to-day variations of $PM_{2.5}$ showed a long-term trend of fluctuations, with 2–6 peaks each month. $PM_{2.5}$ concentration was significantly higher during the night than the day ($p < 0.0167$). They also mentioned that the meteorological factors were associated with daily $PM_{2.5}$ concentration using the GAMM model ($r^2 = 0.59$, AIC = 7373.84). On the other hand, Razib et al. [11] indicated that the rainfall (mm/h) was strongly negatively and significantly correlated with the concentration of $PM_{2.5}$, due to the ambient dust that settle down in the lithosphere. The annual concentration of $PM_{2.5}$ was five times higher than the standard level in Dhaka, Bangladesh. The correlation analysis results between $PM_{2.5}$ concentration and meteorological data showed that air temperature (k) had negative correlations while precipitation (mm/h) had positive correlations with $PM_{2.5}$ [79]. They found a threshold in the correlation between humidity (kg m^{-2}), wind speed (m s^{-1}), and $PM_{2.5}$. The correlation was positive or negative depending on the meteorological variable values. From the relationship with wind direction, it can be depicted that the west wind might bring the most pollutants to Nagasaki.

The higher concentration of $PM_{2.5}$ and its adverse effects on urban communities and inhabitants are exposed as a common public health problem in Bangladesh. Most public health concerns are pulmonary, cardiovascular, cancer, diabetes, chronic respiratory infection, low birth weight, and premature deaths [80]. In this study, almost 2 million children (between 0 and5 years old) and almost 0.5 million elderly people (between 50 and 69 years old) were found to be at risk due to the higher level of $PM_{2.5}$. In China, 341,701 and 67,325 premature deaths were recorded due to stroke and lower respiratory infection, respectively [81]. Almost 25 million people are at risk of air pollution in Delhi, India, due to different human, societal, developmental, and industrial reasons [82]. These reasons are identified as similar problems for this study area too.

6. Conclusions

This paper investigated the relationship between $PM_{2.5}$ and land use and climatic variables and tried to identify the most vulnerable areas and population groups using geographic information systems and statistical analyses. Finally, the results derived from the study show that land use and climatic variables are significantly associated with $PM_{2.5}$ in the study area. A proper mitigation plan considering the main outcomes of the paper is suggested to reduce the over-concentration of $PM_{2.5}$. However, the critical summaries of the paper are as follows:

- About 41% of $PM_{2.5}$ concentration (µg/m^3) has increased between 2002 and 2021 in the study area.
- The highest concentration of $PM_{2.5}$ was found between 2012 and 2021.
- The concentrations of $PM_{2.5}$ were higher over barren lands, forests, croplands, and urban areas. About 64%, 62.7%, 57%, and 55% concentrations (µg/m^3) have increased over barren lands, forests, cropland, and urban areas between the study period.
- The highest concentration level of $PM_{2.5}$ (84 µg/m^3) was found in urban land in 2021.
- The regression analysis showed that air pressure (hPa) ($r^2 = -0.26$), evaporation (kg m^{-2}) ($r^2 = -0.01$), humidity (kg m^{-2}) ($r^2 = -0.22$), rainfall (mm/h) ($r^2 = -0.20$), and water vapor (kg m^{-2}) ($r^2 = -0.03$) were negatively correlated with $PM_{2.5.}$
- On the other hand, air temperature (k) ($r^2 = 0.24$), ground heat (W m^{-2}) ($r^2 = 0.60$, Figure 5d), and wind speed (m s^{-1}) ($r^2 = 0.34$) were positively correlated with $PM_{2.5}$.
- More than 60 Upazilas with a total population of 11.3 million containing almost 2 million children and 0.5 million elderly people were found to live amongst the most polluted areas and were in the high-risk/hotspot zone.

The outcomes and gained knowledge of this study will be useful for local and regional governments, the United Nations, and International Non-Governmental Organizations for making any health and environmental policies and action plans. The maps and data derived from this study could be used for taking location-based interventions to reduce $PM_{2.5}$ in the study area as well as in other cities in South Asia. Organizations and people who will work on this specific issue can use these results as baseline information, due to the lack of pixel-based $PM_{2.5}$ data, in their new project formation and relevant intervention design. Future studies will consider multi-dimensional sessional data of $PM_{2.5}$ and other topographic and metrological variables to mitigate $PM_{2.5}$ pollution.

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