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

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Article

Land Use and Climatic Determinants of Population Exposure

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Abstract: The major industrial cities of Bangladesh are heavily experiencing 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 and to identify the riskiest area and population groups using a Geographic information system and regression analysis. The results show that about 41% of $PM_{2.5}$ concentration 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. About 64%, 62.7%, 57%, and 55% concentrations were increased annually over barren lands, forests, cropland, and urban regions, respectively, from 2002-2021. The highest concentration level of $PM_{2.5}$ (84 mg m-3) among other land use classes was found in urban areas in 2021. The regression analysis shows that air pressure (r2= - 0.26), evaporation (r2= - 0.01), humidity (r2= - 0.22), rainfall (r2= - 0.20), and water vapor (r2= - 0.03) were negatively correlated with $PM_{2.5}$. On the other hand, air temperature (r2= 0.24), ground heat (r2= 0.60), and wind speed (r2= 0.34) were positively correlated with $PM_{2.5}$. More than 60 Upazilas were the most polluted areas, with 1,948,029 populations (ages 0-5), 485,407 (ages 50-69), and a total population of 11,260,162 were in the high-risk/hotspot zone. The government line department may use the main results paper's key results, policymakers, stainable development practitioners, academicians, and others for integrated air pollution mitigation and management in Bangladesh and other geographical settings worldwide.

Keywords: Bangladesh; Dhaka; climatic variables; land use; $PM_{2.5}$; statistical relationship,

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 the cost of environmental pollution [3,4]. Infrastructural damage to ecological imbalance is happening at an alarming rate because of uncontrolled air pollution worldwide, especially in South and East Asian cities. Besides, air pollution is accused of a significant amount and economic cost 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 of Bangladesh [7–9]. The air pollution level in Dhaka and its adjacent areas are very severe as it is ranked second in the world's most polluted cities [10–12]. Dhaka is also considered one of the most polluted urban cities in the world, where 82 $\mu g/m^3$ annual average $PM_{2.5}$ concentration from a wide variety of pollution sources [13–15].

$PM_{2.5}$ (particulate matter aerodynamic diameter less than 2.5 µm) is one of the major air pollutants in the city area, which is a significant threat to human health and all living organisms

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[16,17]. 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 is covered by the brick kiln operated in and around Dhaka and also followed by 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 used as a secondary fuel which ultimately contributes to the concentration of almost two third of $PM_{2.5}$ found in the air of Dhaka [7,18,19]. However, western countries suggest reducing the level of $PM_{2.5}$ concentration on a both daily and annual basis [20]. In contrast, developing countries like Bangladesh still emit higher levels of $PM_{2.5}$ concentration in the atmosphere. Moreover, every year more than 1.59 billion US dollars, equivalent to 134 billion Bangladeshi takas the cost of the capital alone in terms of loss of human health and life [21].

Many researchers have completed research on the relationship between $PM_{2.5}$ and land use. [22] 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, construction, and others. The study's main limitation was that it used a small number of sample points that did not represent the whole study area. [23] 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 increased over time. His studies revealed that vegetation cover and $PM_{2.5}$ concentration strongly correlate negatively ($r = -0.75$). The lack of proper land use information and the limited number of sample points did not give an appropriate relationship, which is the opposite of our paper. On the other hand, [24] 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. [25] 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 [19] in Dhaka, Bangladesh using temporal air pollutant data from 2003-2019. 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. [26] completed research to investigate the statistical relationship between $PM_{2.5}$ and temperature, wind speed, and wind direction. They found that these factors accounted for 94% of the total variability.

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 (6,043 square kilometers). 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''E longitudes, which covers about 6,043 square kilometers, including 22,066,710 million populations [27] (Figure 1). Having tropical wet and dry climate, the study area has an annual average rainfall of 1,854

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millimeters while the yearly average temperature of 25^{0}C. This study area was selected to conduct this study due to 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 [28–31]. [32] mentioned that this area has the most significant density of industrialization due to well access to finance, enormous transportation, location-based advantage, spatial context, and different management service.

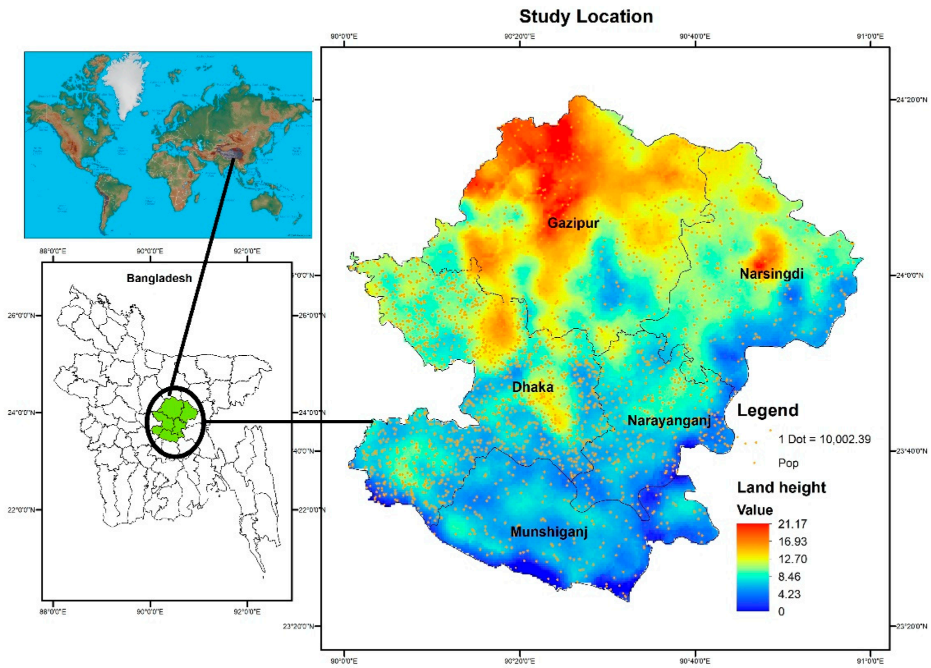

Figure 1. The location map of the study area shows topographic and population information.

3. Materials and Methods

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

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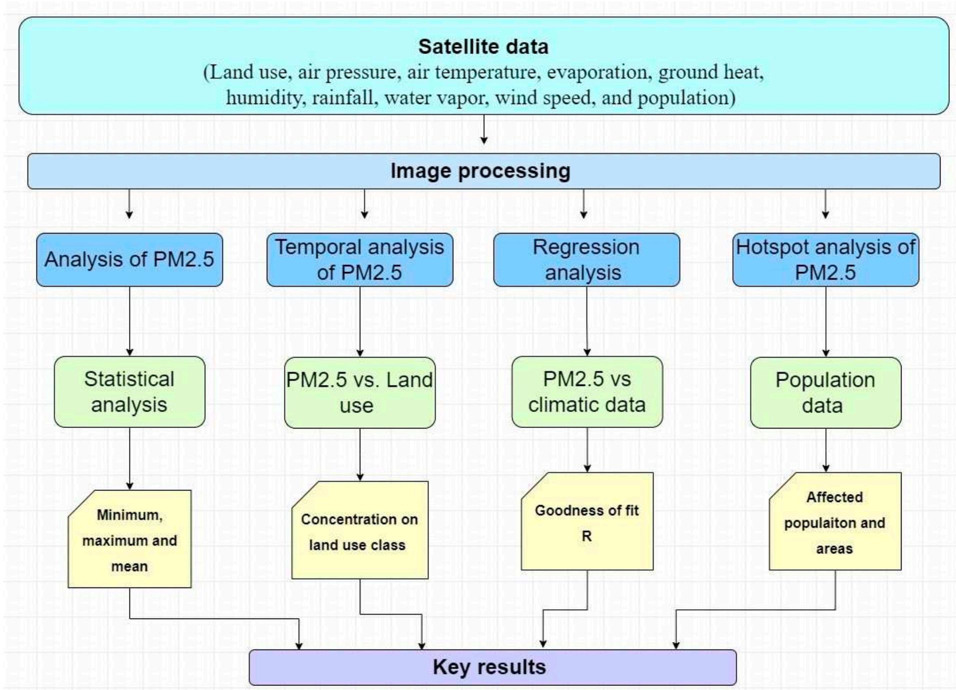

Figure 2. Major methodological steps of this research work.

Multi-date data of $PM_{2.5}$, the main dependent variable of the study, from 2002-2021 were collected from two sources (Table 1). Nine diverse types of variables were used in this paper, which were collected from several satellite sensors (Table 1). Land use, air pressure, air temperature, evaporation, ground heat, humidity, rainfall, water vapor, and wind speed were downloaded from 2021. Raster-based population data, ranging from 0-5, 50-69, and total population, was used to map the most affected people and areas, which was collected from the WorldPop [33]. 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	2021
	Air Temperature	k	https://disc.gsfc.nasa.gov/datasets/NCALDAS_NOAH0125_D_2.0/summary	2021
	Evaporation	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/M2TMNXLND_5.12.4/summary	2021
	Ground Heat	W m^{-2}	https://disc.gsfc.nasa.gov/datasets/NLDAS_NOAH0125_M_2.0/summary	2021
	Humidity	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/NLDAS_FORA0125_H_2.0/summary	2021
	Rainfall	mm/hr	https://disc.gsfc.nasa.gov/datasets/TRMM_3B43_7/summary	2021
	Water Vapor	kg m^{-2}	https://disc.gsfc.nasa.gov/datasets/AIRX3STM_7.0/summary	2021
	Wind Speed	m s^{-1}	https://disc.gsfc.nasa.gov/datasets/M2TMNXFLX_5.12.4/summary	2021
	Land Use	Class	http://www.globallandcover.com/	Nov 2022
Dependent variables	$PM_{2.5}$	mg 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 databases, data masking, resizing, and other image-processing tasks were done. These tasks were needed to prepare the final output of each variable for next-level spatial analysis [34,35]. Due to different data characteristics and patterns, this paper used the Z-Score Normalization process for databases used in this paper [36]. The equation below was used to normalize the whole dataset.

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

where Xnew= 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 done in ArcGIS 10.8 version. Each of the yearly data of $PM_{2.5}$ was transferred to an excel data format to find the mean, minimum, and maximum values. Finally, a graph was prepared to differentiate the temporal variations of $PM_{2.5}$.

3.3. Risk Modeling using Hotspot Area

To identify the most risk areas, a hotspot analysis was done in the paper using the temporal $PM_{2.5}$ database. It is a widely used tool to analyze the most concentrated areas in $PM_{2.5}$ or air pollution research [37–40]. The main calculation of a hotspot is described below:

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

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, $\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$, and $s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - (\bar{X})^2}$. A Getis–Ord Gi* produces z-scores and p-value. A higher z-score and a small p-value of a cluster signify the hottest spot while a negative z-score and a small p-value present the coldest area [41].

3.4. Regression Analysis

A leaner regression was used in this paper to find out the internal relationships among the different variables. A correlation is the most helpful tool in understanding the positive and negative correlated variables among air pollutants and other factors [38,42].

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

where y= dependent variable ($PM_{2.5}$), m= regression slope, x= independent variable, b= constant [43].

3.5. Raster Overlay Analysis

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

4. Results

4.1. Descriptive Analysis of $PM_{2.5}$

Figure 3 represents an overall descriptive statistical analysis of $PM_{2.5}$ from 2002 to 2021. It is estimated that about 41% of $PM_{2.5}$ has increased within 19 years in the study area. The annual trend of $PM_{2.5}$ from 2002 to 2006 was 4.58%, while 0.82% was from 2007-2011, 4.03% was from 2012-2016, and 3.47% was from 2017-2021. The minimum values of $PM_{2.5}$ from 2012 to 2021 changed from 55% to 78%, while the maximum values showed significant variation from 2002-2021 (Figure 3). The highest values of $PM_{2.5}$ was found from 2012 to 2021. In addition, an upward trend in the mean values of $PM_{2.5}$ was observed from 2007 to 2016. These statistical values exceeded the annual standard limit of WHO's 15 μg/m³ of Bangladesh.

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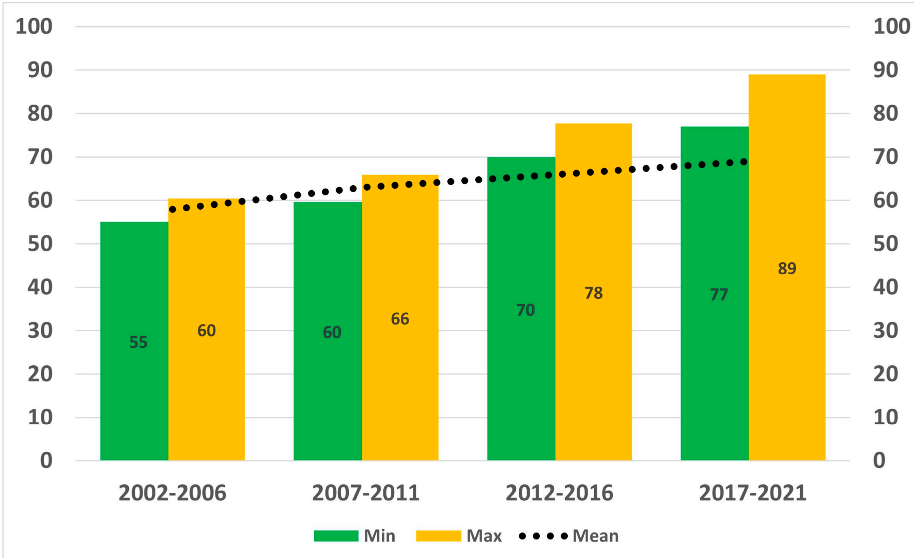

Figure 3. Temporal analysis of minimum, maximum, and mean of $PM_{2.5}$ from 2002-2021.

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

The spatial and statistical relationship between different land use classes and temporal $PM_{2.5}$ data is shown in Figure 4. This table shows that the temporal variations of $PM_{2.5}$ were significant in barren lands, forests, croplands, and urban areas (Figure 4). In barren lands, about 64% of the concentration has increased from 2002-2021, which also revealed an incremental change from the base year (2002) to the final year (2021). Nearly 62.75% of the concentration of $PM_{2.5}$ has increased from 2002-2021 in forestry areas in the study area. A large increase was found from 2007-2011, 2012-2016, and 2017-2021. In the largest land use class in the study area (croplands), about 57.70% of the $PM_{2.5}$ concentration has increased from 2002 to 2021. In the study area, urban land is dominant due to different economic and urban functionalities. Figure 4 shows that about 55.6% of the concentration level increased from 2002 to 2021. In addition, the highest concentration level of $PM_{2.5}$ (84 mg m-3) among other land use classes was found in urban land in 2021.

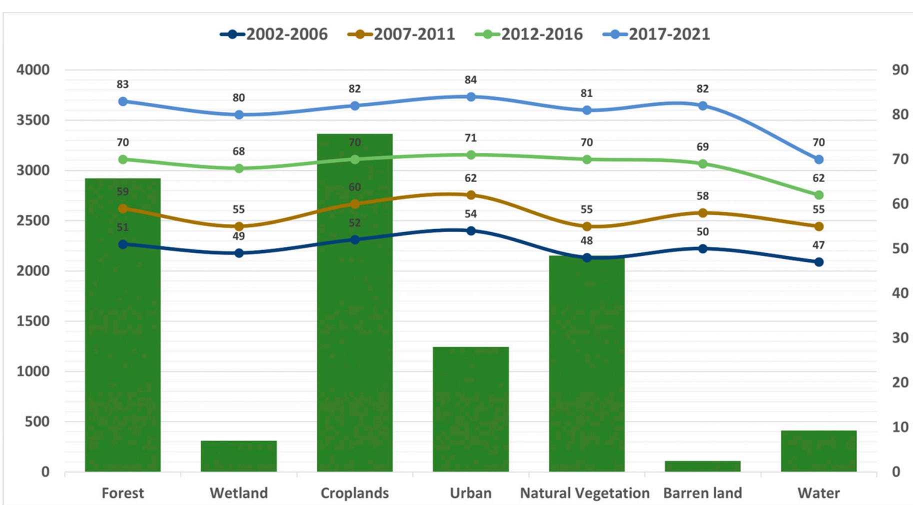

Figure 4. Relationship between temporal $PM_{2.5}$ and different land use classes.

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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 (r^2= - 0.26, Figure 5a) and evaporation (r^2= - 0.01, Figure 5c) were negatively correlated with $PM_{2.5}$ (Figure 5). On the other hand, air temperature (r^2= 0.24, Figure 5b) and ground heat (r^2= 0.60, Figure 5d) were correlated positively with $PM_{2.5}$. It means that if air pressure is higher and evaporation is higher, these two factors may contribute to generating less $PM_{2.5}$. On the other hand, higher air temperature and ground heat may generate higher $PM_{2.5}$.

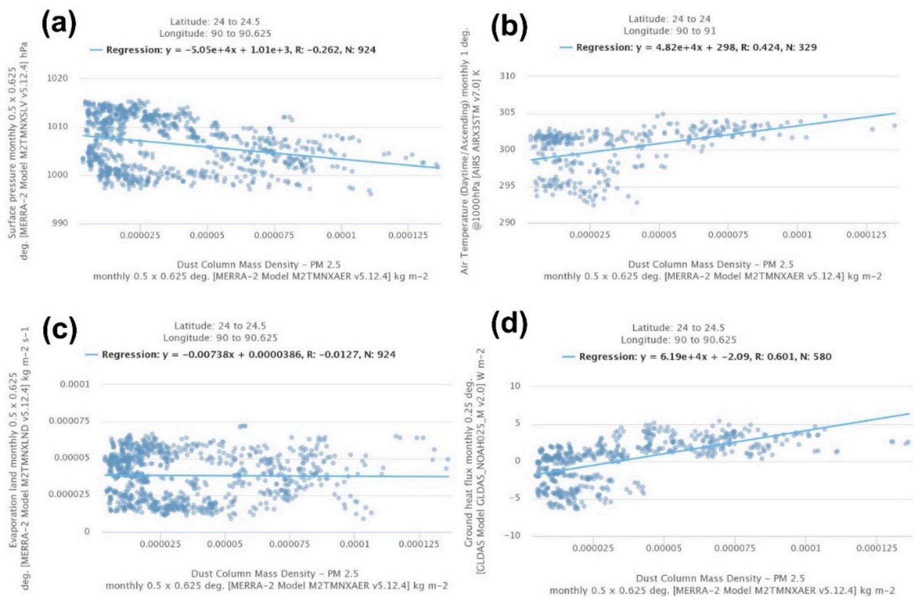

Figure 5. Regression between $PM_{2.5}$ and climatic variables, (a) air pressure, (b) air temperature, (c) evaporation, and (d) ground heat.

The regression analysis (Figure 6) also revealed that humidity (r^2= - 0.22, Figure 6a), rainfall (r^2= - 0.20, Figure 6b), and water vapor (r^2= - 0.03, Figure 6c) were correlated negatively with $PM_{2.5}$, while wind speed 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 $PM_{2.5}$.

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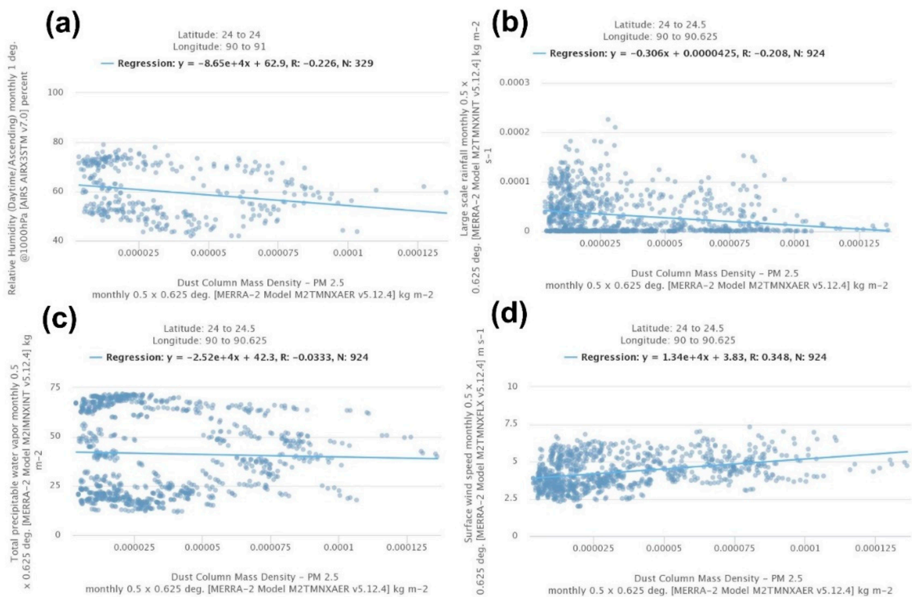

Figure 6. Regression between $PM_{2.5}$ and climatic variables, (a) humidity, (b) rainfall, (c) wind vapor, and (d) wind speed.

4.4. Hotspot Zoning

The average annual values of $PM_{2.5}$ from 2002-2021 were used to identify the most pollutant and affected areas in the study area (Figure 7). From the analysis, it was observed that five districts, including 60 Upazilas were the most polluted areas. The annual $PM_{2.5}$ values in Dhaka were 65 to 67 μg/m³, while 62-65 and 60-66 μg/m³ were in Narayanganj and Gazipur districts, respectively. Likewise, Narshingdi and Munshiganj were from 61 and 64 μg/m³. However, all of the values exceed the standard WHO's value of 15 μg/m³. Dhaka, the central part of the study area had more signs of air pollution than other parts. The southern part is affected due to substantial industrial and development activities, while the northern part is to be concentrated slowly because of less commercial and industrial activities than other parts of the study area (Figure 7).

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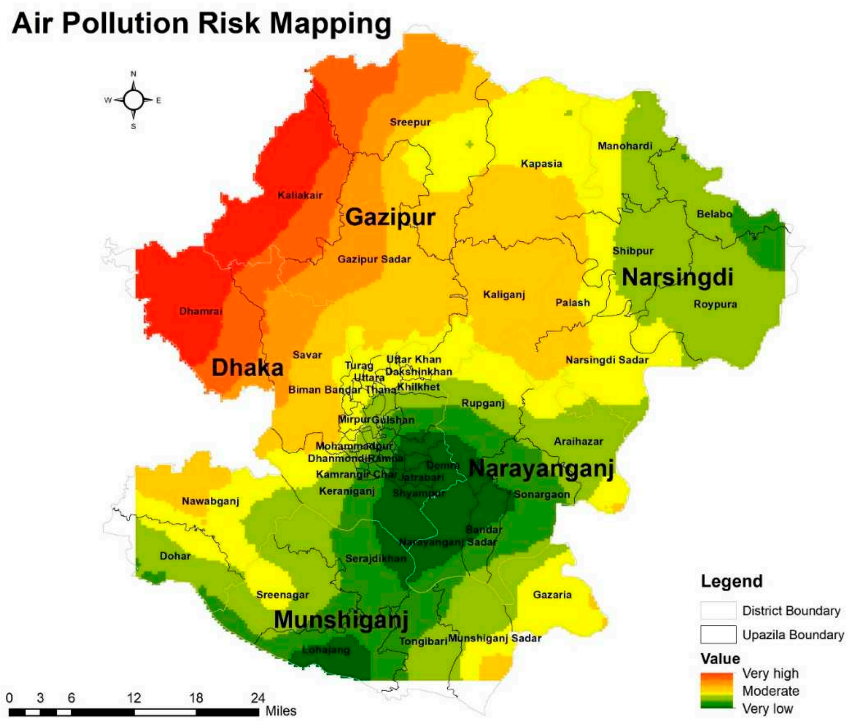

Figure 7. The average concentration of $PM_{2.5}$ from 2002-2021. Red is the most affected area, while green is significantly less.

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

The resultant hotspot map, created using all the mean values from 2002-2021, was used to demarcate vulnerable people in the study area. The hotspot map was crossed with Upazila-wise population data to estimate vulnerable people considering 0-5 and 50-69 ages. Table 2 shows that 1,948,029 and 485,407 populations of 0-5 and 50-69, respectively, are living in the high spot 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 0-5 and 50-69 aged people were found respectively, while 523,128 and 181,445 populations of 0-5 and 50-69 aged respectively found in low spot areas.

Table 2. Spatial correlation between population and hotspot areas.

$PM_{2.5}$ (Annual)	0-5 age	50-69 age	Total Population
High spot area (65 μg/m^3)	1,948,029	485,407	11,260,162
Medium spot area (50 μg/m^3)	1,231,066	370,124	5,720,467
Low spot area (45 μg/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 concern. This study used a set of $PM_{2.5}$ concentration data to map a hotspot area and analyze the statistical relationship between land use and eight climatic variables. In addition, the derived $PM_{2.5}$ data was used to find out the most affected people and areas. Due to a similar urbanization pattern between China and Bangladesh, the average $PM_{2.5}$ value in 2021 was 82 μg/m^3 and 77 μg/m^3 in China and Bangladesh, respectively. In Bangladesh and its mega-cities, about 35% of ambient PM_{10} and 15% of $PM_{2.5}$ are generated from brick kiln emissions and transportation systems [8,44,45]. Even emissions from diverse kinds of diesel and petrol vehicles and poorly maintained automobiles are generating air pollution due to $PM_{2.5}$

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pollutants in urban areas of Bangladesh [46,47]. 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 [48], and some meteorological factors like wind speed, air relative humidity, cloud cover, and ambient temperature [49]. The result 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 these districts with relatively higher annual $PM_{2.5}$ concentration, which is similar with the $PM_{2.5}$ concentration in India, Tanzania, and Iran [50–52]. In contrast, the other two study areas, Narshingdi and Munshiganj, have a relatively lower level of $PM_{2.5}$ concentration regarding their pollution sources than in Europe [53]. 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 [54].

Land use has an important role in changing the nature and pattern of $PM_{2.5}$. This paper has explored that the highest level of $PM_{2.5}$ concentration and their annual pattern has been increased over barren lands, forests, cropland, and urban areas between 2002-2021 because of urbanization, huge construction sites, road networks, industrial activities, agricultural practices, huge traffic movement, impervious surface, and permeable pavement. The relationship between $PM_{2.5}$ and different land use patterns is complex, comprehensive, and dynamic. [22] mentioned that vehicle emissions, brick kilns emissions, and industrial smoke are the main key factors for environmental problems and public health risks, particularly $PM_{2.5}$ pollution in Ghazipur and Mymensingh districts in Bangladesh. [55] also indicated that the dominant factor affecting $PM_{2.5}$ pollution was the traffic condition 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 $PM_{2.5}$ in 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 good air. Often trees and vegetation reduce wind direction which can help the circulation of $PM_{2.5}$ from one area to another. [23] mentioned that the vegetation cover and $PM_{2.5}$ concentration have a strong negative correlation (r^2 = -0.75). It means that the higher vegetation will reduce the level of $PM_{2.5}$ concentration in Bangladesh. This is also observed by [56] that the forest experienced $PM_{2.5}$ of 35–50 μgm^{-3} (lower than other land cover types), likely due to the potential filtering and absorption function of the forests and vegetation.

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 reducing or increasing $PM_{2.5}$. [26] mentioned that wind speed and direction did not significantly influence $PM_{2.5}$, although other wind parameters have the highest variability, which is opposite to our paper. Our paper found that wind speed has a positive correlation (r2=0.34) while air pressure has a negative (r2=-0.24) correlation. [25] found that the Pearson correlation coefficient (r) between the $PM_{2.5}$ and meteorological variables was negative with rainfall (r2=- 0.62) and humidity r2= (- 0.82) but positive with wind speed (r2=0.09) and temperature (r2=- 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, which is similar to our paper's result. [19] mentioned that surface temperature is signified because of vehicular emissions, road/soil dust, biomass burning, and industrial emissions in Dhaka, Bangladesh. [57] 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.

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

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pulmonary, cardiovascular, cancer, diabetics, chronic respiratory, low birth weight, and premature death [58]. In this study, a huge number of populations ages 0-5 (1,948,029) and 50-69 (485,407) are 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 [59]. Even about 25 million populations are at air pollution risk in Delhi, India, due to different human, societal, developmental, and industrial reasons [60]. These reasons are identified as similar problems for this study area too.

6. Conclusions

This paper aimed 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. 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 $PM_{2.5}$ was increased within 19 years (2002-2021) in the study area
- 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. About 64%, 62.7%, 57%, and 55% concentrations were increased over barren lands, forests, cropland, and urban areas, respectively, from 2002-2021.
- The highest concentration level of $PM_{2.5}$ (84 mg m^{-3}) was found in urban land in 2021.
- The regression analysis has shown that air pressure (r^2= - 0.26), evaporation (r^2= - 0.01), humidity (r^2= - 0.22), rainfall (r^2= - 0.20), and water vapor (r^2= - 0.03) were negatively correlated with $PM_{2.5}$.
- On the other hand, air temperature (r^2= 0.24, ground heat (r^2= 0.60, Figure 5d), and wind speed (r^2= 0.34) were positively correlated with $PM_{2.5}$.
- More than 60 Upazilas were found to be the most polluted areas, where 1,948,029 populations (ages 0-5), 485,407 (ages 50-69), and a total population of 11,260,162 were in the high-risk/hotspot zone.

The outcomes and gained knowledge of this study will be useful for local and regional governments, United Nations, and International Non-government Organizations for making any health and environmental policy 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. 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-dimension sessional data of $PM_{2.5}$ and other topographic and metrological variables to mitigate $PM_{2.5}$ pollution.

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