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Spatiotemporal Mapping and Modeling Hotspot of $PM_{2.5}$ in the Central part of Bangladesh

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Abstract Particulate matter ($PM_{2.5}$) is one of the critical sources of ambient air pollution and poses the most significant public health threat. In Bangladesh, particularly in the major urban cities, $PM_{2.5}$ has been identified as an important public health hazard. This research aims to perform a spatiotemporal mapping of $PM_{2.5}$ from 2002-2019 to determine the hotspots in central Bangladesh. A time series of remotely sensed $PM_{2.5}$ is used in mapping spatiotemporal and hotspot analysis, applying Geographic Information Systems (GIS) and remote sensing. This research reveals that the annual concentration of $PM_{2.5}$ increased by 47% during 2002-2019. On the other hand, the high hotspot zones are found in the middle of the study areas, the core urban areas of Dhaka, Narayanganj, and Gazipur Districts. Moreover, this research found that 16.5% (3,640,748 persons out of the total population) were in the age group 0-9, 0.95% (2,109,99 persons) were in the age group 60^{+}, 5% (12,062,419 persons) were pregnant women, and 1% (24,621 persons) were pneumonia patients in very high- and high-hotspot zones. The relevant policymakers and departments may use these findings on the policy applications for health hazard risk reduction and local and regional air pollution mitigation.

Keywords Air pollution, GIS, MODIS recorded $PM_{2.5}$, Spatiotemporal $PM_{2.5}$, Geostatistical analysis.

Introduction

Particulate Matter ($PM_{2.5}$) is one of the primary pollutants for ambient air pollution, which often imposes the greatest threat to public health, causing about 4.2 million global deaths a year (Godoy et al. 2021; Landrigan et al. 2018; Srivastava et al. 2021; WHO 2016). The $PM_{2.5}$ (diameter < 2.5 µm) has been exposed as the fundamental biological and environmental aspects by creating an adverse impact on regional and local public health (Bayat et al. 2019; Hossen et al. 2018). Long-term and short-term exposures to the high-level concentration of $PM_{2.5}$ are correlated with various public health problems, including death, respiratory difficulty, coronary disease, lung cancer, cardiac pain, asthma, and skin problem predominantly in urban and peri-urban areas (Andersen et al. 2012; Hoek et al. 2013; Raaschou-Nielsen et al. 2013; Beelen et al. 2014; Dirgawati et al. 2016; Chen et al. 2018).

$PM_{2.5}$ has been considered one of the leading air pollutants in Dhaka and its adjacent areas, which has also been evidenced as an inevitable threat to human health and all living organisms (Kim et al. 2015; Liang et al. 2016a). It happens because a large share of Dhaka's air (~58% of total PM2.5) and its adjacent areas are mixed by the toxic gasses mainly from brickfields operated in and around Dhaka (Begum et al. 2013). Moreover, other reasons are 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%) (Begum et al. 2013).

Geographic Information System (GIS), together with remote sensing techniques, is a widely used method for mapping spatiotemporal and modeling hotspots analysis of $PM_{2.5}$ (Hoque et al. 2014; Cao et al. 2018). In Bangladesh, especially Dhaka city and its surrounding, the spatiotemporal mapping of $PM_{2.5}$ has been done considering small geographic areas with specific sample points (Begum et al. 1970; Islam 2000; Pavel et al. 2021). The sample-based $PM_{2.5}$ data collection and analysis were also found in some areas of Bangladesh too (Arif et al. 2018; Begum 2016a, 2016a; Hossen et al. 2018; Tiwari et al. 2015a). On the other hand, mapping and modeling hotspot areas is also observed in very few areas in Asian and other countries (Bank 2018; Jana and Sar 2016a; Liang et al. 2016b; Songchitruksa and Zeng 2010a). However, it is still unknown what is happening in larger cities and places.To fill this knowledge gap, this paper has considered a wider geographic area to map spatio-temporal scenarios and modeling a hotspot using multidate satellite data and ground information, which will play an instrumental role in policy formulation and proper mitigation of $PM_{2.5}$. Therefore, this research aims to (i) map spatiotemporal mapping and (ii) identify a hotspot zone applying GIS using remotely sensed pixel-based time series $PM_{2.5}$ data in a broader geographic areas.

Study Area

The study area of this research is located in the Dhaka Division of Bangladesh, covering its five central industrial Districts; Dhaka, Narayanganj, Munshiganj, Narshingdi, and Gazipur (Fig. 1). It lies between 23°20'N-24°20'N latitudes and 90°00'E-91°00'E longitudes, covers about 6,043 square kilometers, including 22,066,710 populations (Fig. 1). This study area was selected due to some pragmatic reasons: (a) colossal population pressure, (b) massive industrial developments, (c) higher level of traffic concentration, (d) internal migration, and (e) unplanned urban products, which are the key controlling factors for its local and regional atmospheric conditions. Many industries operate in the study area, which is the critical trigger for producing enormous emissions and gaseous particulates (Salam et al. 2008). These industries include, e.g. ready-made garments, textiles, pharmaceuticals, cement, brickfields, fertilizer, motorcycle assembly, bus, trucking Compress Natural Gas, raw material processing, food and sugar, and electrical power.

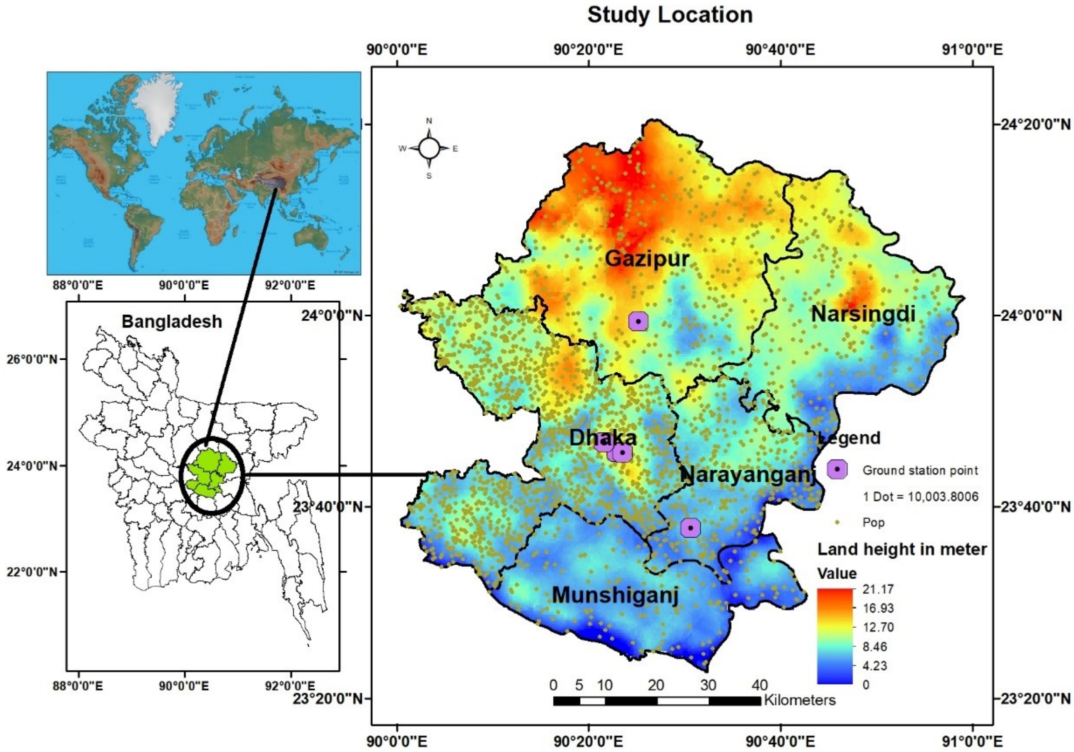

Fig. 1 The location of the study area with ground stations' place for $PM_{2.5}$ measurement, topography (The National Aeronautics and Space Administration-NASA 2019), and population data (Bangladesh Bureau of Statistics-BBS 2020).

Data and Methods

This study used the annual average data of $PM_{2.5}$ between 2002-2019 for the quantitative measures. The detailed methodological steps are described below:

Retrieving $PM_{2.5}$ data

The annual average data of $PM_{2.5}$ were collected in raster-ASCII format with a 0.01 X 0.01 deg spatial resolution from Van Donkelaar et al. (2016), a study group at the Atmospheric Composition Analysis Group of Dalhousie University, Canada. They derived the $PM_{2.5}$ from Aerosol Optical Depth (AOD) using the Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), and SeaWiFS sensors. A robust Geographically Weighted Regression (GWR) method and GEOS-Chem Models were applied to simulate the spatiotemporal variations across the world (Van Donkelaar et al. 2016). The raster data were converted to point feature data within the study area using a district boundary (shapefile) as a mask applying open-source GIS software, QGIS 3.14 (QGIS 2016), where each pixel generated one point feature. The shapefile (mask) was collected from Bangladesh Local Government and Engineering Department (LGED 2020) with a coordinate reference system, World Geodetic System 1984 (WGS84). The converted point features were further used for geostatistical, hotspots, and risk zone analysis.

$PM_{2.5}$ data validation

The $PM_{2.5}$ derived from satellite images was validated using ground stations' data during 2002-2019 from the Department of Environment, Government of Bangladesh (CASE 2019). Only five ground stations (Fig. 1) are available in the study area. The annual average MODIS and ground-measured $PM_{2.5}$ data were used in a statistical correlation (Ni et al. 2018a).

Mapping Spatio-temporal analysis

In the paper, the Spatio-temporal analysis considered the basic statistics, e.g., minimum, maximum, and mean value of $PM_{2.5}$ during 2002-2019. Time series analysis of $PM_{2.5}$ is an important and reliable source for local and regional level planning and mitigation in urbanized areas (Hu et al. 2014a; Ni et al. 2018b, 2018a; Rao et al. 2014; D. Zhao et al. 2018).

Modeling Hotspot area

The spatial process of the statistical clustering method was considered to identify the concentration of $PM_{2.5}$ pollutants in the long-term spatiotemporal pattern of air pollution (e.g., Habibi et al. 2017). In the hotspot analysis, the Getis–Ord Gi*cluster statistic method was selected as a local spatial statistic using average temporal vector data (point feature) of $PM_{2.5}$. The Gi*cluster statistic works based on the weights and heterogeneity in each data point of $PM_{2.5}$ (Songchitruksa and Zeng 2010b). The Gi* statistic uses the following measures as mentioned by Environmental Systems Research Institute (ESRI) (ESRI 2019) to identify the hotspots areas:

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

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 (Jana and Sar 2016a). Then the raster overlay was applied using the resultant hotspot areas, area-specific population, and most critical public health data to find the riskiest zones (e.g., Kumar et al. 2015). Further, the hotspot map was overlaid with Upazilas' total population (Fig. 5b), population 0-9 (Fig. 5c), population 60^+ (Fig. 5d), pneumonia patients (Fig. 5e), and pregnant women (Fig. 5f). The Upazilas' specific population data was collected from the Bangladesh Bureau of Statistics (BBS) (BBS 2020) to calculate area-specific, most vulnerable population groups whose ages between 0-9 and 60^+ years. The Upazilas' specific pregnant and pneumonia patients were collected from the Bangladesh Directorate General of Health Services (BDGHS) (DGHS 2019).

Results

$PM_{2.5}$ data validation

The Correlation Coefficient (R^2) and the Adjusted Correlation Coefficient were estimated (Fig. 2). The extracted $PM_{2.5}$ data from MODIS provided a good fit with the ground base measurement as $R^2 =$ 92.05% (Fig. 2). It revealed that the derived $PM_{2.5}$ data were estimated with high accuracy.

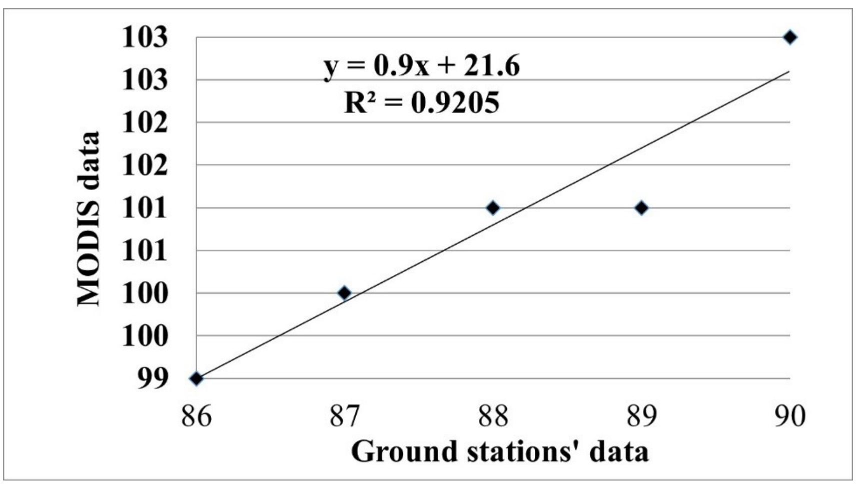

Fig. 2 A linear regression of estimated $PM_{2.5}$ using MODIS data in the x-axis (Sat) and ground monitoring data in the y-axis (CASE 2019).

Spatio-temporal analysis

The mean annual rate of $PM_{2.5}$ increased by ~42% in the study area (Fig. 3a-c). The yearly trend of minimum values of $PM_{2.5}$ increased by 40%. In comparison, the maximum value is increased by 37% (Fig. 3). The concentration of $PM_{2.5}$ is almost stable to 60±2 μg/m^3 during 2003-2008 (Fig. 3b). The highest variation of $PM_{2.5}$ is 8%, found from 2012 to 2016 (Fig. 3b). Besides, an upward trend of the mean values is observed from 2013 to 2019 (Fig. 3b), and the highest (Dhaka District) and lowest (Narsingdi District) increment happen with the gradient of 1.82 and 1.74, respectively (Fig. 3d, h). All these statistical values exceed the annual standard limit of the World Health Organization (WHO), which is 15 μg/m^3 (Fig. 3a).

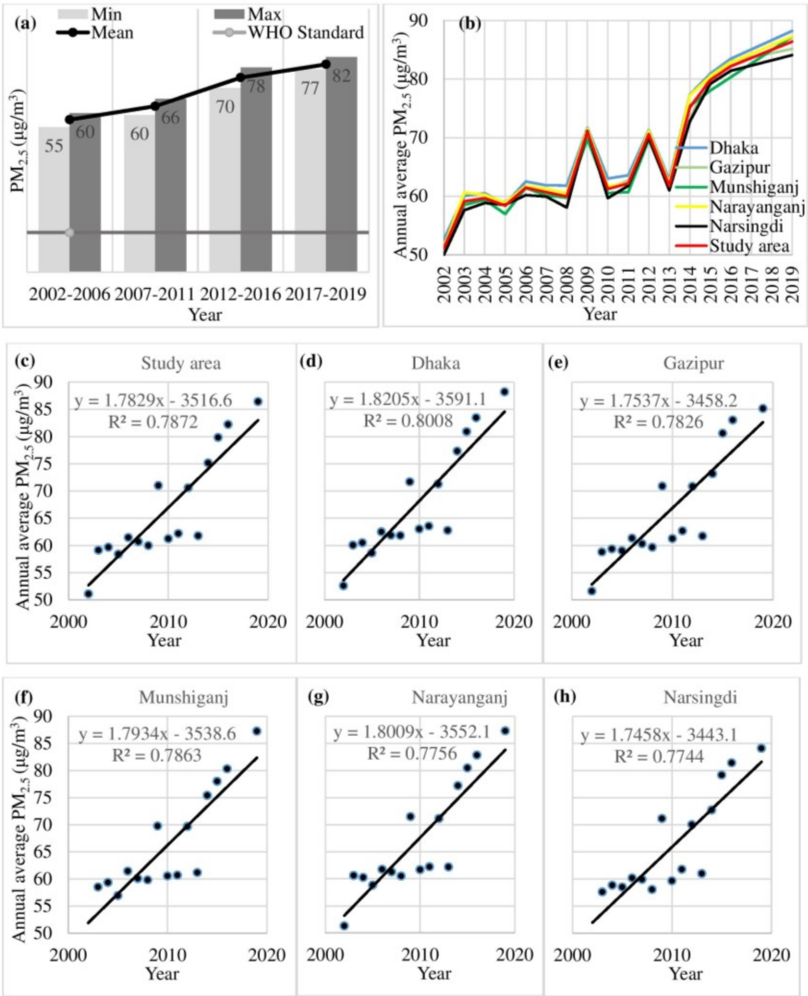

Fig. 3 A minimum, maximum, and mean value of $PM_{2.5}$ (μg/m^3) from 2002-2019 (a) and annual average $PM_{2.5}$ (μg/m^3) in the study area in a different year (b). District-specific linear regression analysis is also presented here (c-h).

A time-series mapping was created using a specific year's average values of $PM_{2.5}$ between 2002 and 2019 to visualize the spatiotemporal trend of $PM_{2.5}$ (Fig. 4). However, to identify the most pollutant and affected zones in the study area, a general map was prepared using average value considering the entire study period (2002-2019), the average map in Fig 4. In the Dhaka District, the average annual $PM_{2.5}$ is 65-67 μg/m^3, while it is 62-65 μg/m^3 in Narayanganj, 60-66 μg/m^3 in Gazipur, 61-64 μg/m^3 Narshingdi, and 63-67 μg/m^3 in Munshiganj Districts (Fig. 4). The Dhaka District, the central part of the study area, has more signatures of air pollution than other parts. Predominantly, all urban cities in the middle part have higher concentrations of $PM_{2.5}$. On the other hand, the northern and southern parts of the study area have less pollution because of peri-urban and less industrial and brickfield activities (Fig. 4).

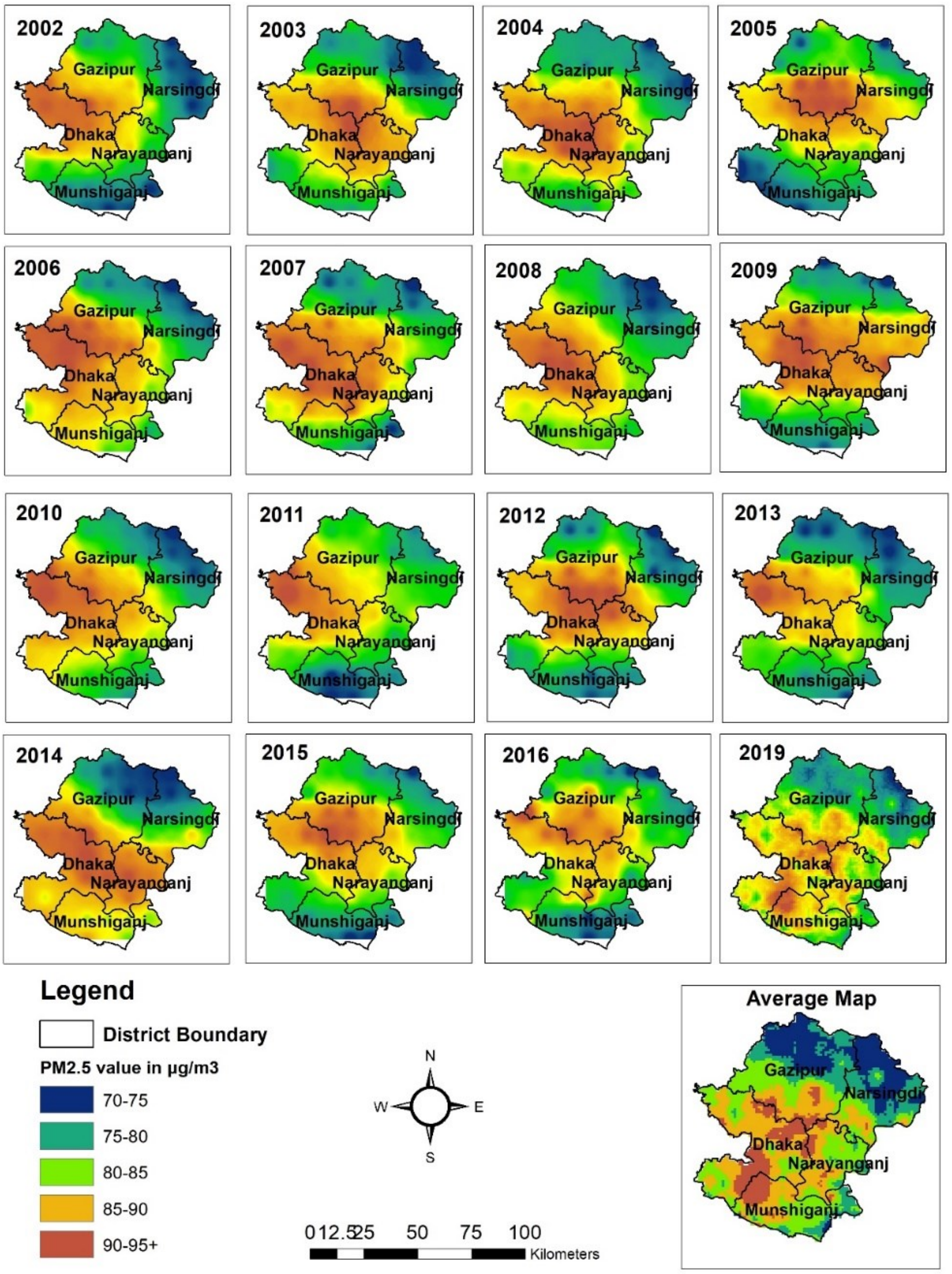

Fig. 4 The average concentration of $PM_{2.5}$ from 2002-2019.

Hotspot analysis

Near about one-third area is found as very high- and high-hotspot zones in the study (Fig. 5a). The spatial difference between the very high- and high-hotspot zones is almost negligible (Fig. 5a). Most of these very high-spot zones were found in all city areas of Dhaka, Gazipur *sadar*, Kaliganj, Rupganj, Sonargaon, Savar, and Dhamrai areas. Moreover, this research found that 16.5% (3,640,748 persons out of the total population; Fig. 5b), 4.39% (9,692,61 persons) were in age group 0-9 (Fig. 5c), 0.95% (2,109,99 persons) were age group 60^+ (Fig. 5d), 5% (12,062,419 persons) were pregnant women (Fig. 5e), and 1% (24,621 persons) were pneumonia patients (Fig. 5f) in very high- and high-hotspot zones.

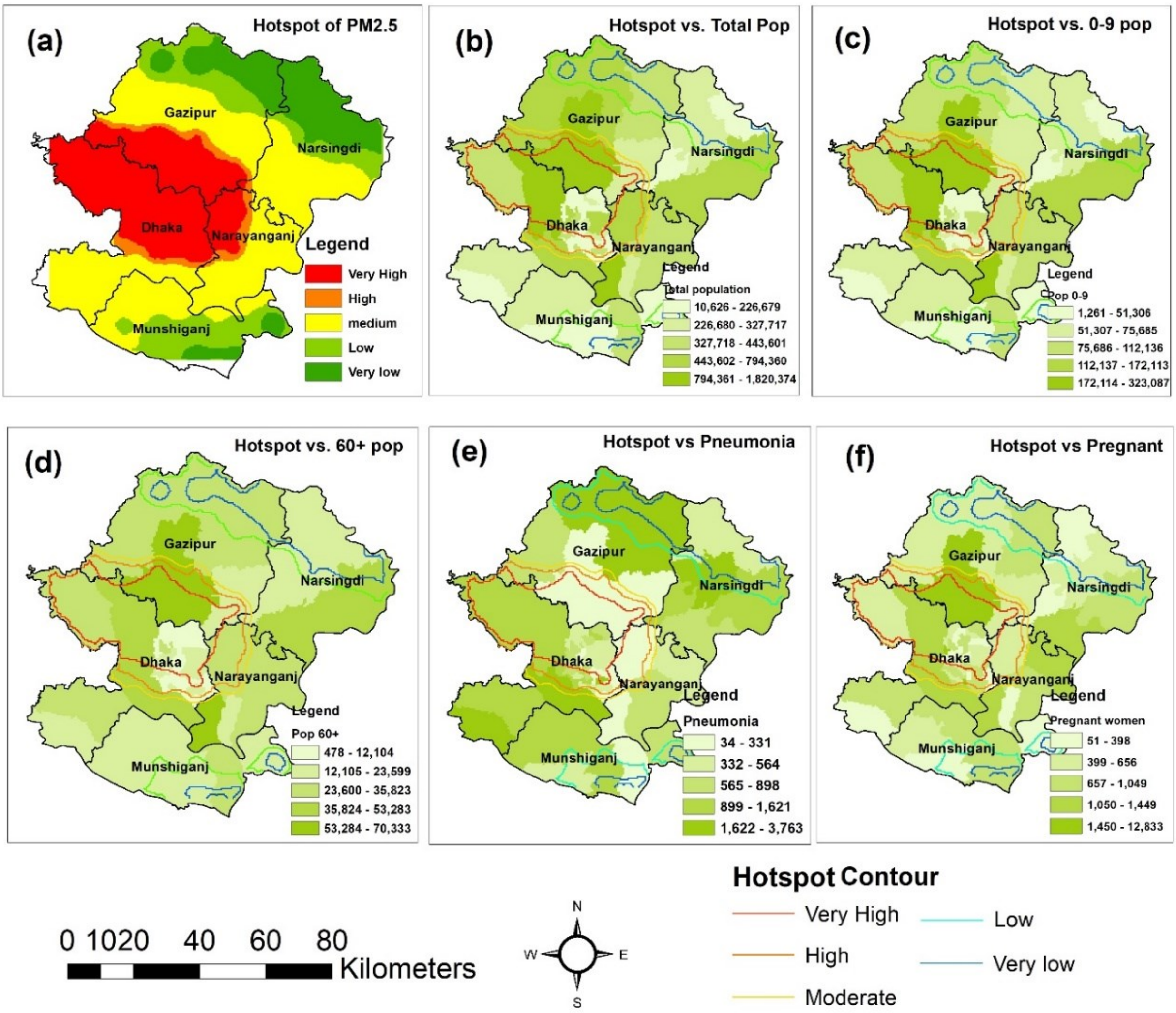

Fig. 5 The extracted (a) hotspot map was overlaid with (b) total population, (c) population age 0-9, (d) population age 60$^+$, (e) pneumonia patients, and (f) pregnant women.

Discussions

For a better understanding of the spatial effects of $PM_{2.5}$, this study is unique, particularly in the context of Bangladesh in many ways; e.g., (i) a large-scale geographic area is considered what is usually ignored in many pieces of research (e.g., Begum et al. 2010, 2013; Azkar et al. 2012; Hoque et al. 2014; Rana et al. 2016; Begum 2016; Cao et al. 2018; Rahman et al. 2019; Zhao et al. 2019), (ii) remotely sensed $PM_{2.5}$ data is used that can be applied as an independent data source of $PM_{2.5}$ (Cao et al. 2018; J. Zhao et al. 2019). However, it is further validated using ground-based stations' data. A group of researchers conducted a validation of extracted $PM_{2.5}$ values from satellite images with ground station data, resulting in R^2=0.54% in Beijing, China, which is less than this study (~0.92%) (Ni et al. 2018a). The Chinees research group has used a very scattered location of many ground stations' data (Ni et al. 2018a). Han et al. (2018) found a very high R^2-value ranging from 0.72% to 0.97% using 35 ground-based monitoring station data. Therefore, it is recommended to use many scattered locations of ground stations' data for statistical validation of satellite-recorded $PM_{2.5}$. However, validity estimation also depends on regional topography and weather patterns, e.g., relative humidity, atmospheric temperature, wind speed, and sessional climate variability (Al-Hamdan et al. 2019).

Estimating the spatiotemporal concentration of $PM_{2.5}$ is a critical issue for managing local and regional atmospheric pollution strategies and a public health concern. The average annual concentration of $PM_{2.5}$ is increased by 42% during 2002-2019 (Fig. 3). It is because of excessive emissions of different kinds of diesel and petrol vehicles, as well as poorly maintained automobiles, that are generating $PM_{2.5}$ pollutant in urban areas of Bangladesh (Begum 2016b). Begum et al. (2013) suggest that 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%) are responsible for $PM_{2.5}$ in the Dhaka city and its adjacent areas. In Bangladesh and megacities like Dhaka, ~35% of ambient PM_{10} and ~15% of $PM_{2.5}$ are generated from brick kiln emissions and transportation systems (Motalib and Lasco 2015). Comparable to China (60 μg/m^3), Bangladesh (77 μg/m^3) generated a higher level of $PM_{2.5}$ in 2016 even though both countries have a similar pattern of population growth (Cao et al. 2018). Likewise, in Bangladesh, ~88% of the areas in China had an increasing trend of $PM_{2.5}$ in the last 18 years due to huge traffic, transportation, and industrialization (J. Zhao et al. 2019), that is also similar in India (Kandlikar and Ramachandran 2000). However, the dominant factors for increasing the concentration of $PM_{2.5}$ in Vietnam are mainly agriculture, cooking, heating, construction, and urbanization (Nguyen et al. 2018). However, the concentration of $PM_{2.5}$ in the atmosphere depends on several anthropogenic factors such as transportation, industrial developments, and cooking and heating activities (Gautam et al. 2016; Al-Hamdan et al. 2019). It also depends on meteorological factors like wind speed, air relative humidity, cloud cover, and ambient temperature (Al-Hamdan et al. 2019). They suggest a large geographic area for investigation, and it is considered in this study.

The results of this study reveal that the areas, i.e., Dhaka, Narayanganj, and Gazipur, have more anthropogenic sources like manufacturing factories, high traffic congestion, and other combustion activities, ultimately leading to a relatively higher annual $PM_{2.5}$ concentration, which is similar to the $PM_{2.5}$ concentration in the other developing countries like China, India, Iran, and Tanzania (Mkoma et al. 2010; Tiwari et al. 2015; Arfaeinia et al. 2016). The other two study areas, the Narsingdi and Munshiganj Districts, have a relatively low level of $PM_{2.5}$ concentration (Figs. 4, 5a). The central part of the study area has been found in a higher concentration of $PM_{2.5}$ than the northern and southern parts (Figs. 4, 5a). However, the incorporation of meteorological factors and seasonal variations could give more precise information about the concentration of $PM_{2.5}$ fluctuation instead of just depending on annual average concentration, which could often be misleading in describing the short-term anthropogenic activities or weather conditions, such as in Beijing–Tianjin–Hebei regions of China (Rajput et al. 2013; Mangal et al. 2018). There are more than 1,850 ground-based air pollution monitoring stations in European cities, and among all, the sources of the maximum concentration of $PM_{2.5}$ in 12 cities are traffic-related (Kiesewetter et al. 2015), which is also similar in Bangladesh. The Saharan desert advection in the Mediterranean area (Adães and Pires 2019) and the relative humidity with the traffic dust in Sacramento and California in the USA is the dominant factor for $PM_{2.5}$ (Mukherjee et al. 2019), which may not be comparable with $PM_{2.5}$ in this study.

Urbanization, road vehicles, brickfield and construction activities, and industrial emissions are the key controlling factors for increasing $PM_{2.5}$ in the study area. These are common phenomena in most Asian countries (Autrup 2010). Besides, chemical and physical components like sea salt, biomass burning, Pb, road dust, black carbon, SO_2, NO_2, O_3, and CO are also responsible for $PM_{2.5}$ concentration (Rahman et al. 2019). Note that the concentration level of $PM_{2.5}$ and other metal substances in the air of Dhaka and its adjacent areas is higher than in Europe, East Asia, and other South Asian countries (Salam et al. 2008).

Conclusions and further research

In this research, the concentration of $PM_{2.5}$ during 2002-2019 and the identification of hotspots are mapped in the central part of Bangladesh using spatiotemporal $PM_{2.5}$ datasets. The results of this study can be summarized as followings:

- The concentration of $PM_{2.5}$ increased by 42% during 2002-2019.
- The susceptible hotspot zones are located in the central part of the study area, the urban areas of the Dhaka, Narayanganj, Munshiganj, Narsingdi, and Gazipur Districts.
- This research found 16.5% (3,640,748 persons out of the total population) were in the age group 0-9, 0.95% (2,109,99 persons) were in the age group 60$^+$, 5% (12,062,419 persons) were pregnant women, and 1% (24,621 persons) were pneumonia patients in very high- and high-hotspot zones.

Suppose the concentration of $PM_{2.5}$ and its high-spot zone increase, the vulnerability of public health along with all strata of the population will be affected over the next period. Moreover, overall urban ecology and morphology will be affected the most due to $PM_{2.5}$.

Note that this study may be helpful for the government of Bangladesh, particularly for the Ministry of Environment and Climate Change and their urban and environmental officials for designing an appropriate plan for local and regional air pollution mitigation. The Ministry of Health may consider the outcomes of this research to identify the most hotspot zones for establishing mobile health services and public-awaeness activities. The methodology of the paper may be replicated to research other areas of Bangladesh. Future research is recommended based on (i) high-resolution (spatial and temporal) $PM_{2.5}$ of satellite data as it can be used as an independent data source for $PM_{2.5}$ concentrations where the ground-based stations' data are time-consuming and expensive, and (ii) a sufficient sample of primary health data from different respondents and communities. Future studies, including a wide range of scientific data, may be considered in a wider geographic area to overcome these limitations.

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References

Adães, J., & Pires, J. C. M. (2019). Analysis and modelling of PM2.5 temporal and spatial behaviors in European cities. *Sustainability (Switzerland)*, *11*(21), 2–26. https://doi.org/10.3390/su11216019

Al-Hamdan, M., Crosson, W., Burrows, E., Coffield, S., Crane, B., & Barik, M. (2019). Development and validation of improved PM2.5 models for public health applications using remotely sensed aerosol and meteorological data. *Environmental Monitoring and Assessment*, *191*(2), 328. https://doi.org/10.1007/s10661-019-7414-3

Andersen, Z. J., Bønnelykke, K., Hvidberg, M., Jensen, S. S., Ketzel, M., Loft, S., et al. (2012). Long-term exposure to air pollution and asthma hospitalisations in older adults: A cohort study. *Thorax*, *67*(1), 6–11. https://doi.org/10.1136/thoraxjnl-2011-200711

Arfaeinia, H., Hashemi, S. E., Alamolhoda, A. A., & Kermani, M. (2016). Evaluation of organic carbon, elemental carbon, and water soluble organic carbon concentration in PM 2.5 in the ambient air of Sina Hospital district, Tehran, Iran Citation: Arfaeinia H, Hashemi SE, Alamolhoda AA, Kermani M. Evaluation of organic carbon,. *J Adv Environ Health Res*, *4*(2), 95–101. http://jaehr.muk.ac.ir/index.php/jaehr/article/view/article_40221_c2f93f6a2a1fad4f8a1a88484b5baf6f.pdf

Arif, M., Kumar, R., Kumar, R., Eric, Z., & Gourav, P. (2018). Ambient black carbon, PM2.5 and PM10 at Patna: Influence of anthropogenic emissions and brick kilns. *Science of the Total Environment*, *624*, 1387–1400. https://doi.org/10.1016/j.scitotenv.2017.12.227

Autrup, H. (2010). Ambient air pollution and adverse health effects. *Procedia - Social and Behavioral Sciences*, *2*(5), 7333–7338. https://doi.org/10.1016/j.sbspro.2010.05.089

Azkar, M., Chatani, S., & Sudo, K. (2012). Simulation of urban and regional air pollution in Bangladesh. *Journal of Geophysical Research Atmospheres*, *117*(7). https://doi.org/10.1029/2011JD016509

Bank, W. (2018). *Enhancing Opportunities for Clean and Resilient Growth in Urban Bangladesh*. *Enhancing Opportunities for Clean and Resilient Growth in Urban Bangladesh*. https://doi.org/10.1596/30558

Bayat, R., Ashrafi, K., Shafiepour Motlagh, M., Hassanvand, M. S., Daroudi, R., Fink, G., & Künzli, N. (2019). Health impact and related cost of ambient air pollution in Tehran. *Environmental Research*, *176*(April). https://doi.org/10.1016/j.envres.2019.108547

BBS. (2020). Upazila specific population data. Bangladesh Bureau of Statistics. http://www.bbs.gov.bd/. Accessed 25 July 2020

Beelen, R., Raaschou-Nielsen, O., Stafoggia, M., Andersen, Z. J., Weinmayr, G., Hoffmann, B., et al. (2014). Effects of long-term exposure to air pollution on natural-cause mortality: An analysis of 22 European cohorts within the multicentre ESCAPE project. *The Lancet*, *383*(9919), 785–795. https://doi.org/10.1016/S0140-6736(13)62158-3

Begum, B. A. (2016a). Dust Particle (PM 10 and PM 2 . 5) Monitoring for Air Quality Assessment in Naryanganj and Munshiganj , Bangladesh. *Nuclear Science and Applications*, *25*(1), 45–47.

Begum, B. A. (2016b). Dust Particle (PM 10 and PM 2 . 5) Monitoring for Air Quality Assessment in Naryanganj and Munshiganj , Bangladesh. *Nuclear Science and Applications*, *25*(1), 45–47. http://baec.portal.gov.bd/sites/default/files/files/baec.portal.gov.bd/page/1f00cd0e_737d_4e2e_ab9f_08183800b7a2/9%3D2503 -F-Short Comm-.pdf

Begum, B. A., Biswas, S. K., & Nasiruddin, M. (1970). Trend and Spatial Distribution of Air Particulate Matter Pollution in Dhaka City. *Journal of Bangladesh Academy of Sciences*, *34*(1), 33–48. https://doi.org/10.3329/jbas.v34i1.5490

Begum, B. A., Biswas, S. K., & Nasiruddin, M. (2010). Trend and Spatial Distribution of Air Particulate Matter. *Journal of Bangladesh Academy of Sciences*, *34*(1), 33–48.

Begum, B. A., Hopke, P. K., & Markwitz, A. (2013). Air pollution by fine particulate matter in Bangladesh. *Atmospheric Pollution Research*, *4*(1), 75–86. https://doi.org/10.5094/APR.2013.008

Cao, Q., Rui, G., & Liang, Y. (2018). Study on PM2.5 pollution and the mortality due to lung cancer in China based on geographic weighted regression model. *BMC Public Health*, *18*(1), 1–10. https://doi.org/10.1186/s12889-018-5844-4

CASE. (2019). Clean Air and Sustainable Development. Department of Environment. http://case.doe.gov.bd/index.php?option=com_content&view=article&id=5&Itemid=9. Accessed 23 August 2020

Chen, C., Zhu, P., Lan, L., Zhou, L., Liu, R., Sun, Q., et al. (2018). Short-term exposures to PM2.5 and cause-specific mortality of cardiovascular health in China. *Environmental Research*, *161*, 188–194. https://doi.org/10.1016/j.envres.2017.10.046

DGHS. (2019). Real Time Health Information Dashboard. *Directorate General of Health Services*. Bangladesh Directorate General of Health Services. http://103.247.238.81/webportal/pages/index.php. Accessed 20 August 2020

Dirgawati, M., Heyworth, J. S., Wheeler, A. J., McCaul, K. A., Blake, D., Boeyen, J., et al. (2016). Development of Land Use Regression models for particulate matter and associated components in a low air pollutant concentration airshed. *Atmospheric Environment*, *144*, 69–78. https://doi.org/10.1016/j.atmosenv.2016.08.013

ESRI. (2019). ArcGIS Online Help - How Hot Spot Analysis Works. ESRI. http://pro.arcgis.com/en/pro-app/tool-reference/spatial-statistics/h-how-hot-spot-analysis-getis-ord-gi-spatial-stati.htm. Accessed 17 August 2020

Gautam, S., Yadav, A., Tsai, C. J., & Kumar, P. (2016). A review on recent progress in observations, sources, classification and regulations of PM2.5 in Asian environments. *Environmental Science and Pollution Research*, *23*(21), 21165–21175. https://doi.org/10.1007/s11356-016-7515-2

Godoy, A. R. L., Silva, A. E. A. da, Bueno, M. C., Pozza, S. A., & Coelho, G. P. (2021). Application of machine learning algorithms to PM2.5 concentration analysis in the state of São Paulo, Brazil. *Brazilian Journal of Environmental Sciences*, *56*(1), 152–165. https://doi.org/10.5327/z21769478782

Habibi, R., Alesheikh, A. A., Mohammadinia, A., & Sharif, M. (2017). An assessment of spatial pattern characterization of air pollution: A case study of CO and PM2.5 in Tehran, Iran. *ISPRS International Journal of Geo-Information*, *6*(9). https://doi.org/10.3390/ijgi6090270

Han, W., Tong, L., Chen, Y., Li, R., Yan, B., & Liu, X. (2018). Estimation of high-resolution daily ground-level PM2.5 concentration in Beijing 2013-2017 using 1 km MAIAC AOT data. *Applied Sciences (Switzerland)*, *8*(12), 1–17. https://doi.org/10.3390/app8122624

Hoek, G., Krishnan, R. M., Beelen, R., Peters, A., Ostro, B., Brunekreef, B., & Kaufman, J. D. (2013). Long-term air pollution exposure and cardio-respiratory mortality: A review. *Environmental Health: A Global Access Science Source*, *12*(1), 1–16. https://doi.org/10.1186/1476-069X-12-43

Hoque, M. M., Begum, B. A., Shawan, A. M., & Ahmed, S. J. (2014). Particulate Matter Concentrations in the Air of Dhaka and Gazipur City During Winter : A comparative study. In *International Conference on Physics Sustainable Development & Technology (ICPSDT-2015)* (pp. 140–149). Dhaka.

Hossen, M. A., Pal, S. K., & Hoque, A. (2018). Assessment of Air Quality for Selected Locations in Chittagong City Corporation Area, Bangladesh. *International Journal of Innovative Research in Engineering & Management*, *5*(4), 121–128. https://doi.org/10.21276/ijirem.2018.5.4.1

Hu, X., Waller, L. A., Lyapustin, A., Wang, Y., & Liu, Y. (2014a). 10-year spatial and temporal trends of PM2. 5 concentrations in the southeastern US estimated using high-resolution satellite data. *Atmospheric chemistry and physics*, *14*(12), 6301.

Hu, X., Waller, L. A., Lyapustin, A., Wang, Y., & Liu, Y. (2014b). 10-year spatial and temporal trends of PM2.5 concentrations in the southeastern US estimated using high-resolution satellite data. *Atmospheric Chemistry and Physics*, *14*(12), 6301–6314. https://doi.org/10.5194/acp-14-6301-2014

Islam, M. (2000). Chemical speciation of particulate matter pollution in urban Dhaka City. *Bangladesh Environment 2000*, 51–58.

Jana, M., & Sar, N. (2016a). Modeling of hotspot detection using cluster outlier analysis and

Getis-Ord Gi* statistic of educational development in upper-primary level, India. *Modeling Earth Systems and Environment*, *2*(2), 60.

Jana, M., & Sar, N. (2016b). Modeling of hotspot detection using cluster outlier analysis and Getis-Ord Gi* statistic of educational development in upper-primary level, India. *Modeling Earth Systems and Environment*, *2*(2), 1–10. https://doi.org/10.1007/s40808-016-0122-x

Kandlikar, M., & Ramachandran, G. (2000). The causes and consequences of particulate air pollution in urban India: A synthesis of the science. *Annual Review of Energy and the Environment*, *25*(1), 629–684. https://doi.org/10.1146/annurev.energy.25.1.629

Kiesewetter, G., Borken-Kleefeld, J., Schöpp, W., Heyes, C., Thunis, P., Bessagnet, B., et al. (2015). Modelling street level PM10 concentrations across Europe: Source apportionment and possible futures. *Atmospheric Chemistry and Physics*, *15*(3), 1539–1553. https://doi.org/10.5194/acp-15-1539-2015

Kim, Y. P., Grinshpun, S. A., Asbach, C., & Tsai, C. J. (2015). Overview of the special issue "selected papers from the 2014 international aerosol conference." *Aerosol and Air Quality Research*, *15*(6), 2185–2189. https://doi.org/10.4209/aaqr.2015.11.SIIAC

Kumar, A., Mishra, R. K., & Singh, S. K. (2015). GIS Application in Urban Traffic Air Pollution Exposure Study: A Research Review. *Suan Sunandha Science and Technology Journal*, *2*(1January), 25–37.

Landrigan, P. J., Fuller, R., Acosta, N. J. R., Adeyi, O., Arnold, R., Basu, N. (Nil), et al. (2018). The Lancet Commission on pollution and health. *The Lancet*, *391*(10119), 462–512. https://doi.org/10.1016/S0140-6736(17)32345-0

LGED. (2020). District/ Upazila Digital Map. Local Government and Engineering Department. https://oldweb.lged.gov.bd/ViewMap.aspx. Accessed 20 July 2020

Liang, C. S., Duan, F. K., He, K. Bin, & Ma, Y. L. (2016a). Review on recent progress in observations, source identifications and countermeasures of PM2.5. *Environment International*, *86*, 150–170. https://doi.org/10.1016/j.envint.2015.10.016

Liang, C. S., Duan, F. K., He, K. Bin, & Ma, Y. L. (2016b). Review on recent progress in observations, source identifications and countermeasures of PM2.5. *Environment International*, *86*, 150–170. https://doi.org/10.1016/j.envint.2015.10.016

Mangal, A., Satsangi, A., Lakhani, A., & Kumari, K. M. (2018). Investigation of PM 10 , PM 2 . 5 and PM 1 during Pollution Episodes : Fog and Diwali Festival. *IOSR Journal of Environmental Science, Toxicology and Food Technology*, *12*(9), 16–23. https://doi.org/10.9790/2402-1209011623

Mkoma, S. L., Chi, X., & Maenhaut, W. (2010). Characteristics of carbonaceous aerosols in ambient PM10 and PM2.5 particles in Dar es Salaam, Tanzania. *Science of the Total Environment*, *408*(6), 1308–1314. https://doi.org/10.1016/j.scitotenv.2009.10.054

Motalib, M. A., & Lasco, R. D. (2015). Assessing Air Quality in Dhaka City. *International Journal of Science and Research (IJSR)*, *4*(12), 1908–1912. https://doi.org/10.21275/v4i12.sub159291

Mukherjee, A., Brown, S. G., McCarthy, M. C., Pavlovic, N. R., Stanton, L. G., Snyder, J. L., et al. (2019). Measuring spatial and temporal PM2.5 variations in Sacramento, California, communities using a network of low-cost sensors. *Sensors (Switzerland)*, *19*(21), 4701. https://doi.org/10.3390/s19214701

NASA. (2019). Giovanni Earth data. https://earthdata.nasa.gov/earth-observation-data

Nguyen, T. N. T., LE, H. A., MAC, T. M. T., NGUYEN, T. T. N., PHAM, V. H., & BUI, and Q. H. (2018). Current Status of PM2.5 Pollution and its Mitigation in Vietnam. *Global Environmental Research*, *22*(June), 073–083.

Ni, X., Cao, C., Zhou, Y., Cui, X., & Singh, R. P. (2018a). Spatio-temporal pattern estimation of PM2.5 in Beijing-Tianjin-Hebei Region based on MODIS AOD and meteorological data using the back propagation neural network. *Atmosphere*, *9*(3), 105. https://doi.org/10.3390/atmos9030105

Ni, X., Cao, C., Zhou, Y., Cui, X., & Singh, R. P. (2018b). Spatio-temporal pattern estimation of PM2.5 in Beijing-Tianjin-Hebei Region based on MODIS AOD and meteorological data using the back propagation neural network. *Atmosphere*, *9*(3). https://doi.org/10.3390/atmos9030105

Pavel, M. R. S., Zaman, S. U., Jeba, F., Islam, M. S., & Salam, A. (2021). Long-Term (2003–2019) Air Quality, Climate Variables, and Human Health Consequences in Dhaka, Bangladesh. *Frontiers in Sustainable Cities*,

3(July). https://doi.org/10.3389/frsc.2021.681759
QGIS. (2016). Q GIS A Free and Open Source Geographic Information System. *Webpage*. QGIS. http://www.qgis.org/en/site/. Accessed 13 April 2020
Raaschou-Nielsen, O., Andersen, Z. J., Beelen, R., Samoli, E., Stafoggia, M., Weinmayr, G., et al. (2013). Air pollution and lung cancer incidence in 17 European cohorts: Prospective analyses from the European Study of Cohorts for Air Pollution Effects (ESCAPE). *The Lancet Oncology*, *14*(9), 813–822. https://doi.org/10.1016/S1470-2045(13)70279-1
Rahman, M. M., Mahamud, S., & Thurston, G. D. (2019). Recent spatial gradients and time trends in Dhaka, Bangladesh, air pollution and their human health implications. *Journal of the Air and Waste Management Association*, *69*(4), 478–501. https://doi.org/10.1080/10962247.2018.1548388
Rajput, P., Sarin, M., & Kundu, S. S. (2013). Atmospheric particulate matter (PM2.5), EC, OC, WSOC and PAHs from NE-Himalaya: Abundances and chemical characteristics. *Atmospheric Pollution Research*, *4*(2), 214–221. https://doi.org/10.5094/APR.2013.022
Rana, M. M., Mahmud, M., Khan, M. H., Sivertsen, B., & Sulaiman, N. (2016). Investigating Incursion of Transboundary Pollution into the Atmosphere of Dhaka, Bangladesh. *Advances in Meteorology*, *2016*. https://doi.org/10.1155/2016/8318453
Rao, B. V., Ramjee, E., & Reddy, V. V. (2014). Spatial and Temporal Determination of the Air Quality at Major Transportation Regions of the Hyderabad Metropolitan City :, *4*(1), 9–14.
Salam, A., Hossain, T., Siddique, M. N. A., & Shafiqul Alam, A. M. (2008). Characteristics of atmospheric trace gases, particulate matter, and heavy metal pollution in Dhaka, Bangladesh. *Air Quality, Atmosphere and Health*, *1*(2), 101–109. https://doi.org/10.1007/s11869-008-0017-8
Songchitruksa, P., & Zeng, X. (2010a). Getis-ord spatial statistics to identify hot spots by using incident management data. *Transportation Research Record*, (2165), 42–51. https://doi.org/10.3141/2165-05
Songchitruksa, P., & Zeng, X. (2010b). Getis-ord spatial statistics to identify hot spots by using incident management data. *Transportation Research Record*, *2165*(2165), 42–51. https://doi.org/10.3141/2165-05
Srivastava, D., Xu, J., Vu, T. V., Liu, D., Li, L., Fu, P., et al. (2021). Insight into PM2.5sources by applying positive matrix factorization (PMF) at urban and rural sites of Beijing. *Atmospheric Chemistry and Physics*, *21*(19), 14703–14724. https://doi.org/10.5194/acp-21-14703-2021
Tiwari, S., Hopke, P. K., Pipal, A. S., Srivastava, A. K., Bisht, D. S., Tiwari, S., et al. (2015a). Intra-urban variability of particulate matter (PM2.5 and PM10) and its relationship with optical properties of aerosols over Delhi, India. *Atmospheric Research*, *166*, 223–232. https://doi.org/10.1016/j.atmosres.2015.07.007
Tiwari, S., Hopke, P. K., Pipal, A. S., Srivastava, A. K., Bisht, D. S., Tiwari, S., et al. (2015b). Intra-urban variability of particulate matter (PM2.5 and PM10) and its relationship with optical properties of aerosols over Delhi, India. *Atmospheric Research*, *166*, 223–232. https://doi.org/10.1016/j.atmosres.2015.07.007
Van Donkelaar, A., Martin, R. V., Brauer, M., Hsu, N. C., Kahn, R. A., Levy, R. C., et al. (2016). Global Estimates of Fine Particulate Matter using a Combined Geophysical-Statistical Method with Information from Satellites, Models, and Monitors. *Environmental Science and Technology*, *50*(7), 3762–3772. https://doi.org/10.1021/acs.est.5b05833
WHO. (2016). Global Urban Ambient Air Pollution Database (update 2016). *WHO*. World Health Organization.
Zhao, D., Chen, H., Sun, X., & Shi, Z. (2018). Spatio-temporal variation of PM2.5 pollution and its relationship with meteorology among five megacities in China. *Aerosol and Air Quality Research*, *18*(9), 2318–2331. https://doi.org/10.4209/aaqr.2017.09.0351
Zhao, J., Wang, X., Song, H., Du, Y., Cui, W., & Zhou, Y. (2019). Spatiotemporal trend analysis of PM2.5 concentration in China, 1999-2016. *Atmosphere*, *10*(8), 1–10. https://doi.org/10.3390/atmos10080461