Assessment of Health Impacts of Particulate Matter ($PM_{2.5}$) on the Vulnerable Groups in the Central part of Bangladesh

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Research Article

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Abstract

Particulate matter ($PM_{2.5}$) is one of the critical sources for outdoor 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 a significant public health hazard. This research aims to perform a spatiotemporal mapping of $PM_{2.5}$ from 2002–2019 to identify the hotspots in central Bangladesh and to estimate the health impacts on pregnant women and population aged 60^+. A time-series of remotely sensed $PM_{2.5}$ is used in hotspot analysis, applying Geographic Information Systems (GIS). To explore the health impacts due to $PM_{2.5}$, a questionnaire survey is conducted on pregnant women and population aged 60 + in both high- and low-spots zones. A Mann-Whitney U test of non-parametric statistical analysis is conducted to understand the mean impacts. The findings of this research reveal that the annual concentration of $PM_{2.5}$ is increased by 47% during 2002–2019. Most of the high hotspot zones are identified in the middle of the study areas; the core urban areas of Dhaka, Narayanganj, and Gazipur Districts. The traffic vehicles, urbanization, construction and brickfield activities, and industrial emissions are the main controlling factors for increasing $PM_{2.5}$. Further, the health impacts of both pregnant and population 60^+ are higher in the high-spot zone than in the low-spot area. Note that pregnant women have less $PM_{2.5}$ related information than 60^+ population in both high- and low-spot zones. On the policy applications, the relevant departments may utilize these findings for health hazard risk reduction and local and regional air pollution mitigation.

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 (WHO 2016; Landrigan et al. 2018). 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 (Autrup 2010). 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). The most vulnerable population groups are children under aged five years, pregnant women, and the elderly (60^+) who are sensitive to a high level of $PM_{2.5}$ due to many health issues (Luo et al. 2018; Lei et al. 2019; Zeng et al. 2020).

The $PM_{2.5}$ has been considered as one of the leading air pollutants in Dhaka and its adjacent areas, which has also been evidenced as an inevitable threat to human health as well as all living organisms (Kim et al. 2015; Liang et al. 2016). It happens because of a large share of air (58% of total $PM_{2.5}$) of Dhaka 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). In addition, the physical signature of $PM_{2.5}$ is being increased gradually because of unplanned rapid urbanization and swift industrialization to boost the country's economy by generating the most unexchanged cost of environmental pollution (Zhang and Zhang 2018).

However, scrutiny through the $PM_{2.5}$ in Bangladesh, China, India, and Pakistan, it is found that around 86% of populations are exposed to the most extreme level (i.e., > 75 μg/m^3) of pollution concentration (HEI 2017). If the daily concentration level of $PM_{2.5}$ increases by ten μg/m^3, the prevalence of respiratory and other health problems increases by 2.07%, while the hospital admission rate is increased by 8% (Dominici et al. 2006; Zanobetti et al. 2009; Xing et al. 2016). According to the World Bank report of 2018, every year, around seven million premature deaths occur worldwide due to $PM_{2.5}$ in which 234,000 deaths (3.34%) are recorded in Bangladesh (World Bank 2018; PPI 2017). The mortality rate caused by $PM_{2.5}$ in Bangladesh is presented in Table 1.

Geographic Information System (GIS), together with remote sensing techniques, is a widely used method for Spatiotemporal hotspots analysis of $PM_{2.5}$ (Hoque et al. 2014; Cao et al. 2018). This research aims to (i) perform a spatiotemporal mapping applying GIS using remotely sensed pixel-based time series $PM_{2.5}$ data considering a broader scale geographical context in Bangladesh (ii) measure the health effects of most vulnerable population groups such as pregnant women and population 60^+ using primary health information, a self-reported stakeholders' perception contrasting very high and low concentrations of $PM_{2.5}$ from hotspot areas, and (iii) test a hypothesis that pregnant women and the 60^+ population in the high-spot zones are more vulnerable than low-hot spot areas caused of the high concentration of $PM_{2.5}$.

Previous studies on $PM_{2.5}$ and its' impact on public health

Globally, the remote sensing data coupled with primary health information have been used widely in air pollution-related health research to estimate the spatiotemporal pattern of $PM_{2.5}$, the spatial extent of a hotspot, and impacts on public health, particularly on vulnerable groups. Hoque et al. (2014) and Cao et al. (2018) conducted such a study in the US, Europe, China, and India using Moderate Resolution Imaging Spectroradiometer (MODIS) data without validation with the ground or relevant data, and linked the impact of $PM_{2.5}$ concentration and its exposure to different population groups. The validation process enhances the applicability of integrated MODIS and health data for the decision-making process. Knowing the spatial trend and geographical distribution of $PM_{2.5}$ is a vital policy aspect for the air pollution control mechanism. To understand this, Zhao et al. (2019) used a pixel-based liner pattern of $PM_{2.5}$ in China using 18 years MODIS data and energy consumption. But only energy consumption is not a major contributing factor to measure the increasing trend of $PM_{2.5,}$ which is a limitation.

Several visible and contributing factors from development and anthropogenic aspects may consider in understanding the real situation of an increasing trend. Hu et al. (2014) suggested that the concentration of $PM_{2.5}$ depends on different geographic locations and land use classes. Using a Spatiotemporal Model,

they found that the spatial trend of $PM_{2.5}$ concentration is more in urban areas than in rural or hilly areas (Hu et al. 2014). Used parameters in modeling were limited to five, along with $PM_{2.5}$. However, running a robust model, different important variables, e.g., topographical, environmental, micro-climate, and anthropogenic, may generate more authentic results. Perception about air pollution, particularly on $PM_{2.5,}$ is a critical aspect in terms of public health research because people need to be aware of the adverse impact of $PM_{2.5}$. Jiang et al. (2016) investigated public awareness on smog pollution in rural China and founded that the perception about air pollution at the individual level was much better. However, this study would have been more substantial if they could use children, pregnant women, and older people as critical respondents. Urban and urban slums are most vulnerable due to $PM_{2.5}$ within the urban context. Egondi et al. (2013) conducted a cross-sectional study considering people ages 35^{+} in Nairobi to collect and analyze the perception of air pollution for designing appropriate intervention strategies. The sample size being the representative of this study, it did not consider any parametric or non-parametric statistical analysis to compare their results with any control data, a limitation. However, Pithon (2013) suggests that the control group is essential, and it resembles the impact between two groups with scientific evidence. Besides, Cao et al. (2018) show a robust correlation between $PM_{2.5}$ and mortality of lunch cancer in China, applying a statistical regression model using the old mortality data of 2008. Recent data of a variable can enhance the applicability of a regression model. Miller and Xu (2018) also suggest that panel or primary data are substantial to make a statistical relationship with $PM_{2.5}$. Importantly, primary data can give real scenarios from the respondents, particularly from vulnerable groups.

In the context of Bangladesh, a wide range of research for establishing a nexus between $PM_{2.5}$ and public health has been conducted in and around Dhaka city (Salam et al. 2008; Begum et al. 2010, 2013; Azkar et al. 2012; Hoque et al. 2014; Begum 2016; Rana et al. 2016). Most of the studies were conducted in smaller geographic areas using handheld $PM_{2.5}$ sampling machines' data from only three ground stations, and the primary health data of vulnerable groups considering hotspot zones were ignored. However, to generalize the picture of the concentration of $PM_{2.5,}$ only three stations data, particularly in Dhaka Mega City in Bangladesh and its impact on health hazards, may be misleading. Therefore, in this study, a more broad scale geographic area is selected considering MODIS data combine with peoples' perception of the vulnerable group that enhances the insight into a better understanding of $PM_{2.5}$ concentration and its impact on public health.

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, Narsingdi, and Gazipur (Fig. 1). The entire geographic area lies between 23°20'N-24°20'N latitudes and 90°00'E-91°00'E longitudes, which covers about 6,043 square kilometers, including 22,066,710 populations (Fig. 1). Having a tropical wet monsoon and dry winter climate, the study area has an annual average rainfall of 1,854 mm with an average yearly temperature of 25 ^{0}C (Hossain and Bahauddin 2013). 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. Some scientists mentioned that this area has the largest density of industrialization due to easy access to finance, enormous transportation facilities, location-based advantage, spatial context, and different management services (Islam 2000). Many industries operate activities in the study area, which is the key triggering reasons to produce enormous emission and gaseous particulates (Salam et al. 2008). These industries include, e.g., ready-made garment, textile, pharmaceuticals, cement, brickfields, fertilizer, assembling of a motorcycle, bus, truck, Compress Natural Gas, raw material processing, food and sugar, and electrical power.

Methods And Results

This study used the annual average data of $PM_{2.5}$ between 2002–2016 and 2019 for the quantitative measures. The data for 2017 and 2018 are missing here. To understand the impact of $PM_{2.5}$ on public health, a structured questionnaire survey was conducted, a qualitative analysis. Details of the methods are described here.

Retrieving $PM_{2.5}$ data

The annual average data of $PM_{2.5}$ were collected as 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 along with GEOS-Chem Models to simulate the spatiotemporal variations across the world, was applied (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 were validated using ground stations' data during 2002-2019 from the Department of Environment, Government of Bangladesh (CASE 2019). There are only five ground stations (Fig. 1) 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. 2018). 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.

Multivariable and Spatio-temporal analysis

Temporal analysis of basic statistics, e.g., minimum, maximum, and mean value of $PM_{2.5}$ during the study period 2002-2019, was calculated. In this period, the mean annual rate of $PM_{2.5}$ is increased by 42% in the study area (Fig. 3a-c). The yearly trend of minimum values of $PM_{2.5}$ is increased by 40%, while the maximum value is increased by 37% (Fig. 3). The concentration $PM_{2.5}$ 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) that is 15 μg/m^3 (Fig. 3a) (WHO 2016).

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 of 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).

Hotspots analysis

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 ArcsGIS, the Hot Spot Analysis tool in Spatial Statistics was applied to find out the hottest and coldest areas. In the hotspot analysis, 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 2010). 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 $s = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\bar{X}\right)^2}$. 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 2016). Readers are encouraged to read (ESRI 2019) more about *z*-score and *p*-value. The raster overlay was applied using the resultant hotspots areas and area-specific population and most critical public health data to find out the riskiest zones (e.g., Kumar et al. 2015). Further, the hotspot map was overlaid with upazlias' total population (Fig. 5b), population 0–9 (Fig. 5c), population 60^+(Fig. 5d), pneumonia patient (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 Bangladesh Directorate General of Health Services (BDGHS) (DGHS 2019).

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-hotspots 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 3640748 persons (16.5% out of total population) (Fig. 5b) of which 4.39% (969261 persons) are age group 0–9 (Fig. 5c), 0.95% (210999 persons) are age group 60^+ (Fig. 5d), 5% (12,062,419 persons) are pregnant women (Fig. 5e), and 1% (24621 persons) are pneumonia patients (Fig. 5f) in very high- and high-hotspot zones.

Impact of PM2.5 on public health

The self-reported health impacts due to the $PM_{2.5}$ in the very high-, high-hotspots, and low-spots zones, a primary survey was conducted considering 115 sample populations. For this health survey, a purposive sampling method (Palinkas et al. 2015) was followed to collect the individual specific in-depth information from each respondent using a mini-structured questionnaire from 26 December 2019 to 27 January 2020. The health impacts between very high- and low-spot zones are compared. A total of 85 samples were conducted to the population age 60^+, of which 55 samples were from very high- and 30 samples were from low-spot zones. On the other hand, 30 samples were conducted to the pregnant women, of which 20 samples were from very high- and ten samples were from low-spot zones. For collecting data about pregnant women, the survey team went to government health facilities and practice chambers of the gynecologist.

After getting a consensus from a pregnant woman or her caregivers, data was collected. For the population age 60^+, respondents were selected as one in a 5 km radius to enhance the uniform distribution of the sample. After data collection and editing, significant sources of air $PM_{2.5}$ and self-reported health impacts due to $PM_{2.5}$ were analyzed using descriptive analysis. A non-parametric Mann-

Whitney U (McKnight and Julius 2010) test to compare the health impacts between very high- and low-spot zones was conducted. This non-parametric test was selected because these two groups were not normally distributed, and the sample size was sufficiently small, what is one of the limitations of this study. However, this test tends to be more appropriate in this situation (McKnight and Julius 2010). Stata version 13 (StataCorp LLC) was used to conduct different statistical analyses.

Respondents' knowledge about $PM_{2.5}$

About 71% of the population age 60^+ in the high-spot zone know well about $PM_{2.5}$ (Fig. 6). Contrary, more than 73% of the same group (60+) do not know about $PM_{2.5}$ in the low-spot zone (Fig. 6). Only 55% of pregnant women in the high-spot area know about $PM_{2.5}$, while 70% of pregnant women have no idea about $PM_{2.5}$ in the low-spot zone. In this analysis, pregnant women have less access to information related to $PM_{2.5}$ than the population 60^+ in both zones (Fig. 6).

Respondents' knowledge of sources of $PM_{2.5}$

Population age 60^+ believe that road vehicle (64%), urbanization (84%), construction site (43%), brickfield (38%), and industrial emissions (44%) are responsible for $PM_{2.5}$ in high-spot zone. Contrary, pregnant women in the high-spot zone suggest that dust (25%), construction site (57%), and brickfield (%) are the predominant controlling factors for $PM_{2.5}$ (Table 2). In the low-spot zone, both pregnant women and population age 60^+ mention that the dust (20%) and industrial emissions (56%) are the triggering factors for increasing $PM_{2.5}$.

Respondents' responses about health risk due to $PM_{2.5}$

Breathing problems, cold/cough, eye problems, skin problems, and asthma are identified as significant health problems in both high- and low-spot zones. The Mann-Whitney U test results suggest that the pregnant women group has a higher mean rank (16.43) in the high-spot than the low-spot zone (13.65) (Table 3). The Mann-Whitney U test is estimated to 81.5, and the p-value is to 0.422, which is higher than 0.05. So, the test is not statistically significant, but there the difference exists.

However, a higher mean rank of 48.26 for the population 60^+ is calculated in the high-spot, compared to that in the low-spot zone to 33.35. Besides, the Mann-Whitney U test is 535.5, and the p-value is 0.006., which is less than 0.05 (Table 3). It proves that there is a significant difference in the health impact of pregnant women and population 60^+ between the high- and the low-spot zones. The health effects of pregnant women and population 60^+ in high-spot regions are more significant than low-spot areas that satisfy the hypothesis.

Discussions

For better understanding the effects of PM2.5 on pregnant women and 60^+ population health, this study is unique, particularly in the context of Bangladesh in many ways; e.g., (i) a large scale geographic area are considered what is usually ignored in many pieces of research (Begum et al. 2010, 2013; Azkar et al. 2012; Hoque et al. 2014; Hu 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; Zhao et al. 2019), however, it is further validated using ground-based stations' data, and (iii) qualitative measures by stakeholders' perceptions are combined with the quantitative measures that are very important in this particular issue (Egondi et al. 2013; Hoque et al. 2014). 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. 2018). It is because the Chinees research group has used a very scattered location of many ground stations' data (Ni et al. 2018). Han et al. (2018) found a very high R^2-value ranging from 0.72–0.97% using 35 ground-based monitoring stations data. Therefore, it is recommended to use many and 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). Estimation of the spatiotemporal concentration of $PM_{2.5}$ is a critical issue for managing local and regional atmospheric pollution strategy as well as 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 2016). Begum et al. (2013) suggest that the 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 what is similarly responded by the stakeholders in this study (Table 2). In Bangladesh and its megacities like Dhaka, 35% of ambient PM_{10} and 15% of $PM_{2.5}$ are being generated from brick kiln emissions and transportation systems (Motalib and Lasco 2015). Comparable with China (60 μg/m^3), Bangladesh (77 μg/m^3) generates 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 (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 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 some 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 relatively a higher annual $PM_{2.5}$ concentration which is similar with 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 north and southern parts (Figs. 4, 5a). However, 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 to describe 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 the European cities and among all, the sources of the maximum concentration of $PM_{2.5}$ of 12 cities are traffic-related (Kiesewetter et al. 2015), what is also similar in Bangladesh. Note that, 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) what may not be comparable with $PM_{2.5}$ in this study.

$PM_{2.5}$ is one of the significant public health concerns in urban and peri-urban areas of Bangladesh (Rahman et al. 2019). The excessive standard threshold of $PM_{2.5}$ significantly impacts to vulnerable population groups, particularly pregnant women and population 60^+ (Miller and Xu 2018). The higher concentration of $PM_{2.5}$ and its adverse effects on the urban community is exposed as a common public health problem in Bangladesh (Begum et al. 2013). Most of the public health problems are identified as pulmonary, cardiovascular, cancer, diabetics, chronic respiratory, low birth, weight, and premature death (Lawal and Asimiea 2015). Generally, pregnant women and population 60^+ who are living in urban areas can be affected by the different respiratory and non-communicable diseases in many ways (Luo et al. 2018). The significant health complexity of pregnant women and pneumonia patients is high in the high-spot zones (Fig. 5e-f), which is similarly found in China (Andersen et al. 2012; Arroyo et al. 2019). In Nanjing, China, the concentration of $PM_{2.5}$ is responsible for high incidences of premature death (Li et al. 2019), and in 2015, total premature death in China was recorded to 341,701 persons for stroke and 67,325 persons for lower respiratory infection linked to $PM_{2.5}$ concentration (Wang et al. 2019). By executing the hypothesis test, this research suggests that pregnant women's health is more sensitive to the effects of $PM_{2.5}$ in the high-spot region than population 60^+ in the study area, which is similar in a developed country, like in Spain (Arroyo et al. 2019).

Nevertheless, public perception of $PM_{2.5}$ is a critical issue, and a better understanding of the impact of $PM_{2.5}$ may reduce health burden in Asia and South Asia (Jiang et al. 2016; Cao et al. 2018; Achakulwisut et al. 2019). The pregnant women both in the high- (55%) and low-spot zone (30%) in this study area know little about the impact of $PM_{2.5}$ compare to population age 60^+ (Fig. 6). Gender gaps in Bangladesh may cause it, similarly, found in the case of public information and awareness for pre-disaster preparedness for a tropical cyclone (Röhr 2006). The stakeholders' perceptions in this study suggest that

the awareness activities on $PM_{2.5}$ and air pollution happen more often in urban areas than in rural areas. Therefore, people are more informed about $PM_{2.5}$ in urban areas (high-spot zones) than the peri-urban area (low-spot zones). Besides, urban people have more means of getting air pollution-related information, e.g., high mobility, accessible information, mobile information desk, or portal than rural or peri-urban areas (Qian et al. 2016). However, the perception of air pollution depends not only on physical factors but also on employment, health, wages, place, and working environment (Achakulwisut et al. 2019).

The 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 the common phenomena in most of the 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, 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 the Dhaka and its adjacent areas are higher than Europe, East Asian, and other South Asian countries (Salam et al. 2008).

Despite having some limitations, e.g., (i) a limited number of ground stations' data for satellite data validation and (ii) insufficient sample sizes for a primary health data collection for both pregnant women and the 60^+ population, this research identified (1) the high-pots zone of $PM_{2.5}$ concentrations, the urban areas, and (2) the most vulnerable population groups, the pregnant women and population 60^+. Therefore, the concerned authorities may consider this result in public health-related policy-making and /or modification regarding space and vulnerable population groups.

Conclusions And Further Research

In this research, the concentration of $PM_{2.5}$ during 2002–2019 and its impact on public health is mapped in the central part of Bangladesh, where both quantitative and qualitative measures are conducted. The results of this study can be summarized as followings;

- The concentration of $PM_{2.5}$ has 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.
- The pregnant women and population 60^+ are high sensible in terms of $PM_{2.5}$ both in the high- and low-spot zones.
- The pregnant women as the most vulnerable group but have less information about $PM_{2.5}$ than the population 60^+.

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 useful for the government of Bangladesh, particularly for the Ministry of Environment and Climate Change and their urban and environment 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 satellite and mobile health services. 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) sufficient sample of primary health data from different respondents and/or communities. To overcome these limitations, future studies, including a wide range of scientific data, may be considered in a wider geographic area.

Declarations

Author contribution- Shareful: model conceptualization, methodology, data collection, analysis, writing the original draft. **Tariqul:** writing, review and editing. **Amir:** methodology, writing, review and editing, supervision.

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Data availability- All data generated or analyzed during the current study are presented in this article. However, the raw data will be also accessible from the author group if requested.

Ethics approval- We certify that this manuscript is original and has not been published and will not be submitted elsewhere for publication while being considered by Environmental Science and Pollution Research. This study follows all ethical practices during its writing.

Consent to participate- All authors duly participated.

Consent for publication- This is confirmed that the publication of this manuscript has been approved by all co-authors.

Competing interests- The authors declare no competing interests

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Tables

Table 1 Age-specific average annual mortality rate (per 100,000) due to $PM_{2.5}$ in Bangladesh (Our World in Data 2020).

Year	Under-5 year	5-14 year	15-49 year	50-69 year	70^+ year
1990-1994	65	2	4	95	422
1995-1999	61	3	4	94	435
2000-2004	59	2	4	99	432
2005-2009	47	3	6	112	461
2010-2014	35	4	6	108	452
2015-2019	26	3	5	101	435

Table 2 Respondent's perception about sources of $PM_{2.5}$ in both high- and low-spot zones.

	Pregnant women in low-spot	Pregnant women in high-spot	60+ pop in low-spot	60+ pop in high-spot
Road vehicle	9.1%	13.6%	13.6%	63.6%
Dust	20.0%	25.0%	35.0%	20.0%
Urbanization	16.7%	0.0%	0.0%	83.3%
Brickfield	3.1%	25.0%	34.4%	37.5%
Construction site	0.0%	57.1%	0.0%	42.9%
Industrial emission	0.0%	0.0%	56.3%	43.8%

Table 3 Respondent's self-reported health risk due to particulate matter

Groups	Low spot zone		High spot zone		Mann-Whitney U	p
	n	Mean rank	n	Mean rank		
Pregnant women	10	13.65	20	16.43	81.5	0.422
60^+ population	30	33.35	55	48.26	535.5	0.006*

** Statistically significant at 0.05*

Figures

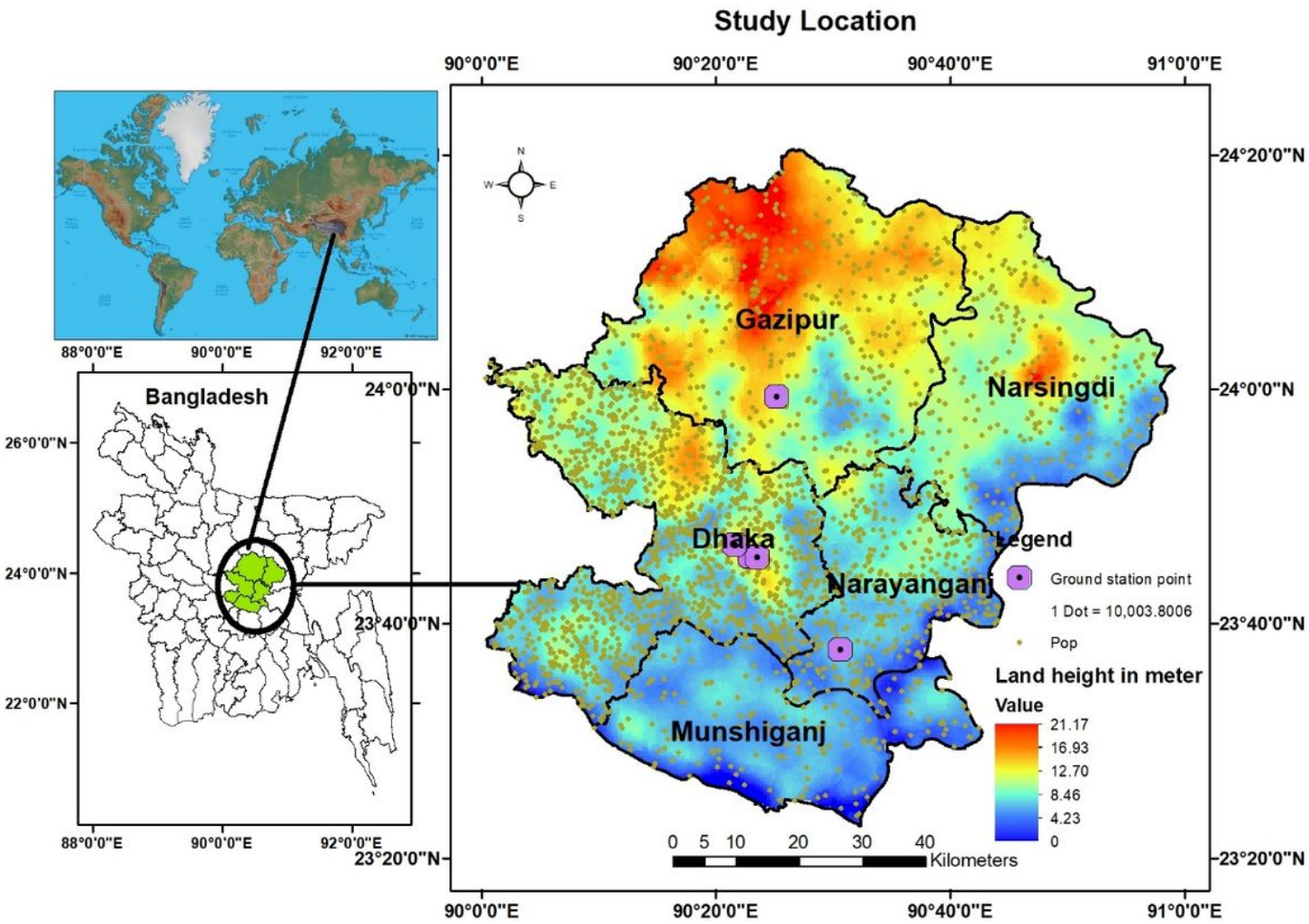

Figure 1

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).

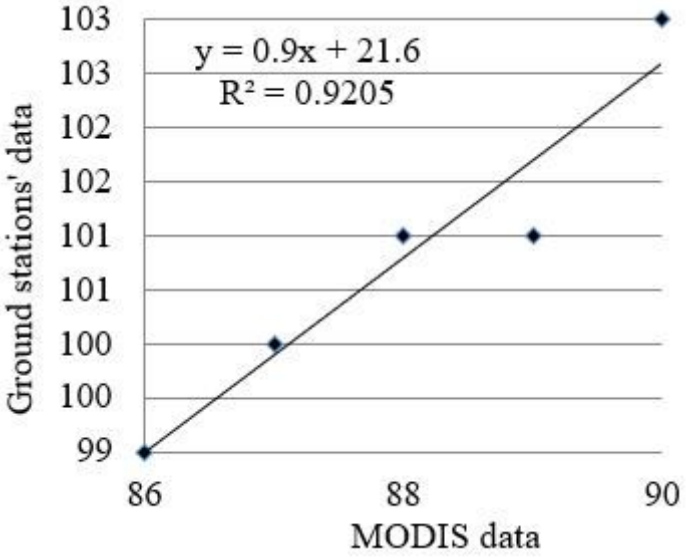

Figure 2

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).

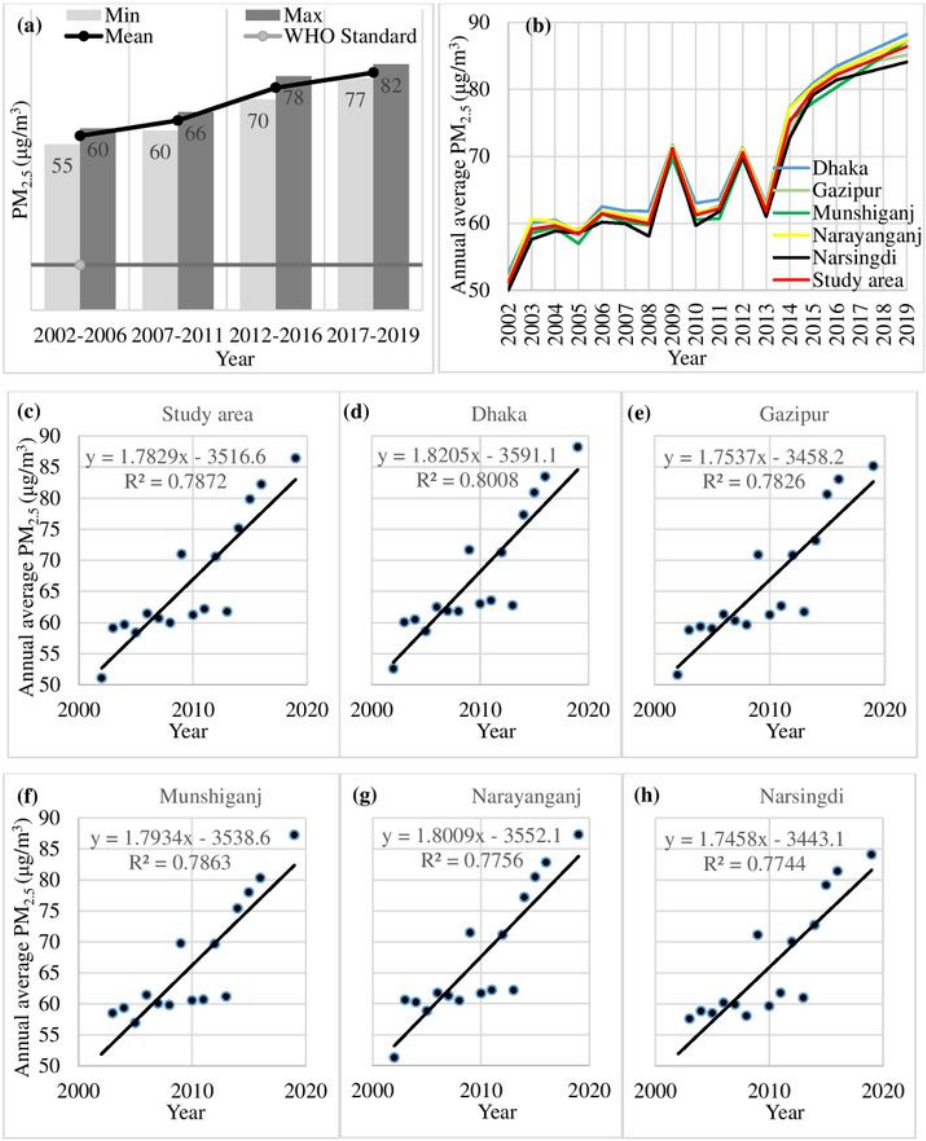

Figure 3

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).

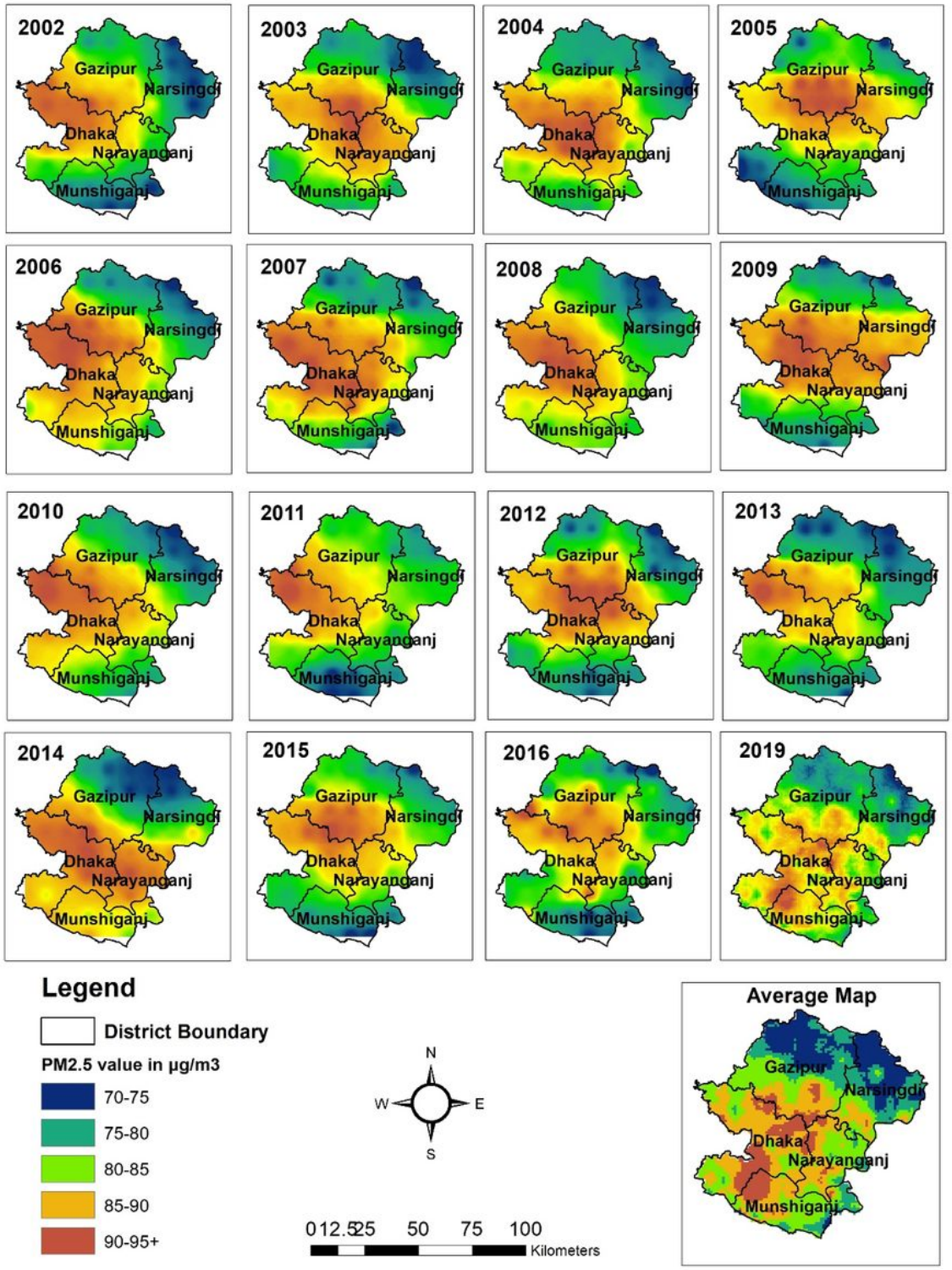

Figure 4

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

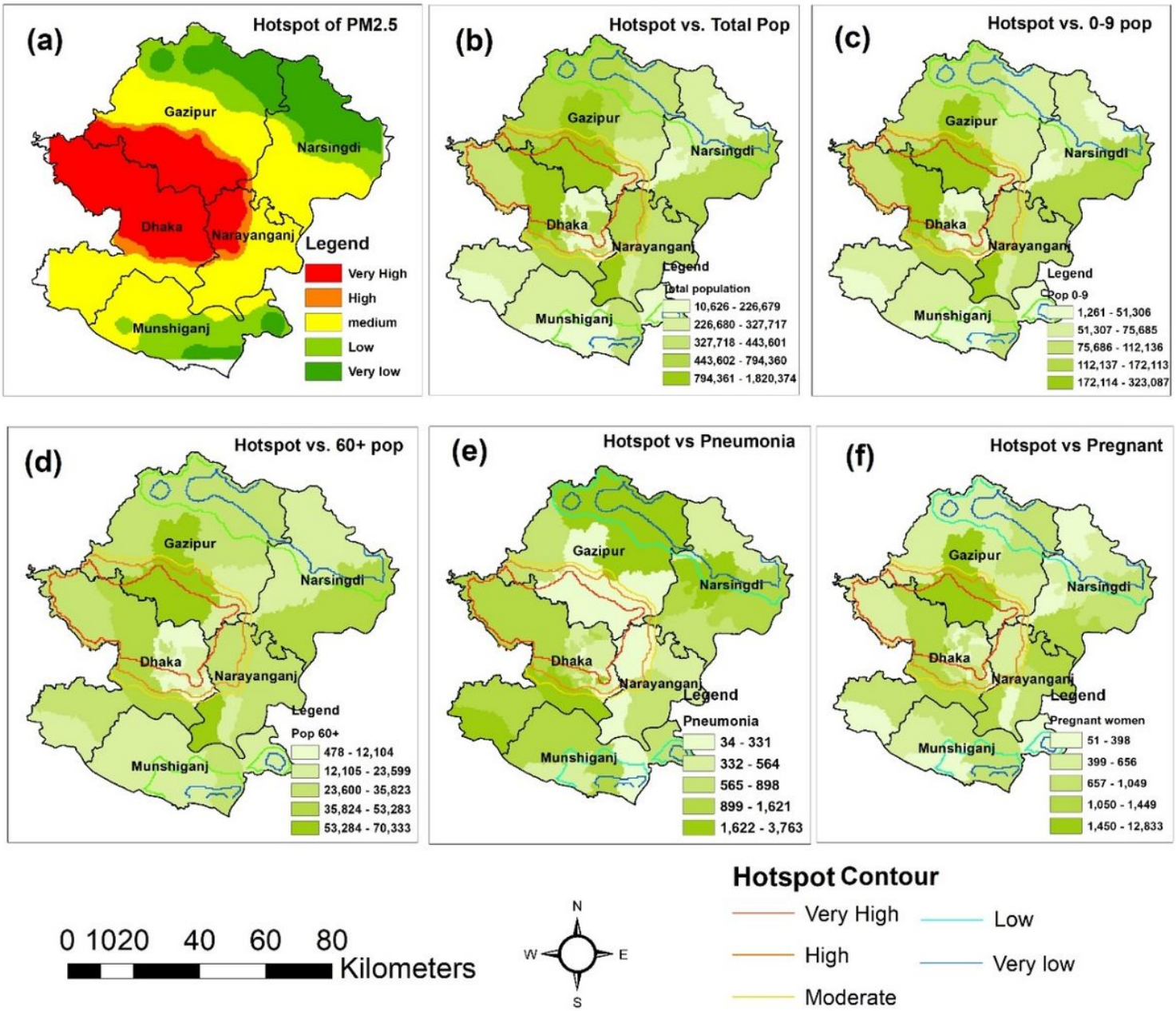

Figure 5

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.

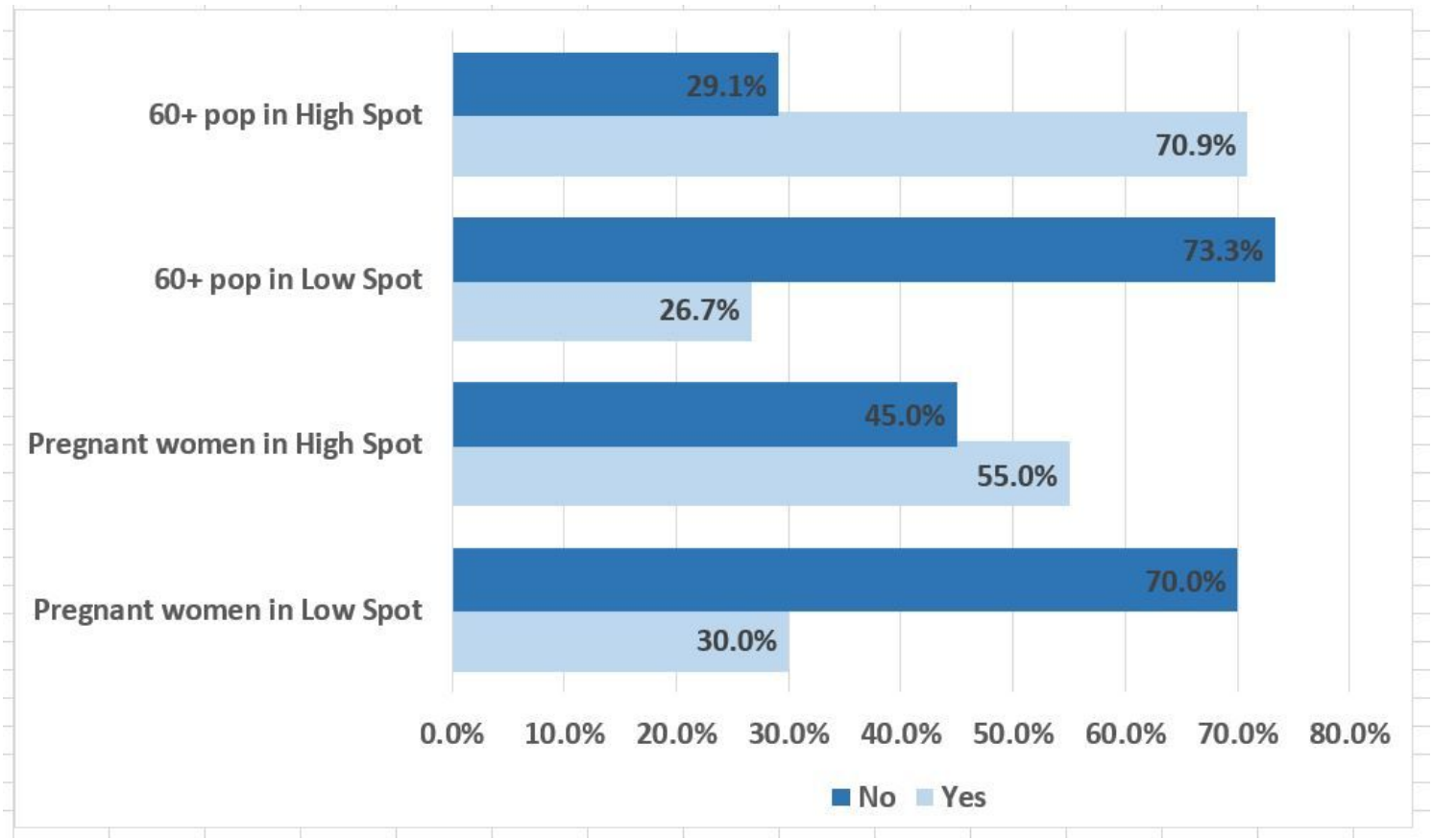

Figure 6

Respondent's knowledge about the sources of $PM_{2.5}$ in both high- and low-spot zones.