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Spatio-temporal evaluation of respiratory disease based on the information provided by patients admitted to a medical college hospital in Bangladesh using geographic information system

Chandan Roy [a,*], Raquib Ahmed [a], Manoj Kumer Ghosh [a], Md Matinur Rahman [b]

[a] *Department of Geography and Environmental Studies, University of Rajshahi, Rajshahi, 6205, Bangladesh*
[b] *Institute of Bangladesh Studies, University of Rajshahi, Rajshahi, 6205, Bangladesh*

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ABSTRACT

In Bangladesh respiratory illnesses are one of the leading risk factors for death and disability. Limited access to healthcare services, indoor and outdoor air pollution, large-scale use of smoking materials, allergens, and lack of awareness are among the known leading factors contributing to respiratory illness in Bangladesh. Key initiatives taken by the government to handle respiratory illnesses include, changing of respiratory health policy, building awareness, enhancing healthcare facility, and promoting prevention measures. Despite all these efforts, the number of individuals suffering from respiratory diseases has increased steadily during the recent years. This study aims at examining the distribution pattern of respiratory diseases over space and time using Geographic Information System, which is expected to contribute to the better understand of the factors contributing to respiratory illness development. To achieve the aims of the study two interviews were conducted among patients with respiratory sickness in the medicine and respiratory medicine units of Rajshahi Medical College Hospital between January and April of 2019 and 2020 following the guidelines provided by the Ethics Committee, Department of Geography and Environmental Studies, University of Rajshahi, Bangladesh (ethical approval reference number: 2018/08). Principal component extraction and spatial statistical analyses were performed to identify the key respiratory illnesses and their geographical distribution pattern respectively. The results indicate, during January–February the number of patients was a lot higher compared to March–April. The patients were hospitalized mainly due to four respiratory diseases (chronic obstructive pulmonary disease, asthma, pneumonia, and pulmonary hypertension). Geographical distribution pattern of respiratory disease cases also varied considerably between the years as well as months of the years. This information seems reasonable to elucidate the spatio-temporal distribution of respiratory disease and thus improve the existing prevention, control, and cure practices of respiratory illness of the study area. Approach used in this study to elicit spatio-temporal distribution of repertory disease can easily be implemented in other areas with similar geographical settings and patients' illness information from hospital.

* Corresponding author.
E-mail address: chandan.roy@ru.ac.bd (C. Roy).

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1. Introduction

Respiratory Diseases (RDs) have become increasingly more prevalent during recent decades and these diseases are among the leading causes of global deaths [1,2]. A study conducted by Xie and coworkers shows that the total number of chronic respiratory patients has increased by 39.5% during 1990–2017 [3]. Chronic Obstructive Pulmonary Disease (COPD), asthma, Lower Respiratory Infections (LRIs), Tuberculosis (TB), and lung cancer are the most prevalent RDs worldwide, which claimed 3.23 million, 461 thousand, 2.4 million, 1.4 million, and 1.76 million lives in 2019 accordingly [2,4]. Non-communicable illnesses, including chronic respiratory diseases (CRDs), accounted for nearly 70% of worldwide mortality in 2017, with low– and middle–income nations having the highest risk of dying from CRDs [5]. Bangladesh, like other low and middle-income nations, is undergoing a significant epidemiological change, with the burden of RDs on the rise [6,7].

The well-known risk factors for RDs include [2]: exposure to polluted ambient air, tobacco smoking, occupational exposure to unsafe air, allergens, and biomass burning for heating and cooking. Since level of exposure to these risk factors determines the prevalence of RD, a large number of studies have been conducted to better understand the nexus between these factors and the prevalence of RDs [1,8–10]. Geographic Information System (GIS) has also been effectively used for mapping spatio-temporal distribution of RD and environmental factors contributing to the distribution [11–13]. However, previous studies assessing RDs in Bangladesh mainly used statistical methods for the assessment [14–16] and employing GIS techniques for RD mapping was limited [17,18]. In this study we attempt to assess respiratory illness from two perspectives: (a) for which RDs the patients are hospitalized and illness issues they are experiencing, and (b) do the RD cases possess any spatio-temporal pattern in their occurrences. Therefore, information related to RD, its location of occurrence, and patients' way of living indicating their exposure to RD risk factors have been collected from the respiratory patients admitted to Rajshahi Medical College Hospital.

The majority of RD risk factors are intimately related to the quality of the ambient air, necessitating that the health authorities not only diagnose the disease but also understand the problems with ambient air quality that helps in developing the disease over space and time [19,20]. Using GIS tools for mapping spatial linkages of disease is not new [21–23]. The earliest known effort for visualizing the connection between disease and space was to map the plague in Italy in 1694 [24]. Though the researchers have experienced a number of challenges to map diseases' spatio-temporal patterns in the beginning [12,25], currently available GIS tools are efficient in visualizing, analyzing, and clustering of disease related data, which have spatial and temporal linkages [25–27]. Therefore, geospatial techniques have been used to analyze and visualize geographical distribution of diseases (spatial clusters) as well as diseases' association with the quality of the surrounding environment [22,28]. These analytical and visualization capabilities have made GIS a suitable tool to deal with spatio-temporal patterns of RDs in this study. Though a number of non-geospatial methods are being used effectively for assessing the prevalence of RDs [14,15,29], GIS can add novel dimensions to the existing methods through enhancing analytical and visualization capabilities.

1.1. Objective

This study aims at revealing the spatial and temporal variations of RD based on the information provided by respiratory patients admitted to a hospital. Conducted just prior to the COVID-19 pandemic, this work assesses respiratory illness through space and time using GIS. Spatio-temporal assessment is particularly essential for RDs, because prevalence of these diseases exhibits large geographical and seasonal differences mainly due to variations in the ambient air quality.

2. Materials and methods

Bangladesh is predominantly a low-lying plain of approximately 144,000 km^2 lying in the deltas of large rivers that originate in the Himalayas. Geographically, it extends between approximately 20° 34′ to 26° 38′ N latitude and from 88° 01′ to 92° 41′ E longitude. Bangladesh is characterized by a subtropical climate with four distinct seasons - pre-monsoon (March to May), monsoon (June to September), post-monsoon (October to November) and dry winter (December to February) [30]. With a west-east gradient of about 7 mm km^{-1}, rainfall varies from 1400 mm in the west to more than 4400 mm in the east. The additional elevation effect of the Meghalaya Plateau contributes to increased rainfall in the Northeast. The wet monsoon winds bring weak tropical depressions from the Bay of Bengal into Bangladesh during the monsoon season, which accounts for more than 75% of Bangladesh's annual rainfall. The coldest and hottest months are January and May, respectively, and the average temperature ranges from 7.2 to 12.8 °C in the winter and 23.9–31.1 °C in the summer [31]. In Bangladesh, outbreak of respiratory disease has a close association with cold and dry atmospheric conditions. During the end of December, as the atmospheric conditions remain cold and dry, a large number of respiratory patients get themselves admitted to hospitals for treatment. This number starts to decrease during the end of March with the gradual increase of atmospheric temperature and humidity. By the end of April, the number of respiratory patients in the hospitals becomes too few for revealing any meaningful pattern. Therefore, we have chosen the time between January and April of the years 2019 and 2020 for spatio-temporal assessment of respiratory disease in this study.

Patient records maintained by the hospitals in Bangladesh were not found suitable for this study mainly due to insufficient information contained in those records. To handle this limitation, two face-to-face interviews (first between January and April 2019 and the second between January and April 2020) were conducted among the patients with respiratory illness in the medicine and respiratory units of Rajshahi Medical College Hospital. Face-to-face interviews are regarded efficient for gathering health-related information from patients and have been effectively employed for data collection among respiratory patients [32–35]. Since this study required everyday information assortment from patients throughout the study period, and the authors of the study live in Rajshahi,

Rajshahi Medical College Hospital was chosen for conducting the interviews. In addition, Rajshahi Medical College Hospital is the largest hospital in the study area in terms of the number of beds available for patients, number of patients get themselves admitted for treatment, as well as number of disease-specific units (dedicated unit for the treatment of respiratory patients is only available at Rajshahi Medical College Hospital in the study area). All these issues have made Rajshahi Medical College Hospital the most suitable hospital for conducting the interviews. A three-person study team, comprising the corresponding and last authors, performed the two interviews among patients. In 2019 and 2020, the number of respondents was 660 and 688, respectively and they came to Rajshahi Medical College Hospital from thirteen districts (administrative unit) for treatment (Fig. 1). Locations of the Rajshahi Medical College Hospital and other major healthcare facilities in the study area are illustrated in Fig. 2.

To represent the impact of ambient air quality on respiratory health in the study area, $PM_{2.5}$ (which is considered to be one of the most critical measures of ambient air quality [36,37]) concentration images were also used. These images were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). As the humidity remains low and no rainfall occurs in dry winter and pre-monsoon periods in Bangladesh, fine dust particles in the air can move longer distances thus able to deteriorate the ambient air quality more effectively compared to rest of the year (Fig. 3(a–d) and 4 (a-d)).

To understand the influence of temperature and humidity (relative humidity) on the spatio-temporal distribution pattern of respiratory patients, interviewed patients' household locations have also been plotted on temperature (Fig. 5(a–d) and 6 (a-d)) as well as on relative humidity (Fig. 7(a–d) and 8 (a-d)) maps (prepared using temperature and relative humidity data recorded during January–April of the years 2019 and 2020) of the study area.

The hospital authorities allowed the interviews on patients' agreement. Approval for the interview was also obtained from the

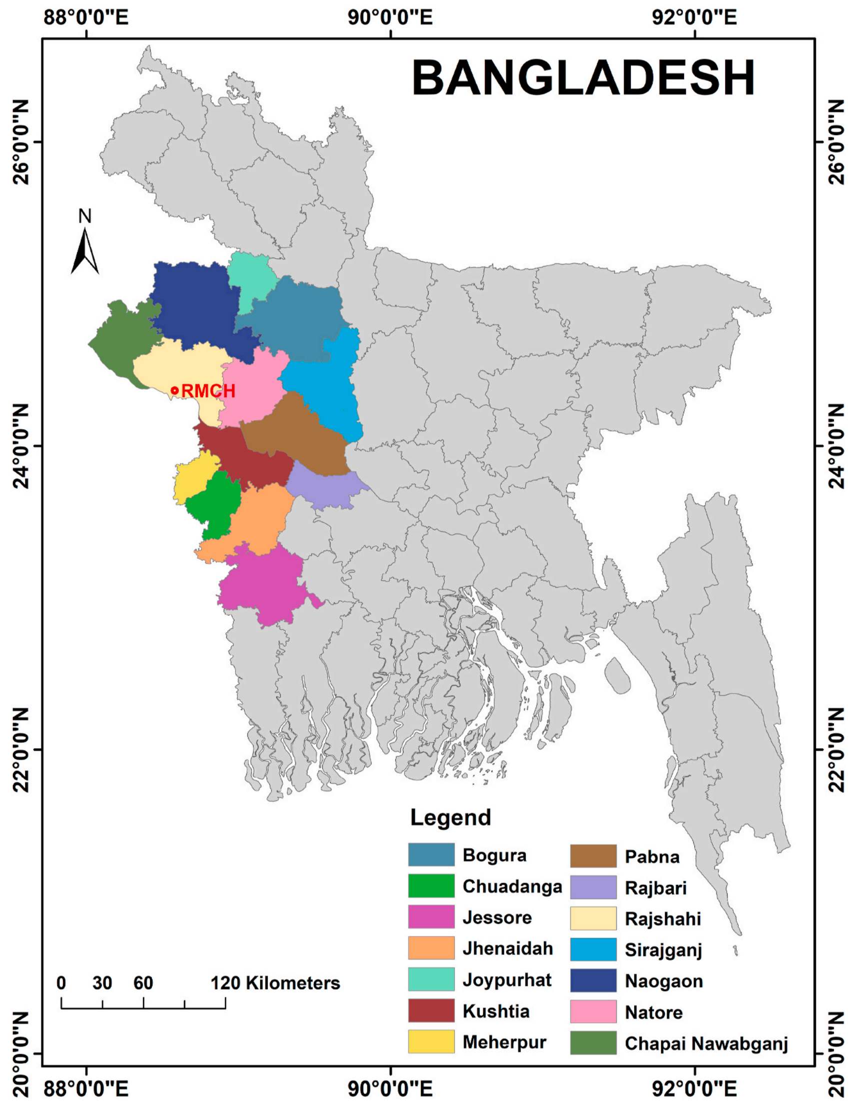

Fig. 1. Study area map showing thirteen districts from which patients came to Rajshahi Medical College Hospital.

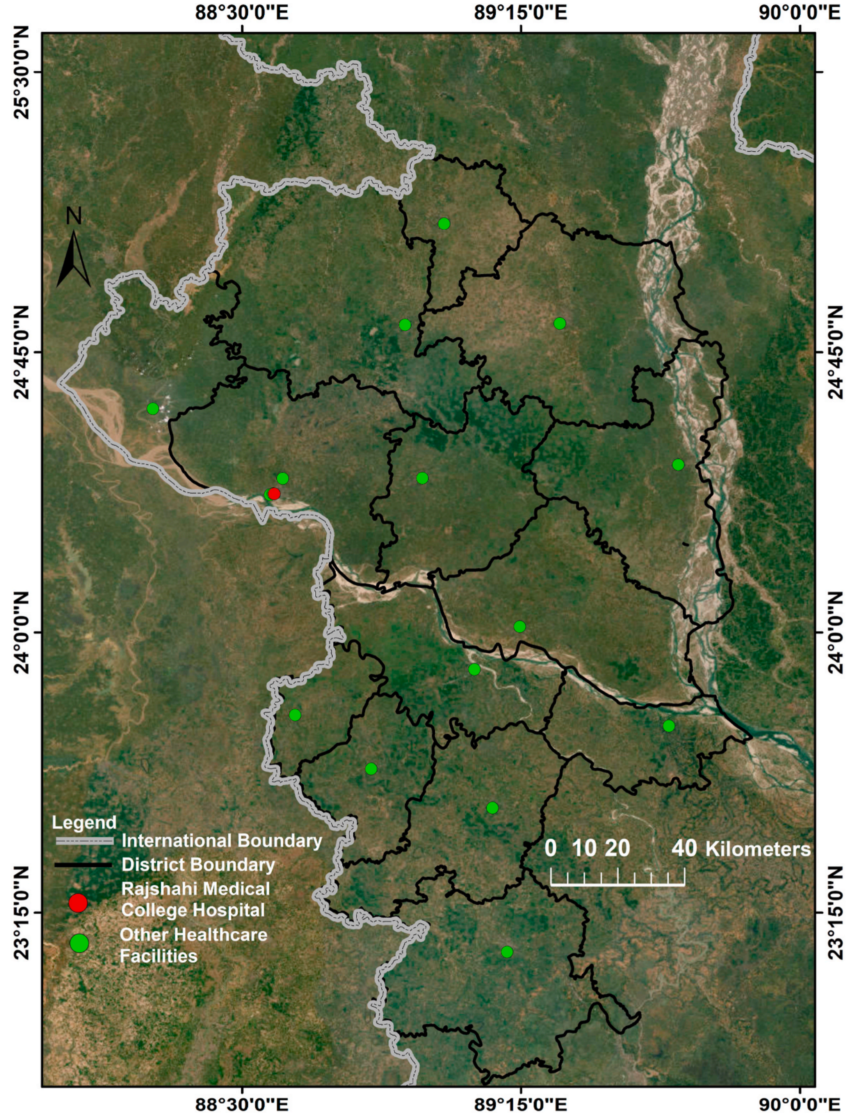

Fig. 2. Locations of the Rajshahi Medical College Hospital and other major healthcare facilities in the study area.

Ethics Committee, Department of Geography and Environmental Studies, University of Rajshahi before conducting the surveys (ethical approval reference number: 2018/08). Guidelines provided by the committee were strictly followed and informed consent was obtained from each of the patients before interviewing them. Information was gathered from patients' attendants in cases of patients were too sick to speak. The respondents were also assured that patients' personal information would not be made public. It would be utilized to illustrate rather a general pattern of respiratory illness. A questionnaire consisted of only structured questions were used for the interviews. When the multiple-choice alternatives supplied in the questionnaire did not match the patients' views, the patients were requested to express themselves freely. Information gathered from the patients during the interviews include:

a) Personal detail and address including household location (noted using Google maps, android version).
b) RD for which the patients were hospitalized, records of visiting doctors and hospitalization.
c) Respiratory issues of the patients, the illness's relationship to a specific event, and the seasonal variation of illness.
d) Patients' dwelling and working environment, transportation used for movement, fuel used for cooking and their smoking habit.

2.1. Data analysis

Household locations (geographical distribution) and relevant information of patients from the interviews were analyzed separately for both 2019 and 2020. Factor analysis using Principal Component Extraction (PCE) was utilized to know: (a) key RDs for which

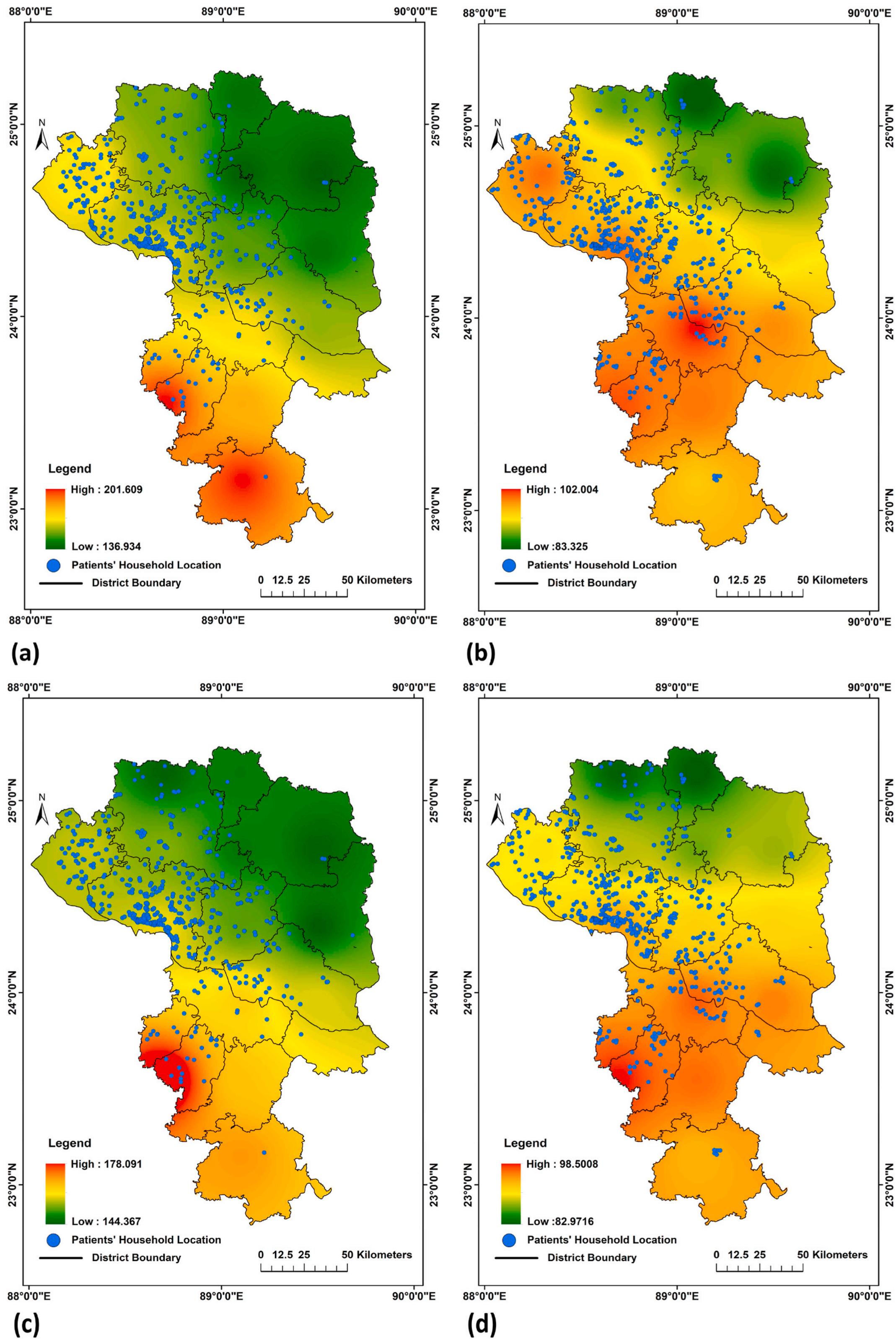

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Fig. 3. Monthly average concentration of $PM_{2.5}$ in µg/m3 in the ambient air and locations of patients' households during January 2019 (a), January 2020 (b), February 2019 (c), and February 2020 (d). Patients' households are mostly located in places, where PM2.5 concentration levels in the ambient air are high. Averaged PM2.5 values during all these months are much higher compared to the national ambient air quality standards for Bangladesh, which is 65 µg/m3 [37].

patients were hospitalized and (b) illness's linkage to a specific situation/thing. PCE is a standard technique for capturing the co-variation (or variance) among high-dimensional data. In comparison to the original data set, PCE enables the data to be described using fewer aggregated dimensions [38,39]. In this study, variables in the original data set relate to two separate questions: why the patients were hospitalized and whether there exists any links between disease and a specific circumstance or thing. Each data point in this high-dimensional space would therefore represent a patient's reaction to these questions. The reason for PCE analysis here was to uncover if patients' responses co-vary with these questions. Queries for which patients' answers co-varied, would reveal the underlying reasons controlling patients' response pattern. Descriptive statistical techniques, such as frequency distribution and multiple-response analysis [40,41] were used to solve patients' response patterns against previous records of visiting doctors and hospitalization, health issues they experienced, as well as situations/things that triggered health issues. Patients' dwelling and working environment, mode of transport used for movement, fuel used for cooking and their smoking habit were also considered because these factors might have influence on the prevalence of RD. All the analyses, namely factor analysis, frequency distribution, and multiple-response analysis were performed using IBM SPSS statistics version 21.

The spatial distribution pattern of respiratory illness was explored using Standard Deviational Ellipse (SDE), Nearest Neighbor Distance Statistics (NNDS), and Hot Spot Analysis (HSA). SDE is used to determine whether a variable has a linear or circular pattern in its geographical distribution. Moreover, SDE can measure elongation (vertical and horizontal), direction, and mean center of the variable's distribution [42–45]. Patterns of the patients' household distribution (linear or circular), distribution direction of the households, and mean center of disease (households) distribution are essential information for assessing spatial distribution RDs. NNDS compares the measured average distance between variables' locations to the expected average distance of a hypothetical random distribution (index ranges between 0 and 2.149), where 0 indicates perfect clustering, 1 indicates perfect randomness, 2 indicates grid of even spacing, and 2.149 indicates perfect triangular lattice [46]. This index is capable of illustrating whether the RD cases are distributed in a clustered or scattered manner in an area.

HSA (Getis-Ord Gi*) represents a phenomenon's spatial distribution pattern by showing its clustering and dissemination within an area. These clusters represent high or low values of the phenomenon, when similar high (hot spot) or low (cold spot) values of it are found in a cluster respectively [47]. This capability has made HSA an effective method of disease mapping [48–51]. Integration of point events into a base-map of polygon features is required for hotspot analysis. Based on the number of occurrences of an event (geographical locations of patients' households), each polygon in the base-map may contain a varied number of points. Area and shape of the processing unit (polygon) have large influence on HSA results [52]. Hence, instead of using the smallest administrative units (*unions*) for processing (which are dissimilar in area and shape), a grid consisting of 2200 m^2 polygons was used for HAS in this study. These polygons are smaller compared to the *unions* and good to provide more detailed geographical distribution pattern of RD. Cold and warm periods might have disparate impacts on RD, therefore HSA was performed separately for the years as well as for the cold (January–February) and warm (March–April) months. SDE, NNDS and HSA were performed using ArcGIS version 10.4.

Though patients from thirteen districts took admission to Rajshahi Medical College Hospital during the study period, majority of them were from five districts (Fig. 9(a–d)). Therefore, NNDS, SDE, and HSA were performed for those 5 districts only. Number of patients from the remaining eight districts was not sufficient to reveal a meaningful geographical pattern of respiratory illness.

3. Results

Of the 660 patients interviewed in 2019, around 70% were male, and 30% were female whereas in 2020 proportion of male and female was 66 and 34, accordingly. Age of the patients was between 15 and 100 years in both 2019 and 2020. Number of patients admitted to the hospital and thus partook in the interviews was higher (as observed) for the months January–February (498 in 2019 and 539 in 2020) compared to the months March–April (162 in 2019 and 149 in 2020).

3.1. Pattern of respiratory disease

Patients took admission to Rajshahi Medical College Hospital with fifteen different respiratory illnesses during the study period. However, key RDs for which patients were hospitalized varied between colder (January–February) and warmer periods (March–April) of the studied years. Results of factor analysis using PCE reveals, during January–February, of 2019-20 patients were admitted to Rajshahi Medical College Hospital mainly due to four RDs and in March–April 2019-20 patients were hospitalized because of three key diseases (Table 1).

About 87% of the patients of 2019 had experienced similar respiratory illness before, 68% visited doctors during the preceding year, and 44% were previously hospitalized due to similar illnesses. While in 2020, approximately 90% of the respondents faced similar respiratory problems earlier, 62% visited doctors, and 39% were admitted to hospital previously. Almost all faced multiple health issues during the interviews.

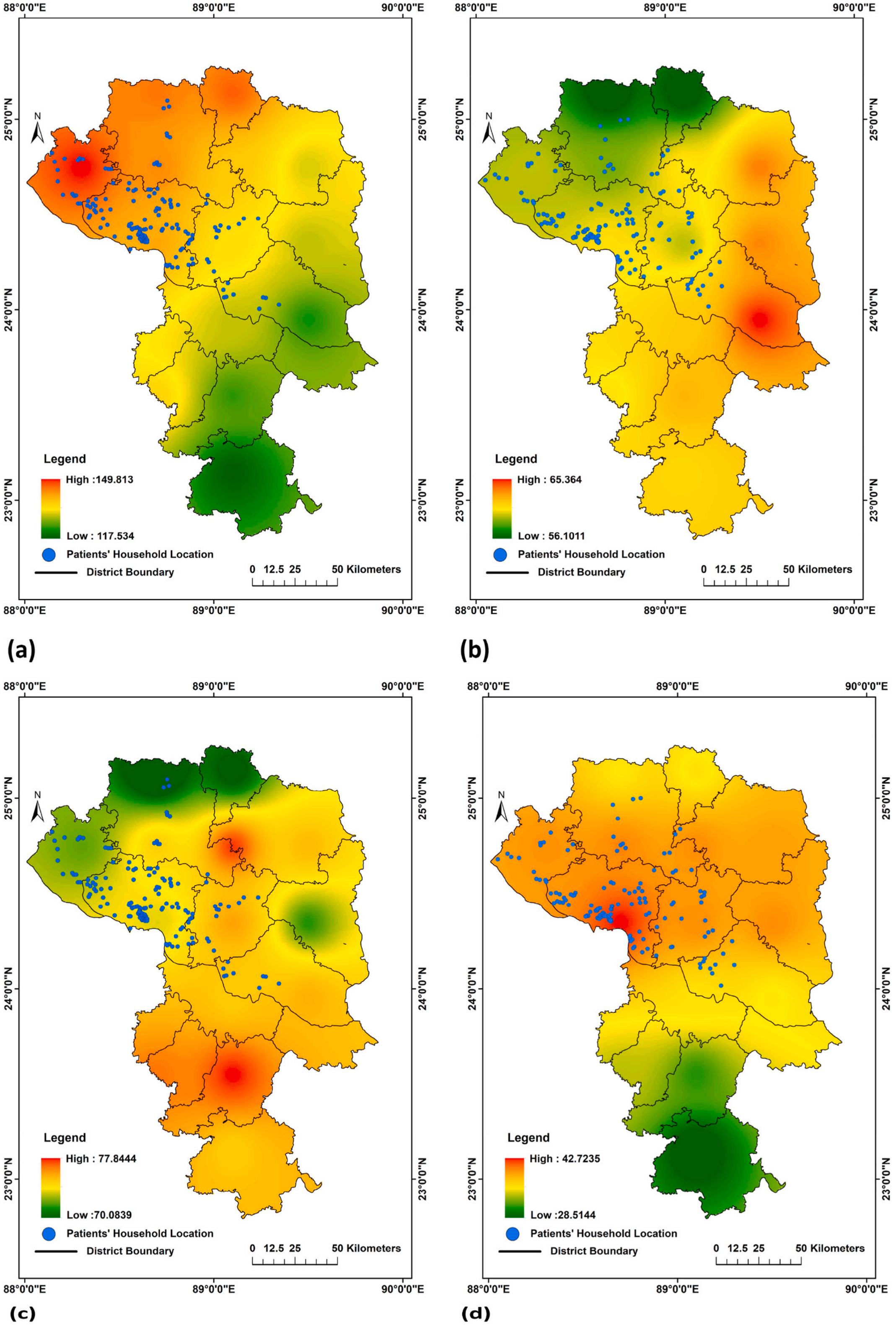

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Fig. 4. Monthly average concentration of $PM_{2.5}$ in μg/m3 in the ambient air and locations of patients' households during March 2019 (a), March 2020 (b), April 2019 (c), and April 2020 (d). Patients' households are mostly located in places, where PM2.5 concentration levels in the ambient air are high. Averaged PM2.5 values during March–April 2019 are higher compared to the national ambient air quality standards for Bangladesh, which is 65 μg/m3 [37]. In March 2020, PM2.5 values are around the danger level and in April 2020, PM2.5 values are below the danger level.

3.2. Health issues of patients

Of twelve health issues, four were dominant in both 2019 and 2020. In 2019 about 98% of patients faced shortness of breath, 82% had a cough, 47% experienced headache, and 18% felt chest pain. During 2020, a fraction of patients who faced shortness of breath, cough, headache, and chest pain were 98%, 73%, 28%, 25% accordingly. Patients' health problems were also related to a specific situation or thing. PCE was used to determine the most essential connections between the health concerns and the specific circumstance (Table 2).

3.3. Living pattern

Housing: Patients interviewed during the interviews mainly live in brick-built (75%) and mud-built (20%) houses. Almost all the houses in the urban and suburban areas are brick-built, whereas mud-built houses are seen in rural areas. Most of the patients (72%) do not renovate their houses on a regular basis.

Occupation: Around 85% interviewed patients in 2019 and 90% patients in 2020 were dependent on smoke and/or dust-producing industries for their livelihood, which includes carpet making, jute mill, construction, garments, rice mill, sugar mill, transport, road-side tea stall, brick kilns, and agriculture.

Transportation: Patients interviewed in 2019 generally used three-wheelers (95%), buses (35%), motorcycles/bicycles (21%), on foot (92%), and personal vehicles (4.2%) for daily movement. In 2020, the mode of transport was almost similar, which includes three-wheelers (92%), buses (30%), motorcycles/bicycles (26%), on foot (93%), and personal vehicles (6.2%). Principal modes of transport used by the patients expose them to polluted ambient air.

Fuel for cooking: One of the most important variables of ambient air quality is the fuel that patients use for cooking. Patients primarily use various forms of biomasses for cooking at home (Table 3).

Smoking habit: Smoking is a prevalent habit among male patients interviewed at Rajshahi Medical College Hospital. Though 56% of the total patients were in this habit during the interviews, 65% of them used to smoke formerly. Those who quitted smoking, mostly (42%) did it during the last 6 months. Cigarettes (98.5%) and *beedi* (thin cigarettes without any filter made using low-grade tobacco) (98%) were the most common smoking material among the patients.

3.4. Geographical distribution pattern of respiratory disease

Results of three different analyses used to reveal the spatial distribution pattern of RD are provided in the three subsections below.

3.4.1. Results of nearest neighbor analysis

Nearest neighbor statistics results range between 0.626 and 0.911 for 2019 and between 0.673 and 0.860 for 2020 (Table 4). These nearest neighbor index values indicate RD cases have formed a moderate clustering pattern in their geographical distribution [46].

3.4.2. Results of hot spot analysis

The results of HSA demonstrate the formation of hot (cluster of high z values) and cold (cluster of low or negative z values) spots in the study area during both January–February (Fig. 10(a and b)) and March–April (Fig. 11(a and b)) of the studied years.

A large variation in hot and cold spots is apparent between the years and months of the same year. High z value clusters are usually observed in the urban and suburban areas, whereas the rural areas are dominated by clusters of negative or low z values with few groupings of high z values.

3.4.3. Results of standard deviational ellipse analysis

Ellipses generated through SDE analysis are dissimilar in extent, elongation, and rotation (Fig. 12(a and b)). Displacement direction of ellipses' mean centers between the years 2019 and 2020 indicates potential spreading direction of RD in all the five districts (Fig. 9 (a–d)). Large standard distances in both X and Y directions reflect a nonlinear spatial distribution pattern of RD. The rotation of the ellipse highlights the distribution direction of RD. Change in distribution direction between the studied years is higher in *Chapai Nawabganj* and *Natore* compared to *Pabna*, *Naogaon*, and *Rajshahi*, which indicates large variation in geographical distribution pattern has occurred in these two districts. When the ellipses are compared between the years, variations in vertical and horizontal elongation are also noticeable. This variation in elongation specifies the areas where new cases of RD have been reported, and the direction of elongation indicates the areas where patients with respiratory illness may be found in the future.

4. Discussion

Respiratory illness among the patients admitted to Rajshahi Medical College Hospital was evaluated from two perspectives: RDs the

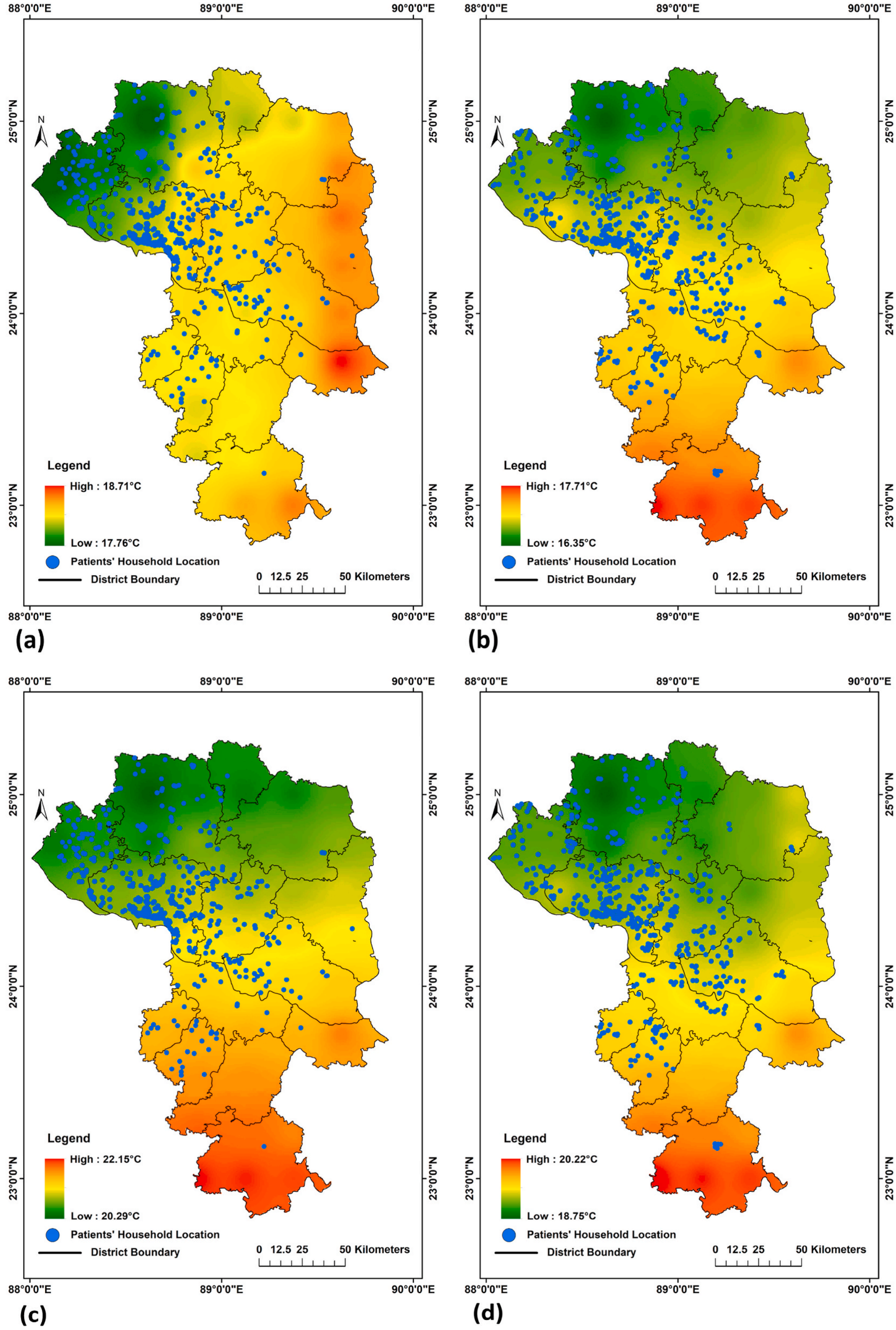

Fig. 5. Monthly averaged temperature in °C and locations of patients' households during January 2019 (a), January 2020 (b), February 2019 (c), and February 2020 (d). Lower temperature appears to be associated with higher number of respiratory patients.

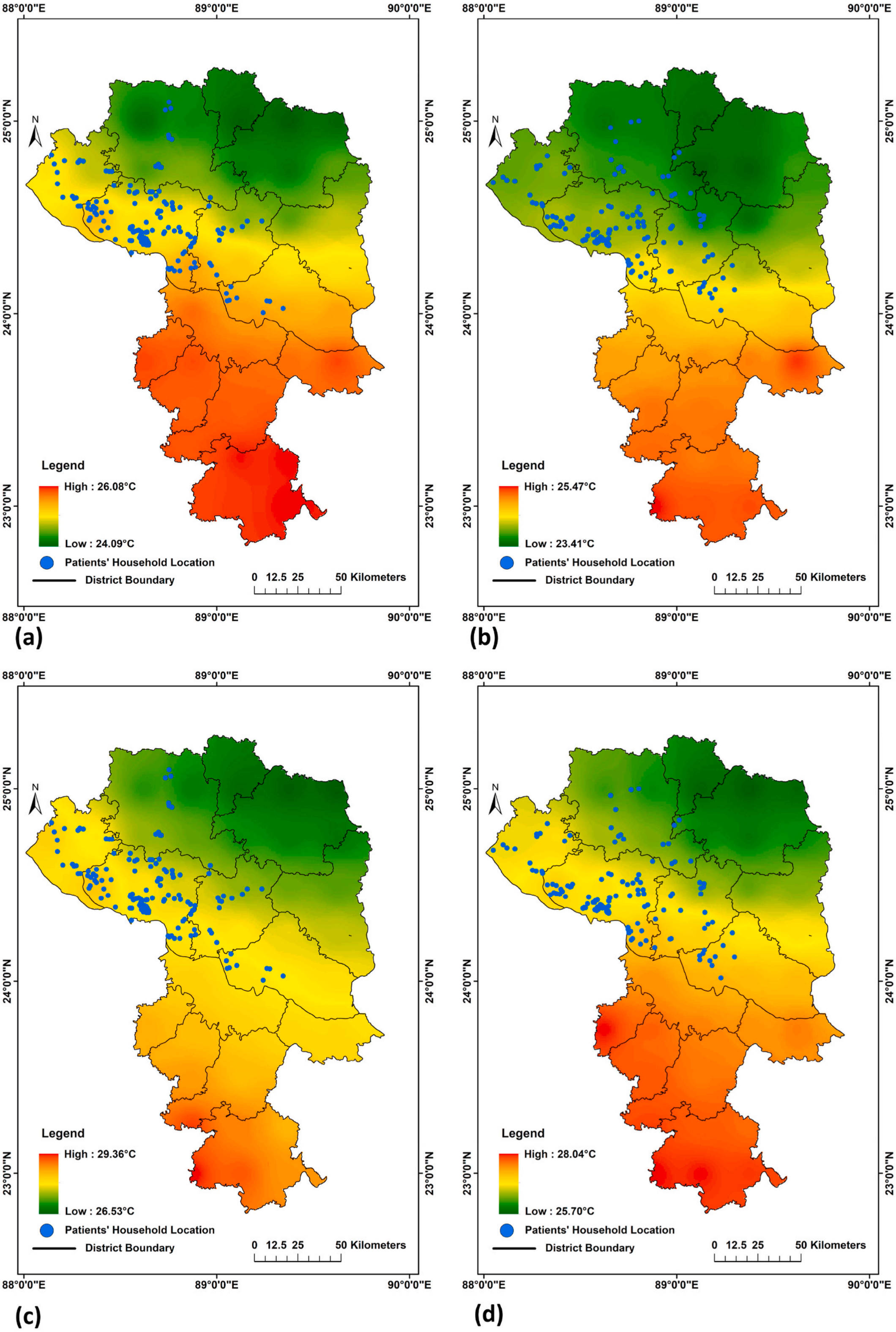

Fig. 6. Monthly averaged temperature in °C and locations of patients' households during March 2019 (a), March 2020 (b), April 2019 (c), and April 2020 (d). Lower temperature appears to be associated with higher number of respiratory patients.

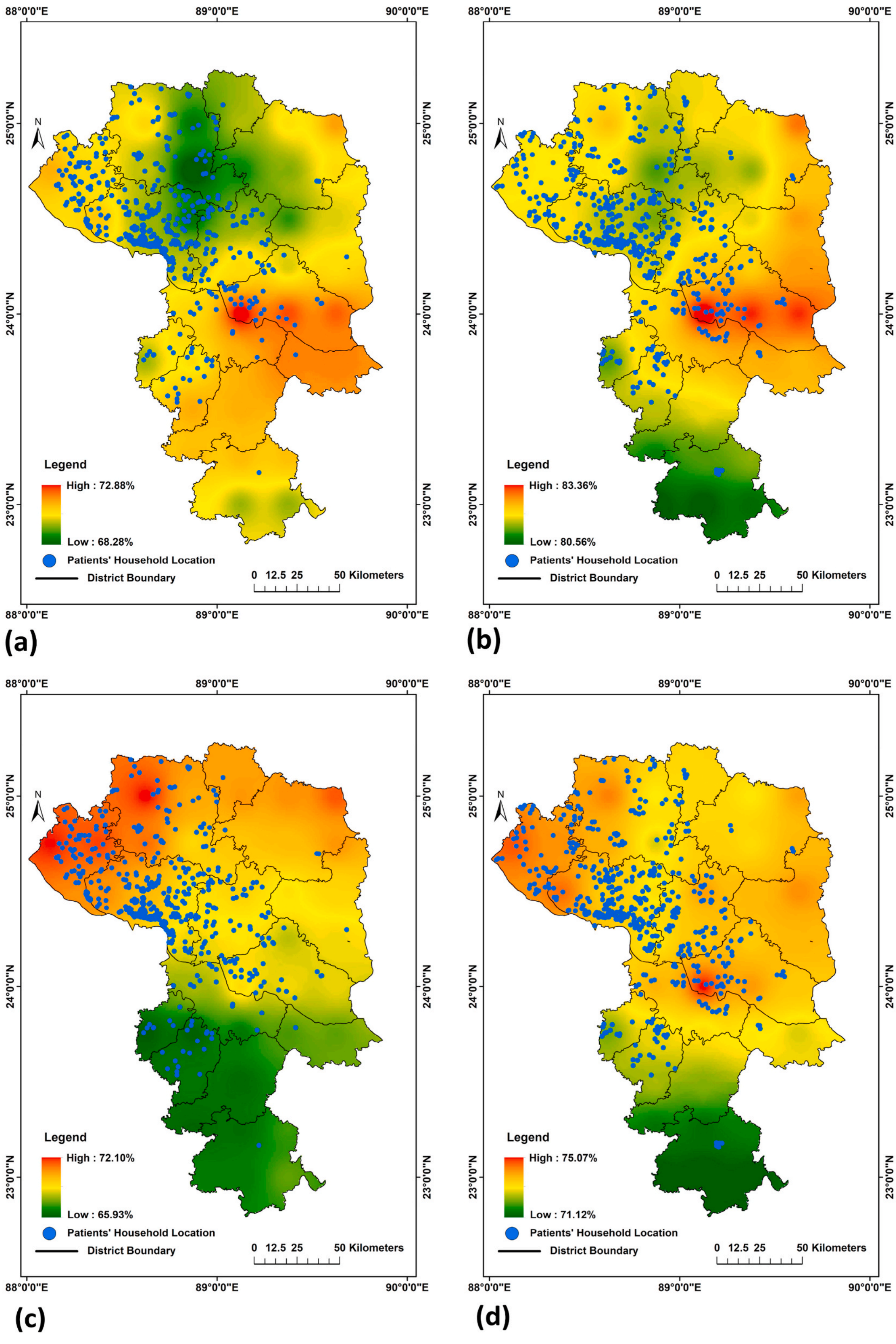

Fig. 7. Monthly averaged relative humidity in % and locations of patients' households during January 2019 (a), January 2020 (b), February 2019 (c), and February 2020 (d). Variations in relative humidity seem inadequately related to the spatio-temporal distribution of patients' households in the study area.

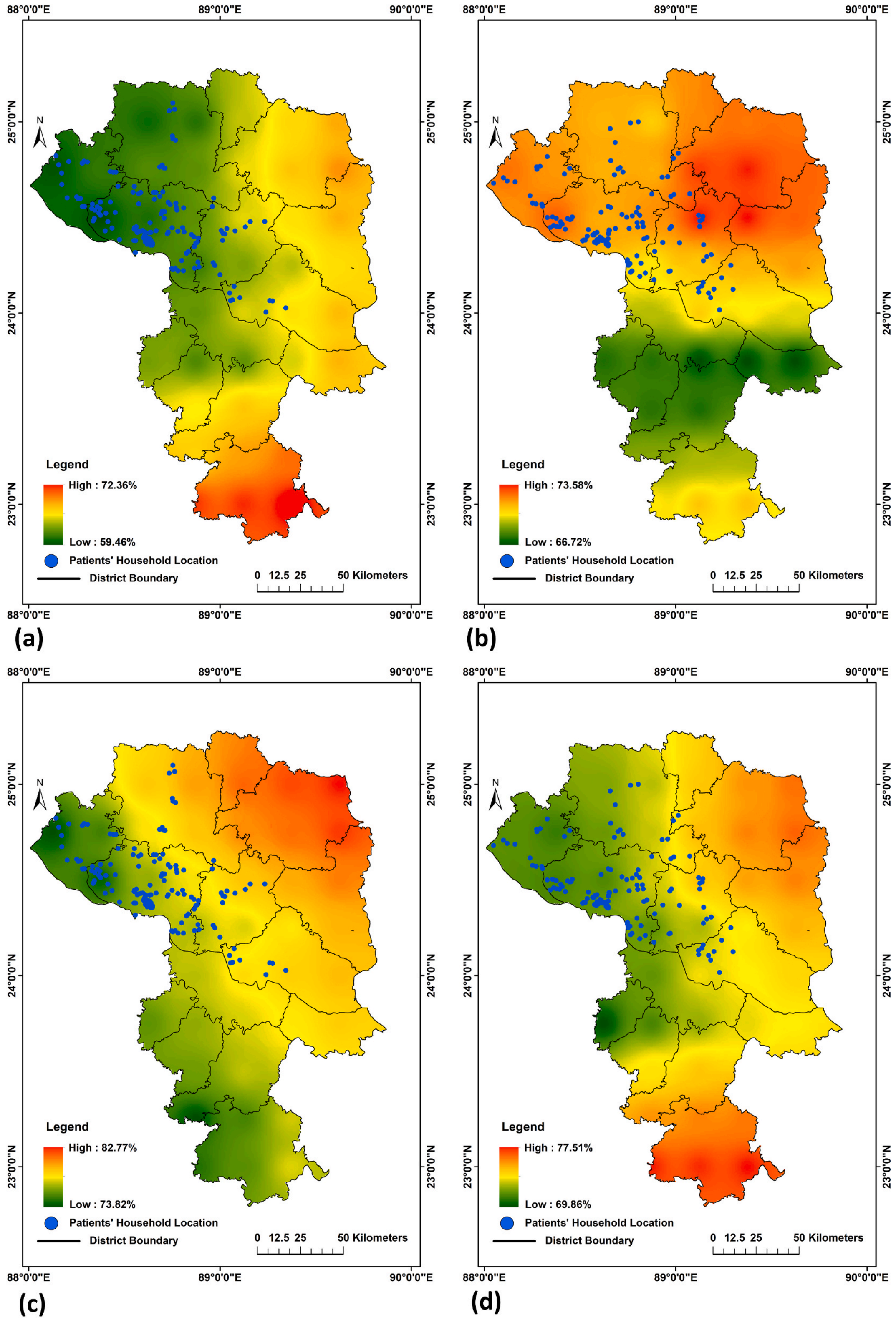

Fig. 8. Monthly averaged relative humidity in % and locations of patients' households during March 2019 (a), March 2020 (b), April 2019 (c), and April 2020 (d). Variations in relative humidity seem inadequately related to the spatio-temporal distribution of patients' households in the study area.

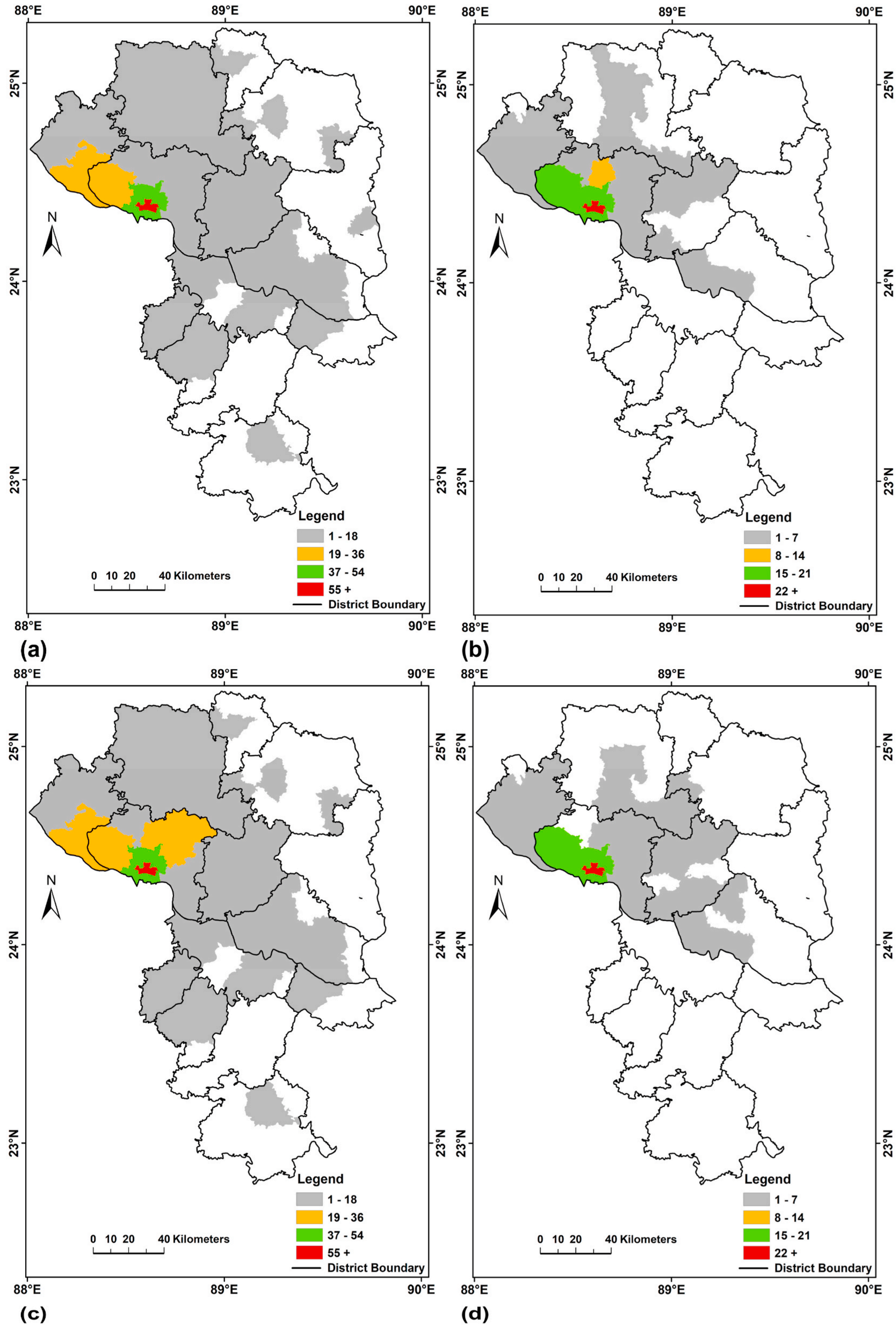

Fig. 9. Number of respiratory patients by upazila (small administrative unit) during: January–February 2019 (a), March–April 2019 (b), January–February 2020 (c), and March–April 2020 (d). Areas with white background indicate, no patients came to Rajshahi Medical College Hospital for treatment from those areas.

Table 1
Components representing main respiratory diseases for which patients were hospitalized.

Component representing respiratory disease	Eigenvalues (>1 were considered)	Variance (in %)	Cumulative variance (in %)	Disease's highest prevalence observed in (calculated using frequency distribution)[a]	Component representing respiratory disease	Eigenvalues (>1 were considered)	Variance (in %)	Cumulative variance (in %)	Disease's highest prevalence observed in (calculated using frequency distribution)[a]
Components extracted (January-February 2019)					**Components extracted (January-February 2020)**				
1: Asthma	3.062	30.625	30.625	Rajshahi Nawabganj	1: COPD	2.736	24.875	24.875	Rajshahi Naogaon
2: COPD	1.243	12.426	43.051	Natore Naogaon	2: Asthma	1.533	13.932	38.807	Nawabganj Natore
3: LRIs (pneumonia)	1.120	11.197	54.248	Pabna Kushtia	3: LRIs (pneumonia)	1.375	12.501	51.308	Pabna Chuadanga Bogura
4: Pulmonary hypertension	1.048	10.479	64.727	Meherpur Chuadanga	4: Pulmonary hypertension	1.149	10.446	61.754	Kushtia Meherpur
Components extracted (March-April 2019)					**Components extracted (March-April 2020)**				
1: COPD	3.989	36.269	36.269	Rajshahi Naogaon	1: COPD	3.573	32.483	32.483	Rajshahi Natore
2: Asthma	1.524	13.855	50.124	Nawabganj Natore	2: Asthma	1.736	15.781	48.264	Nawabganj Naogaon
3: Pulmonary hypertension	1.233	11.209	61.333	Pabna	3: Pulmonary hypertension	1.698	15.438	63.702	Pabna

[a] Number of patients from the remaining districts was too few, therefore names of those districts are not mentioned in the table.

Table 2
Components representing situations or things triggered health issues among patients.

Component representing situation or thing	Eigenvalues (>1 were considered)	Variance (in %)	Cumulative variance (in %)	Component representing situation or thing	Eigenvalues (>1 were considered)	Variance (in %)	Cumulative variance (in %)
Components extracted (January-February 2019)				**Components extracted (January-February 2020)**			
1: Dust	7.435	33.8	33.8	1: Dust	4.383	36.52	36.52
2: Smoke	4.182	19.009	52.809	2: Smoke	2.163	18.025	54.545
3: Food	1.068	4.855	57.664	3: Cold	1.183	9.858	64.403
4: Cold	1.028	4.672	62.336	4: Food	1.013	8.444	72.847
5: Walking	1.009	4.586	66.923				
Components extracted (March-April 2019)				**Components extracted (March-April 2020)**			
1: Smoke	3.53	35.294	35.294	1: Smoke	3.354	30.487	30.487
2: Dust	2.301	23.005	58.299	2: Dust	2.534	23.034	53.521
3: Food	1.099	10.988	69.287	3: Food	1.181	10.740	64.261

Table 3
Fuel used by the patients for cooking.

Fuel for cooking	Used by patients interviewed in 2019 (in %)	Used by patients interviewed in 2020 (in %)
Gas	23.0	24.0
Electricity	19.9	25.3
Firewood	93.7	94.0
Cow dung	61.2	52.9
Dried leaves	70.6	59.6
Other biomass	8.3	2.2

patients were hospitalized for and geographical distribution pattern of RD. Three of the four core RDs for which the patients were hospitalized (COPD, Asthma, and LRIs) are among the five most common causes of illness and death worldwide [2]. The respondents' previous respiratory illness and hospitalization records as well as RDs they were hospitalized for during the interviews point to a degraded state of respiratory health in the north-western part of Bangladesh. Moreover, contexts that triggered health issues among patients (see Table 2) indicate a close association between respiratory illness and patients' way of living. Indoor dust and other pollutants due to poorly maintained houses [53], working in smoke and/or dust producing industries [54], exposure to polluted ambient air because of mode of transport [55], using biomass for cooking [15], and smoking habit among the patients [56] all are considered as eminent risk factors of RD. Correlation between four major RDs for which the patients were admitted to the hospital and the RD risk factors is provided in Table 5.

Prevalence of RDs, assessing the risk factors of RDs, as well as measuring the quality of the ambient air have been the focus of a large number of studies concentrated during the last two decades in Bangladesh [14–16,57–60]. The current study's findings regarding patients' living pattern indicates their level of exposure to different risk factors of respiratory illness. These identified risk factors are also consistent with the RD risk factors that have already been recognized by past studies [14–16,57,61]. Results of this study show a close association between locations of the patients' households and higher concentrations of $PM_{2.5}$ in the ambient air. RD hot spots with higher z values have also been formed in areas, where concentration of $PM_{2.5}$ is high (see Fig. 3(a–d), 4 (a-d), 10 (a-b), and 11 (a-b)). These results further elicit a close association between ambient air quality and respiratory illness, which is also in line with the findings of the earlier studies related to ambient air quality and RD [57,59,60].

The number of patients admitted to Rajshahi Medical College Hospital was around three times higher in January–February compared to March–April of both studied years. It can be attributed to the dominance of multiple activities triggering some of the risk factors, such as smoke from biomass burning in rural areas, smoke and dust from brick kilns, and dust from construction sites in January–February.

Spatial and temporal occurrences of RD cases in the five districts were disparate. Distribution pattern of RD cases, that is the values from NNDS specify RD is not a localized phenomenon but dispersed throughout the area in a semi-clustered way. Unlike NNDS, HAS assigns z values to each polygon depending on the number of RD cases within it. Thus, the larger the z value, the more intense the clustering of RD cases. These clusters of hot and cold spots provide a simple representation of the spatial distribution pattern of RD in five districts. Variations in the formation of hot and cold spots seem to be associated with the risk factors the residents are exposed to. In urban and suburban areas all the previously mentioned risk factors are present. On the contrary, in rural areas, indoor dust, biomass burning, and smoking appear to be the main risk factors.

SDE provides valuable information about respiratory disease's existing and future distribution patterns. As new cases are not always reported in the existing clusters, mean center, extent, elongation, and rotation of the ellipses have changed between the years. The direction of change in these properties of ellipse between the years highlights the future risk zone of respiratory illness.

Results obtained through PCE and spatial statistical analyses can also be utilized to critically assess various issues associated with respiratory disease from biomedical viewpoints. For example, efficient mapping and monitoring of respiratory disease, spatial and

Table 4
Details of nearest neighbor distance statistics.

NNDS for District	Nearest neighbor observed mean distance (in meter)	Expected mean distance (in meter)	Nearest Neighbor Ratio	Nearest neighbor observed mean distance (in meter)	Expected mean distance (in meter)	Nearest Neighbor Ratio
	Performed for the year 2019			Performed for the year 2020		
Pabna	2343.30	3258.03	0.719	2577.18	2996.95	0.859
Chapai Nawabganj	1821.21	2088.15	0.872	2168.88	2653.36	0.817
Natore	2405.22	2641.33	0.911	2024.80	2353.39	0.860
Naogaon	2350.32	3752.49	0.626	2542.76	3778.02	0.673
Rajshahi	1095.74	1472.38	0.744	1062.53	1526.13	0.696

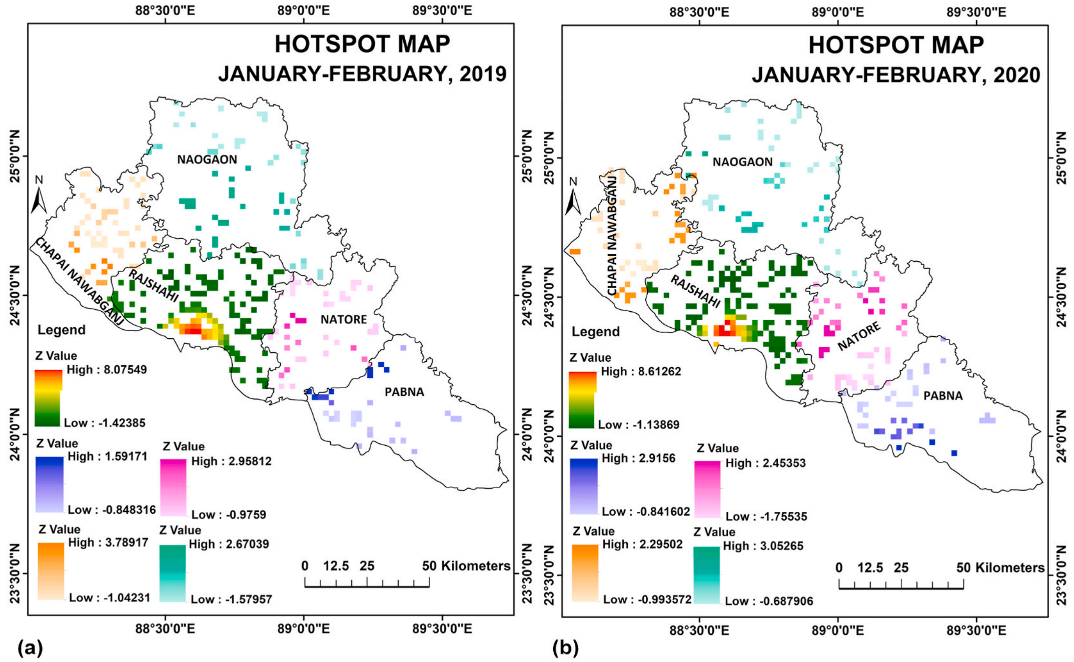

Fig. 10. Maps showing hot and cold spots generated using patients' household locations. Household locations of the patients interviewed during January–February 2019 was used to generate hotspot map of January–February 2019 (a) and household locations of the patients interviewed in January–February 2020 was used to generate hotspot map of January–February 2020 (b). The average nearest neighbor distance of patients' household locations in Rahsahi district (1095 m in 2019 and 1064 m in 2020) was multiplied by 2 to get the polygon cell size (2200 m) [52]. The same cell size was used for all the districts to avoid biased occurrences of hot and cold spots. As the number of patients was less than 30 from each of the remaining eight districts, hotspot analysis was statistically insignificant for those districts.

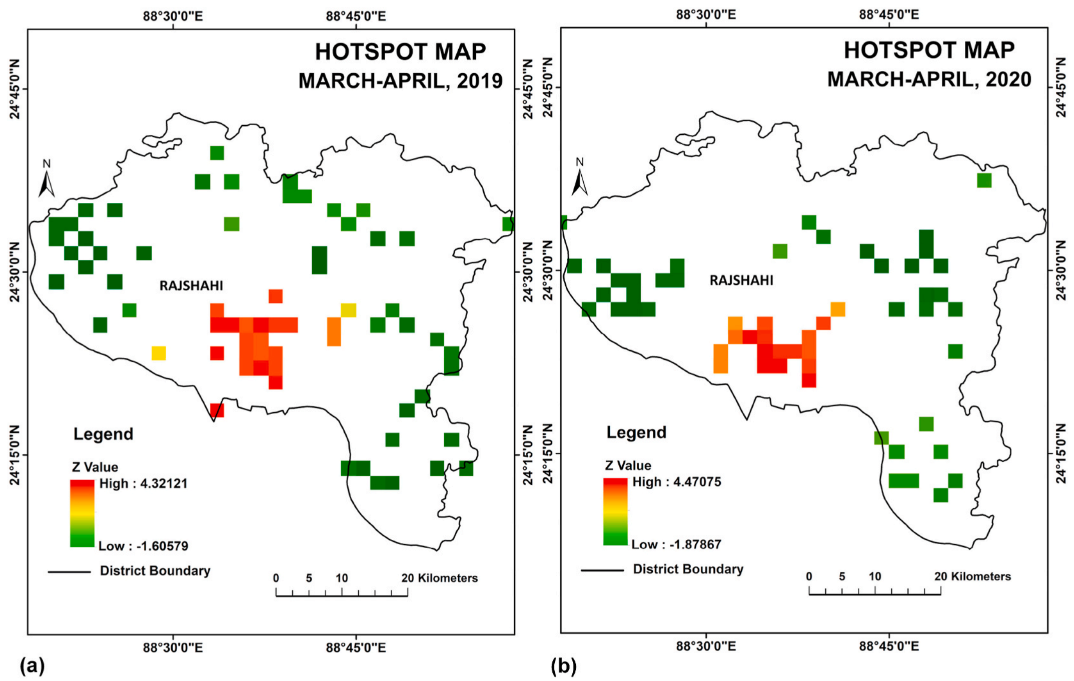

Fig. 11. Maps showing hot and cold spots generated using household locations of the patients interviewed during March–April 2019 (a) and household locations of the patients interviewed in March–April 2020 (b).

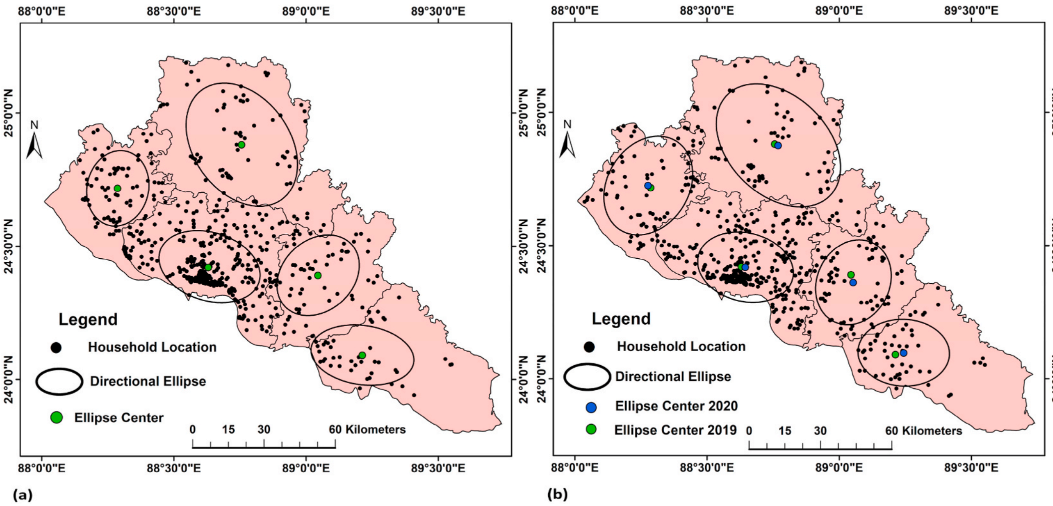

Fig. 12. Standard Deviational Ellipse: generated using household locations of patients interviewed in 2019 (a) and generated using household locations of patients interviewed in 2020 (b). Household locations are represented using black points. Green and blue points in Fig. 12 (b) illustrates mean centers of the ellipses generated using 2019 and 2020 household location data respectively.

Table 5
Correlation between four major RDs and the RD risk factors.

Diseases Risk factors		Asthma	COPD	Pulmonary hypertension	LRIs (pneumonia)
Age	Pearson Correlation	−.218	.315	.096	−.023
	Significance	.000 (0.01)	.000 (0.01)	.011 (0.05)	.541
Work in dust/smoke producing industry	Pearson Correlation	.328	.256	.121	−.152
	Significance	.000 (0.01)	.000 (0.01)	.194	.104
Use biomass for cooking	Pearson Correlation	.387	.305	−.067	−.128
	Significance	.000 (0.01)	.000 (0.01)	.451	.455
Live near smoke/dust producing industry	Pearson Correlation	.212	.158	.185	−.037
	Significance	.021 (0.05)	.019 (0.05)	.098	.325
Use smoking materials	Pearson Correlation	.502	.663	.282	.191
	Significance	.000 (0.01)	.000 (0.01)	.003 (0.01)	.022 (0.05)

temporal distribution pattern of respiratory disease, contribution of the environmental variables, such as particulate matter, humidity, and temperature to respiratory disease, as well as identification of the population at high risk of respiratory disease have remarkable biomedical applications while assessing respiratory health.

Though this study provides a deeper understanding of the spatial and temporal distribution patterns of respiratory diseases taking the contributing environmental factors into consideration, it has few limitations. Of the limitations the most important ones include: (a) respiratory illness information of most of the patients in the study area could not be included in the study due to the lack of a central respiratory disease database, therefore the current study is not a complete but fractional representation of respiratory disease pattern; (b) through the values of hot-spots provide an indication of the number of respiratory patients in a geographical area, these values are not the representative of the proportion of total population affected by respiratory disease; and (c) as the surveys were conducted at a hospital, respiratory patients who were not hospitalized could not been considered in this study, where an additional household survey could play a vital role.

5. Conclusions

This study reveals spatio-temporal distribution pattern of RDs based on the information provided by patients admitted to Rajshahi Medical College Hospital. Employing GIS in combination with statistical techniques has constituted an efficient base for data analysis. Clustering pattern of respiratory patients over space and time, population of which area are at risk of respiratory disease and population of which area may be at high risk of respiratory disease in the future, how ambient air quality is associated with respiratory disease could easily be answered due to the use of these spatial statistical techniques.

Around 90% of the respondents were from five districts, so the results may represent the respiratory illness pattern of those five districts only. However, the results may be extrapolated to reveal a pattern over an extended region. We anticipate that demonstrating the use of geospatial techniques to understand and elucidate the spatio-temporal distribution of respiratory disease can successfully contribute to improving existing respiratory disease prevention, control, and curative practices in the study area, as well as in other areas with similar geographical settings. The successful application of this approach will also motivate other researchers and relevant stakeholders around the world to elucidate the spatio-temporal distribution patterns of respiratory diseases that can be used to improve existing respiratory disease prevention and management practices.

Quality of disease risk factors data could be improved through field observations and inclusion of other air quality measures, such as PM_{10} and PM_1 in addition to $PM_{2.5}$. This could allow us to understand the geographical distribution of RDs in a better way. However, this study has produced a number of findings regarding the spatio-temporal distribution of RDs in the north-western part of Bangladesh, which are expected to contribute to respiratory health care policy development and decision making at the policy level.

Ethics statement

The authors declare that approval for the interviews was obtained from the Ethics Committee, Department of Geography and Environmental Studies, University of Rajshahi, Bangladesh before conducting the surveys. The ethical approval reference number is 2018/08.

Author contribution statement

Chandan Roy: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Raquib Ahmed: Contributed reagents, materials, analysis tools or data.

Manoj Kumer Ghosh; Md. Matinur Rahman: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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