



Hotspot detection and socio-ecological factor analysis of asthma hospitalization rate in Guangxi, China

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ABSTRACT

Background: Asthma is a major public health concern throughout the world. Numerous researches have shown that the spatial-temporal patterns of asthma are inconsistent, leading to the suggestion that these patterns are determined by multiple factors. This study aims to detect spatial-temporal clusters of asthma and analyze socio-ecological factors associated with the asthma hospitalization rate in Guangxi, China.

Methods: Asthma hospitalization and socio-ecological data for 88 counties/municipal districts in Guangxi, China in 2015 was collected. Space-time scan statistics were applied to identify the high-risk periods and areas of asthma hospital admissions. We further used GeoDetector and Spearman correlation coefficient to investigate the socio-ecological factors associated with the asthma hospitalization rates.

Results: There were a total of 7804 asthma admissions in 2015. The high-risk period was from April to June. The age groups of 0–4 and ≥ 65 years were both at the highest risk, with hospital admission rates of $45.0/10^5$ and $46.5/10^5$, respectively. High-risk areas were found in central and western Guangxi with relative risk (RR) values of asthma hospitalizations greater than 2.0. GDP per capita and altitude were positively associated with asthma hospitalizations, while air pressure and wind speed had a negative association. The explanatory powers of these factors (i.e., GDP per capita, altitude, air pressure, wind speed) were 22%, 20%, 14% and 10%, respectively.

Conclusions: The GDP per capita appears to have the strongest correlation with asthma hospitalization rates. High-risk areas were identified in central and western Guangxi characterized by high GDP per capita. These findings may be helpful for authorities developing targeted asthma prevention policies for high-risk areas and vulnerable populations, especially during high-risk periods.

1. Introduction

Asthma is a common chronic inflammatory disease of the airways, characterized by recurrent attacks of breathlessness and wheezing, particularly at night or early in the morning (Al Sallakh et al., 2017; Busse, 2007; Follenweider and Lambertino, 2013). Asthma is a major public health concern throughout the world (World Health Organization, 2017). According to World Health Organization (WHO) estimates released in December 2016, 235 million people at that time were suffering from asthma, and there had been 383,000 deaths due to asthma in 2015 (World Health Organization, 2017). Worldwide, in the last decades, asthma prevalence has been increasing (World Health Organization, 2017). Furthermore, it tends to follow a patient for his or her lifetime (Matthew et al., 2004; Nunes et al., 2017). The factors

influencing the occurrence of asthma include genetic predisposition, environmental factors such as meteorological elements, air pollution, allergens, and airborne chemical irritants, and extreme emotional arousal (Follenweider and Lambertino, 2013; World Health Organization, 2017; Dias et al., 2016; Richard et al., 2015; Zhiwei et al., 2013).

Numerous studies have shown correlations between certain meteorological conditions and the development of asthma, but the associations are inconsistent in different geographic regions (Hyrkäs et al., 2016; Lam et al., 2016). Low humidity and temperature have been found to be associated with more hospital admissions for asthma (Lam et al., 2016; Mireku et al., 2009). Hyrkäs et al. found that cold weather often exacerbated respiratory symptoms in adults with asthma (Hyrkäs et al., 2016). Some studies have indicated that air pressure is positively

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associated with asthma (Zhou, 2018; Garty et al., 1998). Jonathan et al. found distinct peaks of increased asthma-related Emergency Department (ED) visits, which were closely associated with increased tree pollen counts in spring and decreasing temperatures in the fall (Witonsky et al., 2018).

In addition to meteorological factors, many researchers have emphasized the importance of socio-economic determinants of asthma (Nunes et al., 2017; Ebell et al., 2017). Dias et al. suggested that social and environmental factors may be determinants of disparities in asthma (Dias et al., 2016). In Georgia, there are associations between social determinants, such as education, income, and geography, and the prevalence of asthma (Ebell et al., 2017). In low-income and middle-income countries, asthma prevalence has been found to be associated with urbanization (Rodriguez et al., 2019). Some studies have suggested that social factors also influence whether asthma leads to hospital admission (Dias et al., 2016; Gupta et al., 2018). Geographical variations in disease can be attributed either to the physical or social attributes of each geographic region (Brownson, 2004; Keddem et al., 2015). Yao indicated that the prevalence of childhood asthma in China was high, especially in coastal cities and developed cities (Yao, 2015). Thus, hospital admission rate cannot be fully understood without appreciating the contributions of socio-economic factors.

Although a wide range of factors influencing asthma have been reported, substantiation of causality from observational studies is inherently difficult, and few factors have been assessed in primary prevention studies (Richard et al., 2015). Understanding and identifying influencing factors of asthma is a prerequisite for asthma prevention. Due to the complexity of asthma, multiple factors need to be taken into account when analyzing causes for its occurrence. The term “socio-ecological factors” attempts to cover most of the factors potentially involved, including economic, geographic, demographic, and meteorological, as well as individual behavior, and government policies (Li et al., 2012).

Guangxi, an autonomous region in the south of China, is located in the subtropical monsoon climate zone (Hua et al., 2014). It includes both coastal and inland areas with different geographical and meteorological characteristics. The prevalence of asthma in Guangxi has been reported to be at a moderate level in China (Yan et al., 2016). Previous studies in this region have mainly focused on the effect of genetics on asthma (Yan et al., 2019; Cai, 2017). To the best of our knowledge, there is limited evidence on relationships between socio-ecological factors and asthma. It is essential to identify potential causal factors, vulnerable populations and high-risk areas for asthma because such knowledge can help authorities develop future interventions in targeted areas and formulate medical service policies in different regions. In this study, we first identified the high-risk periods and areas. Then, the meteorological, socio-economic, and altitude factors were used to investigate the associations between asthma hospitalization rates and socio-ecological factors.

2. Materials and methods

2.1. Study area

The study covered 88 divisions in Guangxi, including 74 counties and 14 municipal districts (Fig. 1), with a population of 48 million and an area of 237,600 km². Guangxi has four seasons: spring (March–May), summer (June–August), autumn (September–November), and winter (December–February). In Guangxi, the meteorological factors, especially precipitation and temperature, vary distinctly between seasons. The annual average temperature and wind speed decreased from south to north in 2015 (Fig. 2).

2.2. Data collection and study design

Daily asthma admission cases in general hospitals in the study area

from January 2015 to December 2015 were obtained from Guangdong Medical University. The hospital admission records included individual's age, gender, and residential location, diagnostic code, admission date, and duration of hospital stay. Based on the International Classification of Diseases (ICD-10) codes, there were 7804 hospital admissions due to asthma collected by diagnostic coding of ‘J45.xxx’, such as ‘J45.900’, ‘J45.901’, and ‘J45.902’. We aggregated the daily asthma admission cases at the county/district level according to the patient's residential location.

Meteorological data were collected from the National Meteorological Information Center (<http://data.cma.cn/>); they were: average temperature (T), average relative humidity percentage (RHU), average wind speed (WIN), average air pressure (PRS) and total precipitation for the whole year (PRE). The daily meteorological data were collected from 600 sites of China, which were in or around Guangxi. The final meteorological data of 88 divisions in Guangxi were interpolated based on the 600 sites using the empirical Bayesian Kriging method. Altitude data were acquired from the Geospatial Data Cloud (<http://www.gscloud.cn/>). Gross domestic product (GDP) per capita of each region, number of beds in hospitals (Beds), and medical and technical personnel of hospitals (Persons) were collected from Guangxi statistical yearbook in 2016 (Guangxi Statistical Bureau, 2016).

The study design is shown in Fig. 3. The first step was to describe the admission cases from multiple perspectives. The second step was to detect the spatial-temporal hotspots of asthma using the space-time scan statistics. Finally, GeoDetector and Spearman correlation coefficient were performed to examine the associations between socio-ecological factors and asthma, and determine the factors responsible for hotspots. GeoDetector was carried out to quantify the explanatory power of each socio-ecological factor for the asthma hospitalization rate and identify the factors significantly associated with asthma. Based on the factors identified by GeoDetector, the Spearman correlation coefficient was used to determine if the relationship between each factor and asthma was positive or negative.

2.3. Space-time scan statistics

To describe the spatial and temporal distribution of asthma hospitalizations and identify the areas with the highest prevalence and vulnerability to asthma (“hotspots”), space-time scan statistics were used to detect space-time disease clusters (Kulldorff, 2018).

According to the characteristics of the asthma hospitalization data, we used a Poisson model as the probability model. For the discrete Poisson model, we need to specify a population size for each location or region. The population may vary over time. The space-time scan statistic is defined by a cylindrical window with a circular geographic base and with the height corresponding to time (Kulldorff, 2018; Kulldorff et al., 1998). The base is defined exactly as for the purely spatial scan statistic, while the height reflects the time period of potential clusters. Before calculation, we need to define the maximum spatial cluster size, which is the percent of the population at risk, and define the maximum temporal cluster size, which means the percent of the study period. Then, the cylindrical window is moved in space and time, so that for each possible geographical location and size, it also visits each possible time period. The radius of the base varies from zero to the maximum spatial cluster size. The height of the cylinder ranges from zero to the maximum temporal cluster size. In this study, space-time scan statistics was used to detect high-risk clusters in Guangxi, China. To explore the characteristics of asthma in different places at different times, the maximum spatial cluster size was set to 20% of the population at risk, and the maximum temporal cluster size was set to 3 months.

Then, the risk of asthma hospitalization rate in each window was detected, and the statistic log-likelihood ratio (LLR) was calculated for each window. The window with the maximum likelihood is the most likely cluster, that is, the cluster least likely to be due to chance. The space-time scan statistics also identify secondary clusters, and order

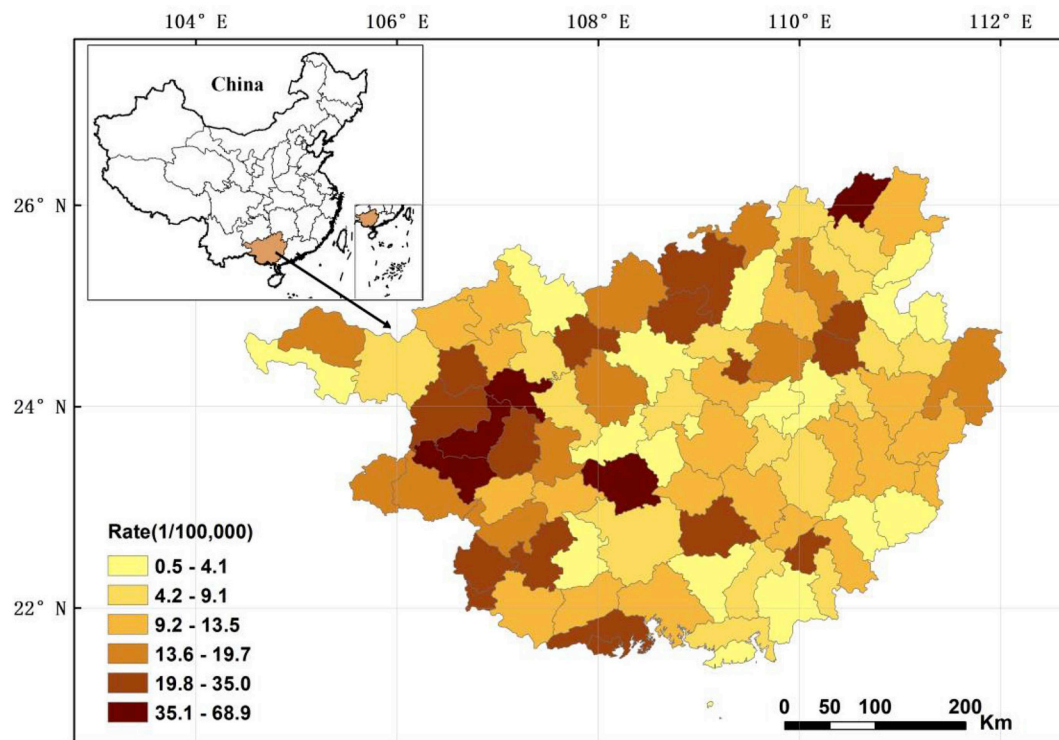


Fig. 1. Geographic location of Guangxi in China, and the asthma hospitalization rates in Guangxi (2015).

them according to the value of LLR. For each location and size of the scanning window, the alternative hypothesis is that there is an elevated risk within the window as compared to outside. Under the Poisson assumption, we scanned only for clusters with high rates, and the likelihood function (Kulldorff, 2018) is expressed as:

$$LLR = \left(\frac{c}{E[c]} \right)^c \left(\frac{C-c}{C-E[c]} \right)^{C-c} \quad (1)$$

where C is the total number of asthma hospitalization records, and c is the observed number of cases within the window. $E[c]$ is the covariate adjusted expected number of cases within the window under the null-hypothesis, and $C-E[c]$ is the expected number of cases outside the window.

The relative risk (RR) can also be calculated for each cluster, which is the estimated risk within the cluster divided by the estimated risk outside the cluster. It is calculated as the observed divided by the expected within the cluster divided by the observed divided by the expected outside the cluster (Kulldorff, 2018). Because true clusters are not exactly circular, it is common to have locations with few cases in the detected clusters (Kulldorff, 2018). It is important to identify relative risk of each location in detected clusters. Therefore, the relative risk for each location in cluster is also provided, which is useful when examining a cluster area in more detail. The p-value for the space-time scan statistics was calculated by Monte Carlo hypothesis testing. Space-time scan statistical analysis was performed using SaTScan v9.5.

2.4. GeoDetector

In this study, GeoDetector was used to assess the association between asthma and socio-ecological factors. The rationale of GeoDetector is that, if a potential factor leads to a disease, this factor may show a temporal-spatial distribution similar to the disease. Furthermore, these disease determinants have distinct spatial distributions across geographical units, so that their adequate study involves the investigation of the associated geographical strata (Wang et al., 2010). It need not assume or restrict the explanatory and response

variables (Wang et al., 2010). The GeoDetector method was implemented using software downloaded from www.geodetector.org. GeoDetector is adapted to discrete risk factors, and it analyzes the continuous factors by discretizing the continuous data into discrete data. The difficulty is how to discretize continuous risk factors using an appropriate discretization method (Cao et al., 2013). In this study, we used K-means to discretize continuous risk factors. In our study, the spatial data were social factors and altitude, and spatial-temporal data were the meteorological data, which varied in different seasons. Meteorological data was divided into four seasons. Different strata variables were prepared before analysis.

GeoDetector uses four detectors based on spatial variation analysis of the geographical strata to assess the environmental risks to health. These detectors are: (1) the risk detector, which is used to identify significant differences in average hospitalization rate of disease between sub-regions. The study area is divided into sub-regions according to the classification of each risk factor; (2) the factor detector, which quantifies the degree of the impact of a geographical stratum responsible for an observed spatial disease pattern (Xu, 2017); (3) the interaction detector, which is used to quantify the interactive effect of two risk factors on disease; and (4) the ecological detector, which is used to determine whether the influence of two factors on the spatial distribution of disease is significantly different or not. In our study, we only used the factor detector and interaction detector.

The factor detector quantifies the degree of the impact of a geographical stratum responsible for an observed spatial disease pattern. In this study, the factor detector used the q value to quantify the impact of each risk factor on hospital admission rate for asthma, with the q value between 0 and 1. If the q value of factor $X1$ is 1, it means $X1$ completely determines asthma. If the q value is 0, it means the factor is completely unrelated to asthma. The value of q means that risk factor explains 100 $q\%$ of the disease, representing the explanatory power of a risk factor (Wang et al., 2010; Xu, 2017). The higher the q value is, the greater this risk factor contributes to the disease. The q -statistic was calculated with the following formulas:

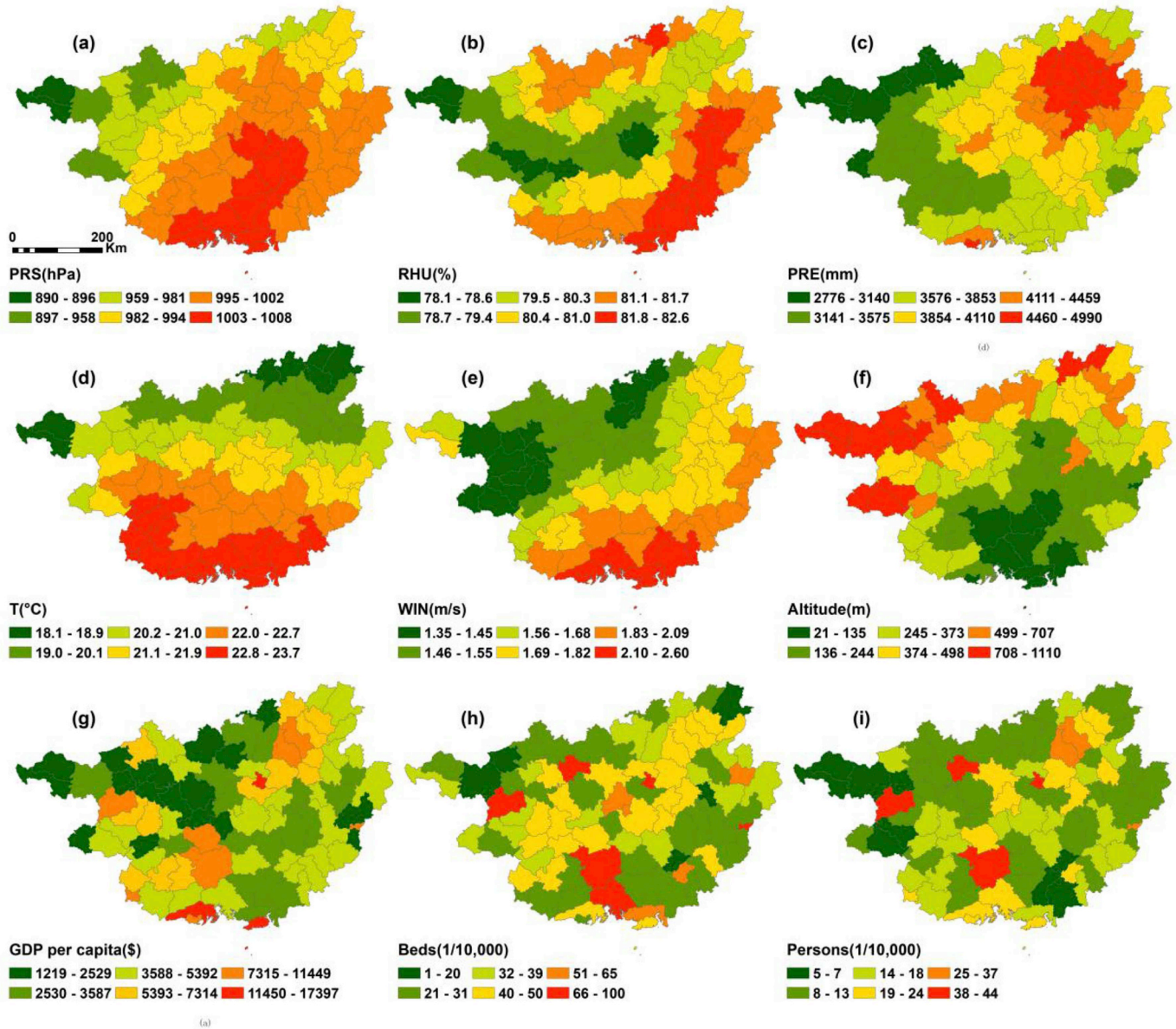


Fig. 2. Distribution of socio-ecological factors in Guangxi (2015).

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST}, \quad SSW = \sum_{h=1}^L N_h \sigma_h^2, \quad SST = N\sigma^2, \quad (2)$$

the study area is stratified into L strata, denoted by $h = 1, 2, \dots, L$. h is the geographical stratum of dependent variable Y (hospital admission rate), or the strata of independent variables (socio-ecological factors), and L is the number of strata. N_h is the unit number of strata h , but N is the unit number of the study area. σ_h^2 is the variance of Y in strata h , and σ^2 is the variance of Y in the study area. SSW indicates the sum of squares within L strata, and SST indicates the total sum of squares. In addition, the non-central F-distribution is used to identify whether the q value is significant or not.

The interaction detector indicates whether the risk factors lead to asthma independently or not, and whether the interaction is inhibitory or synergistic. The interaction detector was used to probe the interactive effect of two risk factors (Xu, 2017), X_1 and X_2 . The q value also applies to the interaction detector. According to the relationships of $q(X_1)$, $q(X_2)$, and $q(X_1 \cap X_2)$, the result of interaction can be classified into several categories, namely nonlinear enhancement, bivariate enhancement, nonlinear decrease, univariate decrease and independence. The interaction relationships are cataloged as follows:

Enhance: if $q(X_1 \cap X_2) > q(X_1)$ or $q(X_2)$

Enhance, nonlinear (nonlinear enhancement): if $q(X_1 \cap X_2) > q(X_1) + q(X_2)$

Enhance, bivariate (bivariate enhancement): if $q(X_1 \cap X_2) > q(X_1)$ and $q(X_2)$

Weaken: if $q(X_1 \cap X_2) < q(X_1) + q(X_2)$

Weaken, nonlinear (nonlinear decrease): if $q(X_1 \cap X_2) < q(X_1)$ and $q(X_2)$

Weaken, univariate (univariate decrease): if $q(X_1 \cap X_2) < q(X_1)$ or $q(X_2)$

Independence: if $q(X_1 \cap X_2) = q(X_1) + q(X_2)$

In this study, we used nine socio-ecological factors from January 2015 to December 2015, namely five meteorological factors, three social factors, and altitude. Meteorological factors were average temperature, average relative humidity, precipitation, average air pressure, and average wind speed; social factors were GDP per capita, number of beds in hospitals per 1000 people, and medical and technical personnel of hospitals per 1000 people. In GeoDetector, the q values were used to quantify the explanatory power of each factor and their interactive

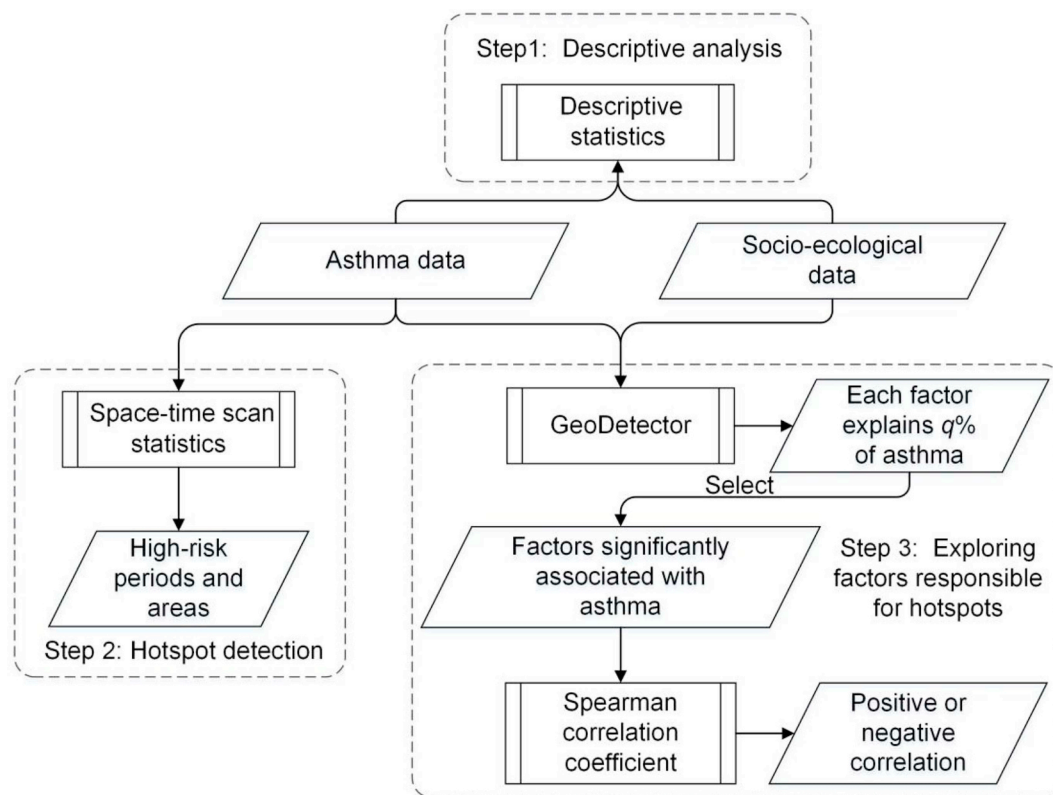


Fig. 3. Study design flowchart.

effects.

2.5. Spearman correlation coefficient

The Spearman correlation coefficient was used to quantify the relationship between asthma hospitalization rate and related factors, and to determine if the relationship was positive or negative. This method is a nonparametric index to measure the dependence of two variables. It uses a monotone equation to evaluate the correlation of two statistical variables. In this study, we used bivariate association analysis with a two-sided test. The formula of correlation coefficient ρ was:

$$\rho = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}} \quad (3)$$

where the value of ρ represents the association between asthma hospitalization rate and each factor, which is between -1 and 1 . Positive value represents positive correlation between two variables and negative value means negative correlation; larger values indicate stronger correlation. The response variable y represented asthma hospitalization rate, and explanatory variables of x were factors selected by GeoDetector. We used this method to assess the correlation between asthma hospitalization rates and related factors one by one. P values smaller than 0.05 were considered statistically significant. Spearman correlation coefficient was calculated by IBM SPSS Statistics (Version 21).

3. Results

3.1. Descriptive statistics

Between January 1, 2015 and December 31, 2015, in total, 7802 hospitalizations were recorded in hospitals in Guangxi. The average age of asthma patients for males was 39, while 48 for females. Among these, the hospitalization rates of males and females were $16.1/10^5$ and $16.5/$

10^5 , respectively. There was little difference in the rate of hospital admission and in the duration of hospital stays for males and females. In the groups aged 0–4 and ≥ 65 years, the hospitalization rates were $45.0/10^5$ and $46.5/10^5$, respectively, which were much higher than any other age groups (Table 1). Patients under the age of 14 had shorter average duration of hospital stays, while others had relatively longer hospital stays. Average expense of hospital stays tended to increase with age (Table 1).

In 2015, the seasonal patterns in asthma hospitalization rate for different age groups are shown in Fig. 4. The general trend varied between age groups, with the groups aged 0–4 and ≥ 65 years being the highest. There were two obvious peaks for the age group of 0–4. The hospitalization rate of group aged 0–4 began to increase rapidly in Jan and reached a peak in March and April with hospitalization rates of $4.90/10^5$ and $4.96/10^5$, respectively, and the next peaks occurred in October and November with hospitalization rates of $4.93/10^5$ and $5.07/10^5$. The seasonal trend for the 5–14 age group was similar to the 0–4 age group, but the average monthly hospitalization rate of the 5–14 age group was lower. For the ≥ 65 age group, there was an obvious peak in June, with a hospitalization rate of $5.66/10^5$. All monthly hospitalization rates were low for the 15–64 age group, and there was no significant seasonal trend.

Table 1
Statistics of hospital stays and hospital admission rate.

Age groups (years)	Cost of hospital stays (\$)	Duration of hospital stays (days)	Hospital admission rate (1/100,000)
0–4	409	6.11	45.0
5–14	443	5.56	5.6
15–64	896	7.05	11.2
≥ 65	1320	8.88	46.5

Note: $P < 0.001$ (P-value for age groups was generated by the Chi-Square test).

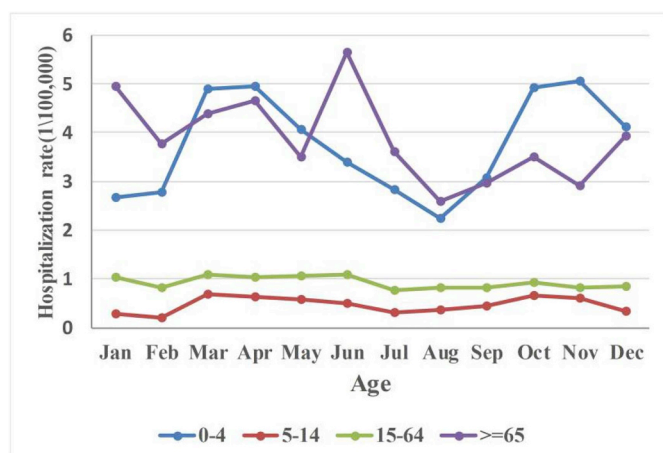


Fig. 4. Monthly hospital admission rate of asthma for different age groups in Guangxi (2015). Note: $P < 0.001$ (P-value for age groups between months was generated by the Chi-Square test).

We also regarded 14 urban districts as urban areas, and 74 counties as rural areas in Guangxi. We found that GDP per capita in urban areas was much higher than that in rural areas. Moreover, in urban areas, asthma hospitalization rates were consistently higher than in rural areas. GDP per capita in urban areas was 8533\$, and in rural areas was 4106\$. In 2015, the hospitalization rate in urban areas was $19.36/10^5$, and the hospitalization rate in rural areas was $14.74/10^5$.

3.2. Spatial-temporal patterns

According to the result of SaTScan, five spatial-temporal clusters were found in the study area. The spatial clusters were in central and western Guangxi. The clusters were sorted in descending by LLR (Table 2). Theoretically, the window with the maximum likelihood value is the most likely cluster, which is least likely to be due to chance. The most likely cluster included 16 regions, and the cluster center was Tiandeng ($23.11^\circ\text{E}, 107.07^\circ\text{N}$), with a radius of 121.6 km (Fig. 5). It consisted of 411 observed cases and 181.8 expected cases, and the value of RR was 2.35. When clusters were examined in more detail, the RR of each region was also calculated (Fig. A1 and Table A1). In Fig. 5, the high-risk regions with RR larger than 2 are marked (oblique line); these regions had high relative risk for asthma hospitalizations. The high-risk period of most likely cluster was from April to June, which was the same with the fourth and fifth clusters. In addition, the high-risk period for secondary cluster 1 was from February to April, and for secondary cluster 2 it was from October to December.

3.3. Related factors analysis

The explanatory powers of socio-ecological factors and their interactive effects are shown in Table 3. In Table 3, the q values on the diagonal line represent the explanatory powers of single factors, which means the independent effect of each single factor on asthma. The other values in Table 3 represent interactive effects on asthma between two

factors. The q values of influence factors on the asthma hospitalization rates (Table 3) were in the order of GDP per capita (0.22) > altitude (0.20) > pressure (0.14) > wind speed (0.10) > Persons (0.07), and each of the P values was less than 0.01. The other socio-ecological factors in this study had no significant correlation with the asthma hospitalization rates. GDP per capita, as a proxy for urbanization (Xu et al., 2019), showed the strongest association with the rate of hospital admission for asthma.

In GeoDetector, the results of interaction detector showed that the interactive effects between any two factors were all nonlinear enhancement compared with their independent influence (Table 3); that was to say, the interaction between any two factors was greater than the sum of their independent influence. The coupled impact of GDP per capita ($q = 0.22$) and altitude ($q = 0.20$) played an important role in asthma hospitalizations, with an explanatory power of 0.76 (Table 3). High GDP per capita and high altitude were associated with a high hospitalization rate for asthma (Tables 3 and 4). High GDP per capita and low air pressure were found to enhance each other to increase the risk of asthma (Tables 3 and 4), q (GDP per capita $\cap$ air pressure) = $0.51 > 0.36 = q$ (GDP per capita) + q (air pressure). The results showed that the impact of wind speed was similar with air pressure (Tables 3 and 4).

The correlation coefficients are shown in Table 4. A positive association was found between asthma hospitalization rate and GDP per capita, and altitude (Table 4). A negative correlation was found with pressure and wind speed (Table 4). The association with GDP per capita was high, with a coefficient 0.21 (95% CI: 0.10, 0.32) and p value smaller than 0.01. The correlation coefficient between hospitalization rate and altitude was 0.12 (95% CI: 0.00, 0.22). The factors of pressure and wind speed were negatively correlated with hospital admission rate, with the correlation coefficients as -0.16 and -0.21 , respectively.

4. Discussion

Asthma is a multifactorial disease and a serious public health problem throughout the world (Dias et al., 2016; Al Sallakh et al., 2017). We detected the high-risk periods and areas of asthma hospitalization, with the method of space-time scan statistics. We used GeoDetector and Spearman correlation coefficient to examine the relationship between asthma hospitalization rate and socio-ecological factors from January 2015 to December 2015 in Guangxi, China. The results indicated that the highest risk was mainly found in central and western Guangxi where the GDP per capita was high.

In this study, the high-risk period was from April to June, and the age groups of 0–4 and ≥ 65 years were at the highest risk. Similar findings were observed in Belo Horizonte, Brazil, where seasonal trends showed a peak of hospitalizations for asthma in March, April, and May, and asthma hospitalization rate was highest in children aged 0–4 years (Dias et al., 2016). Asthma exacerbations showed a bimodal pattern with peaks in spring and summer (Hervás et al., 2015). In the spatial dimension, geographic disparities of asthma hospitalization rates were also found, which were similar to previous studies (Pesce et al., 2016; Chien and Alamgir, 2014). The results of the SaTScan showed that the significant high-risk areas were mostly located in central and western

Table 2
Spatial-temporal clusters of asthma hospitalizations in Guangxi (2015)

Cluster	Center	Number of regions	Start Date	End Date	Observed	Expected	LLR	RR	P value
1*	(23.11°E, 107.07°N)	16	2015/4	2015/6	411	181.8	110.4	2.35	0.00
2	(24.53°E, 109.79°N)	2	2015/2	2015/4	180	62.4	74.2	2.94	0.00
3	(22.77°E, 109.16°N)	1	2015/10	2015/12	80	29.7	29.2	2.71	0.00
4	(21.76°E, 108.09°N)	2	2015/4	2015/6	64	23.2	24.2	2.77	0.00
5	(22.55°E, 110.06°N)	1	2015/4	2015/6	82	36.3	21.3	2.27	0.00

Note: * indicates the most likely cluster, the others indicate secondary cluster. RR: relative risk.

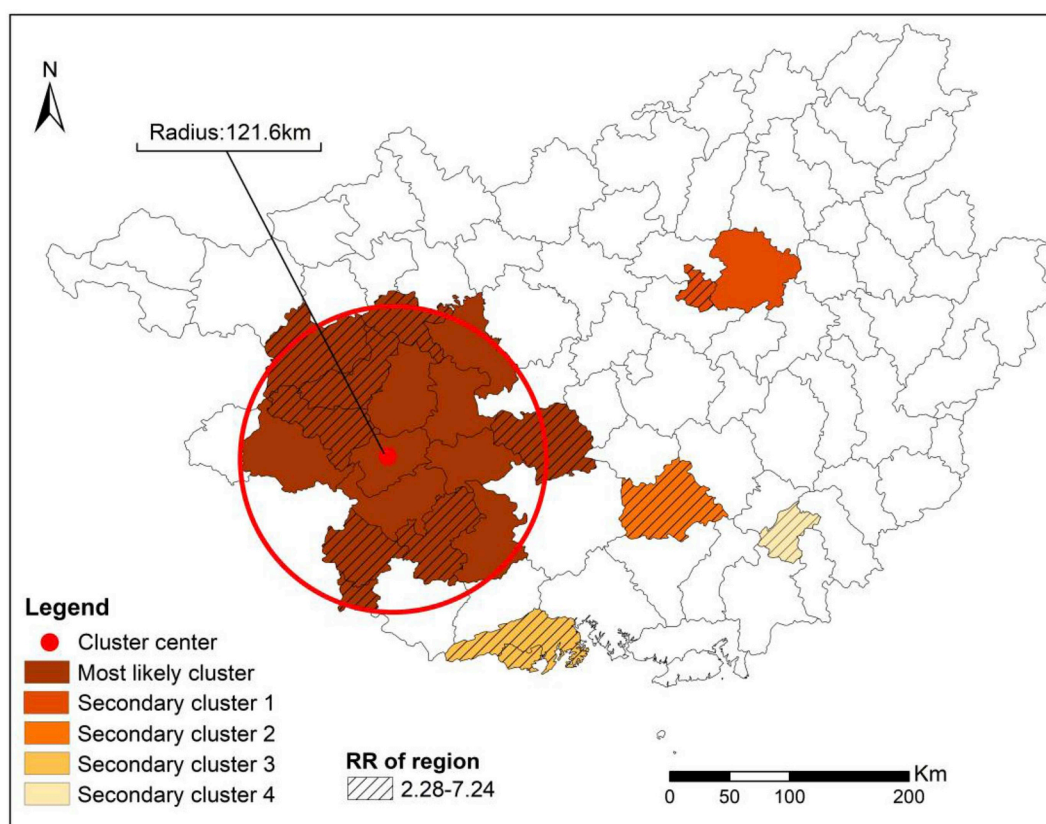


Fig. 5. Detected spatial-temporal clusters of asthma in Guangxi (2015).

Table 3

Explanatory powers of each single factor and their interactive effects on asthma hospitalization.

Variables	Air pressure	Wind speed	Altitude	GDP per capita	Persons
Air pressure	0.14				
Wind speed	0.34	0.10			
Altitude	0.46	0.46	0.20		
GDP per capita	0.51	0.51	0.76	0.22	
Persons	0.31	0.29	0.49	0.38	0.07

Note: *P* values were less than 0.05.

Table 4

Spearman Correlation Coefficient between asthma admission rate and factors.

Variables	Coefficient	P value	Confidence interval (95%)
Air pressure	-0.16**	0.00	(-0.26, -0.06)
GDP per capita	0.21**	0.00	(0.10, 0.32)
Altitude	0.12*	0.03	(0.00, 0.22)
Wind speed	-0.21**	0.00	(-0.32, -0.10)
Persons	-0.03	0.54	(-0.14, 0.08)

Guangxi where the GDP per capita was high. These results were consistent with the findings of GeoDetector and Spearman correlation coefficient. The combined results of GeoDetector and Spearman showed that areas with high GDP per capita had a higher asthma hospitalization rate.

Combining the results of GeoDetector and Spearman correlation coefficient, an increase in asthma hospitalization rate was found to be associated with an increase in GDP per capita, which was similar to some other research studies (Yao, 2015; Zhang et al., 2017; Nunes et al., 2017). In the earliest epidemiological publications on asthma, it was noted that asthma prevalence was higher in social classes with a high

income (Nunes et al., 2017). In addition, we found that GDP per capita in urban areas was much higher than that in rural areas, and the hospitalization rate for asthma in urban areas was higher than in rural areas. Rodriguez et al. analyzed 70 articles on asthma prevalence comparing urban and rural areas, and found urban residence was associated with a higher prevalence of asthma (Rodriguez et al., 2019; Chakravarthy et al., 2002; Solé et al., 2007). In low-income and middle-income countries, urbanization has been associated with temporal and geographical differences in asthma prevalence (Rodriguez et al., 2019). In China, the urban–rural difference for income, education, and access to health care is significant (Hu et al., 2019; Wang, 2014). The acceleration of urbanization in China in the last decade will undoubtedly exert inevitable public health problems (Xu et al., 2019). Urbanization may make people more susceptible to asthma, or create the conditions that cause asthma. It is possibly because that urbanization may bring potential risk factors for asthma, leading to the high hospitalization rate in areas with high GDP per capita. In addition to pathogenic factors, non-pathogenic factors can also influence asthma hospitalization rates, such as economic factors. Asthma is a chronic disease with high cost for individuals and families (Ebell et al., 2017; Nunes et al., 2017). Another possible explanation was that residents with higher incomes can better afford hospitalization and care. Due to the high expense of asthma hospitalization (Nunes et al., 2017; Richard et al., 2015), the lack of affordability may lead to vulnerable groups reducing hospitalizations (Ebell et al., 2017; Harris et al., 2017; Ownby, 2005).

We also found a positive correlation between altitude and asthma; this represented an apparent discrepancy with previous reports. Numerous studies have suggested that altitude higher than 1500m is a major factor in reducing asthma incidence, with the risk of new-onset asthma decreasing as altitude increases (Vargas et al., 2018, 1999). Studies showed that an altitude of 1500–1800 m significantly improved asthma rehabilitation (Massimo et al., 2014; Rijssenbeek-Nouwens et al., 2012; Schultze-Werninghaus, 2006). When altitude was higher

than 1500 m, studies consistently found a negative correlation between asthma and altitude; however, at lower altitudes, the relationship between asthma and altitude was inconsistent. In fact, altitude may be one of the determinants of asthma. In Guangxi, the altitude was lower than 1500 m, which was positively associated with asthma admissions. We here advance the hypothesis that altitude may be positively correlated with asthma hospitalization rates only at low altitudes (under 1500 m). In our study, the influence of wind speed and air pressure on asthma admissions. Numerous studies have shown that relationship between wind and asthma is inconsistent in different areas (Hervás et al., 2015; Zhang et al., 2017).

In this study, the interaction detector showed that the explanatory powers of related factors on asthma hospitalization rates were greatly enhanced when considering interactive effects. The interaction between any two factors was nonlinear enhancement, and the interaction between related factors contributed to explain the spatial heterogeneity of asthma hospitalizations. The interaction between GDP per capita and altitude had the strongest impact on asthma, with an explanatory power of 0.76. Combining the results of Spearman, it indicated that areas with high GDP per capita and high altitude had higher hospitalization rates in Guangxi, China. The interaction between altitude and wind speed was 0.46, which meant that the interactive effect of altitude and wind speed explained 46% of asthma hospitalization rates. Combining Spearman correlation coefficients, it suggested that high altitude and low wind speed were associated with higher hospitalization rate for asthma.

One strength of this study was that the asthma data was detailed; it included age, gender, address and diagnostic code for ICD-10. The method of space-time scan statistics identified the hotspot areas with the highest hospitalization rates and high-risk periods for asthma. GeoDetector provide an efficient and meaningful way to measure spatial heterogeneity of disease, and can be used to explore explanatory factors; thus, it is suitable for detecting risk factors of disease. A second strength of this study is the geographical area that it covered. This study is one of the few studies that compares associations between asthma hospitalizations and socio-ecological factors in an area of 237,600 km², including both urban and rural, and all age groups.

The main limitation of this study is that it assumed that meteorological factors had same effect on all population; differences in life-style and behavioral habits were not taken into account. A second shortcoming is that, while we found that the interaction of environmental factors was significant, we could not determine single direct or indirect effects on asthma. Finally, it was a study conducted with only

hospital admissions; it did not include emergency room visits. Future work will focus on quantitative analysis of the impact of various factors on asthma, and establish models to predict the admission rate of asthma.

5. Conclusions

In summary, the high-risk period was from April to June in Guangxi, and the age groups of 0–4 and ≥65 years were at the highest risk. Asthma hotspots were concentrated in central and western Guangxi where there was high GDP per capita. By identifying high-risk areas, high-risk groups, and high prevalence seasons of asthma, these findings provide evidence for authorities to develop targeted prevention measures and appropriate medical care in Guangxi.

Contributors

Rui Ma analyzed data and wrote the article; Yunfeng Kong determined the core idea of the research and edited the article; Lizhong Liang offered the disease data and funding; Shiyan Zhai and Guangli Zhang edited the article; Jiangyan Gu and Tuanhui Wang processed the data.

Provenance and peer review

Not commissioned; externally peer reviewed.

All authors' individual contributions

Rui Ma: Conceptualization; Writing - original draft, review & editing. Yunfeng Kong: Conceptualization; Data curation. Lizhong Liang: Funding acquisition. Shiyan Zhai: Writing - review & editing. Guangli Zhang: Writing - review & editing. Jiangyan Gu: Data curation. Tuanhui Wang: Data curation.

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Declaration of competing interest

Authors have no conflict of interests.

Appendix A

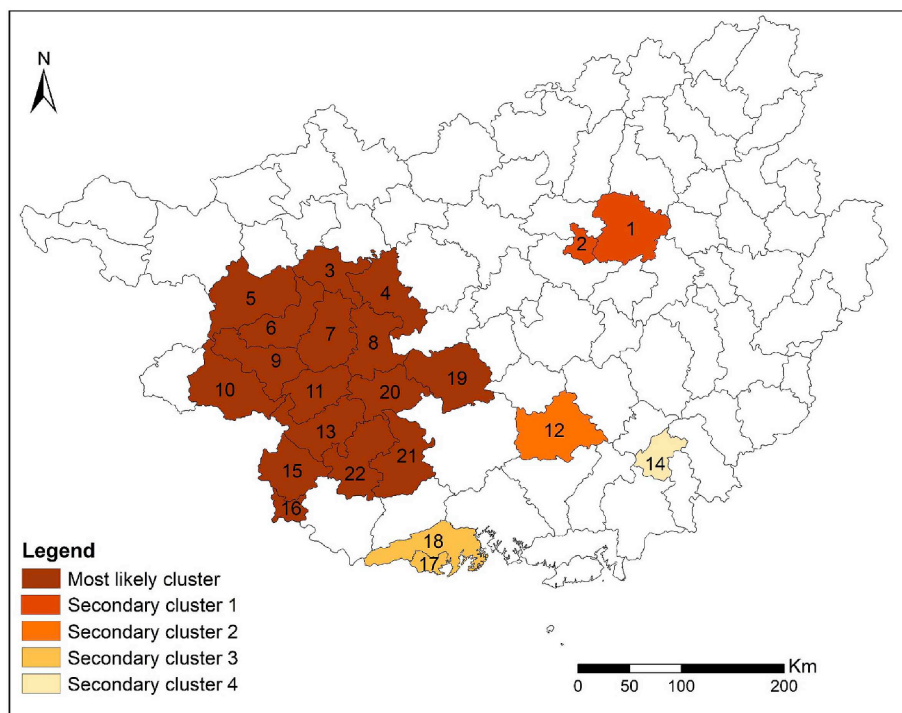


Fig. A.1 Spatial-temporal clusters of asthma in Guangxi. Each region was marked with digital ID. (Note: Refer to Table A1 for the detailed information of each region in clusters.)

Table A.1 Detailed results for space-time analysis in asthma hospitalizations in Guangxi

ID	Cluster	Cluster RR	Observed	Excepted	RR	P value
1	2	2.94	22	11.18	1.97	0.00
2	2	2.94	158	51.2	3.14	0.00
3	1	2.35	26	7.55	3.46	0.00
4	1	2.35	8	12.18	0.66	0.00
5	1	2.35	32	12.95	2.48	0.00
6	1	2.35	31	10.57	2.94	0.00
7	1	2.35	24	12.17	1.98	0.00
8	1	2.35	17	14.87	1.14	0.00
9	1	2.35	72	10.04	7.24	0.00
10	1	2.35	30	16.95	1.77	0.00
11	1	2.35	5	10.83	0.46	0.00
12	3	2.71	80	29.71	2.71	0.00
13	1	2.35	12	9.96	1.2	0.00
14	5	2.28	82	36.28	2.28	0.00
15	1	2.35	18	7.37	2.45	0.00
16	1	2.35	13	3.8	3.42	0.00
17	4	2.77	16	5.1	3.14	0.00
18	4	2.77	48	18.15	2.66	0.00
19	1	2.35	74	18.4	4.06	0.00
20	1	2.35	14	10.17	1.38	0.00
21	1	2.35	1	12.98	0.08	0.00
22	1	2.35	34	11.03	3.09	0.00

Appendix B. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2020.109201>.

Abbreviations

T	average temperature
RHU	average relative humidity percentage
WIN	average wind speed
PRS	average air pressure
PRE	total precipitation for the whole year

GDP	Gross domestic product
Beds	number of beds in hospitals
Persons	medical and technical personnel of hospitals
LLR	log-likelihood ratio
RR	relative risk

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