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Spatio-temporal Distribution Characteristics and Environmental Impact Factors of Lung Cancer Mortality: A Case Study of Yuhui District in Bengbu City, China

TANG Jingjing[1, 2], GU Kangkang[1, 2], MI Jing[3], ZHANG Wenhao[3], FANG Yunhao[4], LI Yuwei[1, 2], WANG Beichen[1, 2]

(1. *School of Architecture & Planning*, *Anhui Jianzhu University*, *Hefei* 230601, *China*; 2. *Research Center of Urbanization Development in Anhui Province*, *Anhui Jianzhu University*, *Hefei* 230601, *China*; 3. *Department of Epidemiology and Statistic*, *Bengbu Medical College*, *Bengbu* 233000, *China*; 4. *School of Architecture and Urban Planning*, *Huazhong University of Science and Technology*, *Wuhan* 430074, *China*)

Abstract: Among cancers, lung cancer is the most common cause of death in China. For the prevention and control of lung cancer, it is necessary to investigate the spatial and temporal distribution of lung cancer mortality, as well as the changes in the trend and the affecting mechanism. Based on statistics and auto-correlation analysis, this paper studied the spatial and temporal distribution of lung cancer mortality in Yuhui District, Bengbu, Huaihe River Basin, from 2017 to 2020. In addition, Spearman's Rank Correlation Assessment Model and Geographic Detector Model were used to examine the relationship between environmental factors and lung cancer mortality to identify impact factors and their mechanisms. The findings indicated that: 1) from the characteristics of temporal distribution, the number of lung cancer deaths exhibited a linear growth tendency, with the highest mortality in winter; 2) from the characteristics of spatial distribution, lung cancer mortality showed a strong spatial agglomeration form, concentrating on two clustering areas, located in the old city and the central city of Bengbu, near the Huaihe River; 3) from the point of view of the whole research area, there were 15 impact factors with significant correlation in the built and natural environment factors. The significant impacting factors in the built environment included land use, road traffic, spatial form and blue-green space, which could indirectly affect lung cancer mortality, while air pollution and temperature constituted the significant impacting factors in the natural environment; 4) the influence of screened environmental factors on lung cancer mortality was different. Spatial stratified heterogeneity assessment, the interaction among environmental factors demonstrated statistical significance, it was found that the interaction between environmental factors in pairs had a significant enhancement effect on lung cancer mortality. To some extent, urban planning and policies could reduce lung cancer mortality.

Keywords: lung cancer mortality; built environment; spatial auto-correlation; Spearman's Rank Correlation; Geographic Detector Model; Bengbu City, China

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1 Introduction

Lung cancer is now the most common tumor with the highest mortality (World Health Organization, 2015; Wang et al., 2020; Huang et al., 2022), whose impacts have been extensively studied. Since the 1970s, the mortality rate of malignant tumors in China has steadily increased (World Health Organization, 2015), making it

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Corresponding author: GU Kangkang. E-mail: kangkanggu@ahjzu.edu.cn

one of the leading causes of death among both urban and rural residents (Cao and Chen, 2019; Yang et al., 2020). As reported in the Third China Residents Cause-of-Death Sample Survey, the mortality rate of malignant neoplasms in China is among the highest in the world, varying by gender and region, and shows a continuous upward trend (Lin and Lin, 2016). In China, lung cancer mortality has increased by 465% over the past 30 yr (Wang et al., 2012). The identification of the factors that influence lung cancer and the development of prevention policies that involve all relevant stakeholders is essential.

The risk factors for lung cancer are usually considered to smoking, occupational and environmental exposures, ionizing radiation, chronic lung infections, atmospheric pollution, and genetic factors (Wang et al., 2019). Nevertheless, the factors that influence lung cancer mortality have become more complex under the bio-psycho-social medicine model, which takes into account environmental factors. It has been reported that lung cancer is more prevalent in urban areas than in rural areas in some developing countries (Cao and Chen, 2019). Rapid urbanization and industrialization have resulted in air pollution and an unsuitable built environment, which pose serious health risks to both urban and rural residents (Pope et al., 2002; Loomis et al., 2013; Li et al., 2020a). Additionally, it affects social and economic development, causing widespread concern.

In recent years, there have been more and more studies on the spatial and temporal distribution of lung cancer and its influential factors. The spatial and temporal dynamic distributions and changing characteristics of lung cancer including factors such as age, gender, and geography (Thun et al., 2006; Samet et al., 2009), were discussed. On the basis of a long time series, more analysis of the degree of aggregation of mortality in different regions (Flores et al., 2017), the distribution of mortality of lung cancer in various age groups (Oliveira et al., 2013), gender differences (Xiao et al., 2022), *etc.* were discussed. But several studies have summarized the epidemiological characteristics of lung cancer from a preventive medicine perspective. Factors affecting lung cancer have been identified and analyzed: smoking is an important factor in lung cancer (Lu et al., 2019), but with effective tobacco control and promotion, the impact of smoking behavior on lung cancer has declined (Cao and Chen, 2019). Consequently, studies have begun to investigate other factors that may affect lung cancer. In 2013, outdoor air pollution was recognized as a carcinogenic factor by the International Agency for Research on Cancer (IARC). Lung cancer mortality in China has been associated with increased levels of SO_2 and suspended particles in the air (Liu et al., 2017a). Evidence suggests that the built environment has no direct impact on lung cancer rates (Wang et al., 2018). The built environment may indirectly affect lung cancer mortality through air pollution (Wang et al., 2016a; 2018), and epidemiological studies suggest that air pollution may increase lung cancer mortality (Hvidtfeldt et al., 2021). Studies on air pollution and lung cancer indicate that lung cancer is more prevalent in the developed industrial areas than in the less-developed industrial areas, and the prevalence of the urban population is higher than that of the rural areas in the suburbs (Li et al., 2020b). Thus, in order to validate the research findings, the study concentrated on the old, highly industrialized cities with high urbanization rates (Wang et al., 2019; Yang et al., 2019). A variety of spatial morphological factors affect the impact of the built environment on particulate matter concentrations. These factors include the use of land, the shape of the space, the traffic flow, the greenbelt, and the function of the environment, such as the growth of the city. The natural environment, which includes climate, air quality, and urban blue and green spaces, can effectively the reduce particulate matter and gaseous pollutants, and the more rivers and green spaces there are in an area, the lower the mortality rate for lung cancer (Fajersztajn et al., 2013; Wang et al., 2018). In winter, it is possible that the body will overreact when it is cold and the temperature falls, leading to the death of lung cancer. Differences in temperature between urban areas can affect mortality rates, *etc.* (Nielsen and Hansen, 2007; Tischer et al., 2017). However, the majority of studies have focused on the relationship between a single environmental factor and the prevalence of lung cancer. (Godden, 1958), and very few studies are classified as indicators, and they do not provide advice on how to optimize planning and design.

The effects of the built environment on air pollution and pollution exposure have typically been studied in previous studies, and due to the relatively independent effects of air pollution and pollution exposure on lung cancer mortality and incidence, specific interventions cannot be recommended (Booth et al., 2005; Brownson et al., 2009). It should also be noted that, although lung cancer risk varies individually, genes and the environment work together best to explain lung cancer incidence and mortality when combined with biological factors within the body that ultimately determine health (Mackellar, 2015). It is possible to reduce lung cancer by improving the environment (Vandenbroucke, 1988; Wu et al., 2016). As a result of environmental factors, including the built environment, the natural environment, and social factors, as well as biological factors within the body, lung cancer develops over time. Thus, we should pay greater attention to the effects of multiple environments on lung cancer mortality, as well as examine factors that can provide references for the prevention and control of lung cancer, as well as reducing its risk.

The research on the spatial and temporal characteristics of lung cancer mortality is mainly in the field of preventive medicine, most of the research focuses on gender, age, cause of death of cancer, *etc.*, and usually based on a single characteristic. The majority of studies are carried out at the macro level, such as at the county level, while small-scale studies, for example, at the community and street level, are scarce. The relationship between environmental factors and variations in the degree of impact caused by various environmental factors is not taken into account in the majority of spatially distributed environmental impact factor analyses.

In summary, this article aims to investigate the factors affecting lung cancer mortality in Bengbu Yuhui District, Huaihe River Basin by analyzing lung cancer mortality data from January 2017 to December 2020. Based on statistical analysis, spatial auto-correlation methods, Spearman's rank correlation and Geodetector models, we investigate the characteristics of the spatial and temporal distribution of lung cancer mortality, as well as the impact of environmental factors on lung cancer mortality. This paper proposes a series of research ideas, which can be used to build healthy cities in Huaihe River Basin and elsewhere. Thus, it provides a theoretical basis and a practical guide to reduce the risk of respiratory disease in urban populations.

2 Materials and Methods

2.1 Study area

In this paper, Yuhui District of Bengbu City, Anhui Province, China is chosen as the study area (Fig. 1), which includes 12 study blocks in the Yuhui District, Bengbu City in the northeastern part of Anhui Province. It is an important industrial city in Anhui Province, with its central and northern area reaching the Huaihe River (Zhao et al., 2014; Ma and Gui, 2017). The study area is

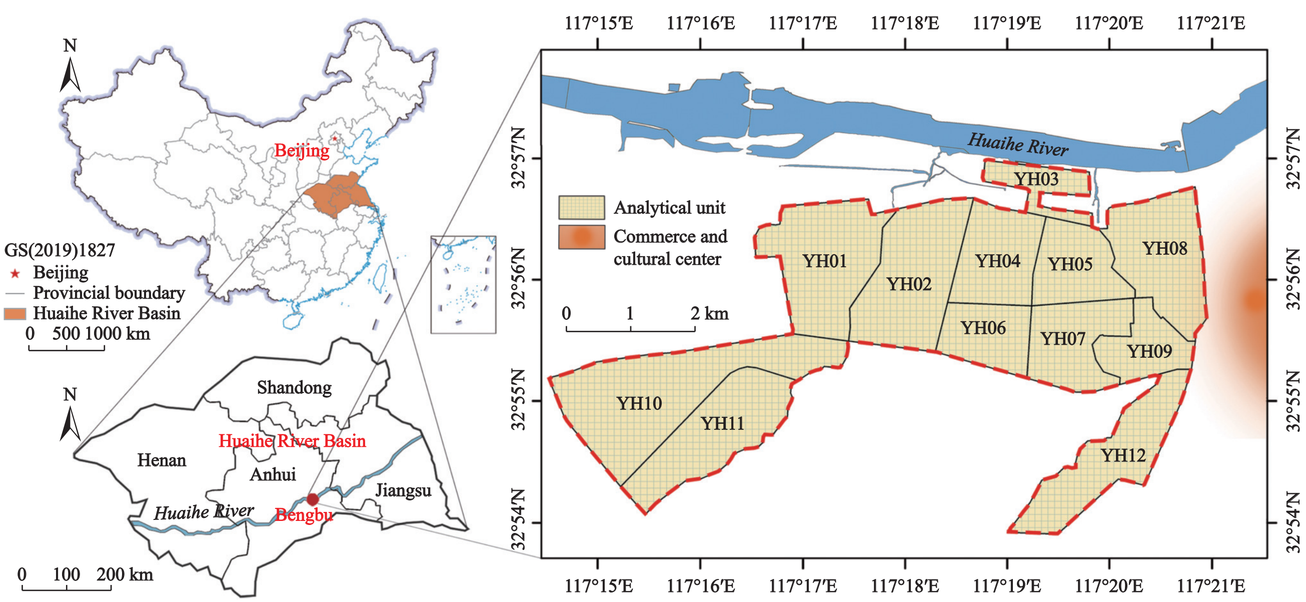

Fig. 1 The location of Yuhui District in Bengbu City, China

located in the western part of Bengbu City, on the south bank of the Huaihe River, and it is the old urban and most densely populated area in Bengbu City. The area is situated in the middle latitude area, with the prevailing northeasterly winds all year round, with an average temperature of 1°C in January and vulnerable to cold waves in winter. In 2019, it was estimated that there were 48.65 deaths from lung cancer for every 100 000 residents in China (National Health Commission of the People's Republic of China, 2020). The mortality in study area was 128/100 000 (data on lung cancer mortality rates collected from the Bengbu City Health Planning Commission), which was significantly higher than the national average value, so it is suitable for the study of population health and environmental impacting factor. The study area consist of 12 blocks numbered YH01–12, which are further divided into 2744 spatial units by 100 m grid, with the outliers excluded from the unavailable data.

2.2 Data source and processing

2.2.1 Dependent variable (*Data related to lung cancer death*)

The Bengbu City Health Planning Commission collected lung cancer deaths data from January 2017 to December 2020 from the ICD-10 (International Statistical Classification of Diseases and Related Health Problems 10th Revision) codes of C33-C34 (https://icd.who.int/browse10/2019/en#/U00-U49), including the deceased's address, age, and gender. Patients with an address and affiliation outside the study area were excluded, which made 343 patients in all. Based on the data entry, the patients were mainly elderly, and 86.88% of them were older than 60 years old. As a result, the mortality rate is calculated as follows:

$$M = \frac{Nc}{Np} \times K \quad (1)$$

where M represents the cumulative lung cancer mortality, Nc is the number of lung cancer deaths per unit in the same time period, and Np is the total number of patients with lung cancer at the same period; the proportionality factor K = 100 000/100 000 (The majority of lung cancers are relatively rare, and in medical practice, the cumulative rate or the cumulative mortality rate is often used, followed by a proportional factor, which is usually a decimal number). The unit of lung cancer mortality is the number of deaths per 100 000 people.

2.2.2 Independent variable (*Environmental data*)

Four types of environmental data were used in this study, including 1) land use data and built environment data obtained from the Anhui Urban & Rural Planning and Design Institute. In Bengbu, the landuse was classified according to *the Code for Urban Use Classes and Standards of Planning Construction Land* (GB 50137−2011) implemented on 1 January 2012, which included road, green space, river, residential land, and industrial land, as well as the number of floors for each building. 2) The data for commercial and bus stops for 2019 are derived from the Baidu Map Open Platform's point of interest (POI) data. Because the POI data has a large sample size, a wide coverage, and detailed spatial resolution, it makes spatial analysis more objective, comprehensive, and in-depth (Fig. 2). 3) Environmental pollution indicators data for 2019 were derived from Bengbu Bureau of Ecology and Environment. 4) Data of land surface temperature and vegetation coverage were derived from Landsat 8 remote sensing data in January 2019 provided by the United States Geological Survey website (USGS, https://www.usgs.gov/).

The data above were analyzed using GIS to determine evaluation indices for the environmental factors in the study, including POI density, building density, bus stop density, intersection density, and vegetation coverage. All variables related to lung cancer mortality are listed in Table 1.

2.3 Methods

2.3.1 Study framework

Firstly, the basic features and spatial distribution of the dead population of lung cancer were analyzed by means of Spatial Automatic Correlation Assessment, so as to find out the distribution features and impact hazards related to environment. Furthermore, the relationship between various environmental influencing factors and lung cancer mortality was examined by means of Spearman's rank correlation analysis, with lung cancer mortality as the dependent variable, and built environment and natural environment as independent variables, as shown in Fig. 3.

2.3.2 Spatial auto-correlation assessment

Spatial cluster analysis of diseases describes characteristics of disease spatial distribution, and determines whether there is a random distribution pattern in disease distribution.

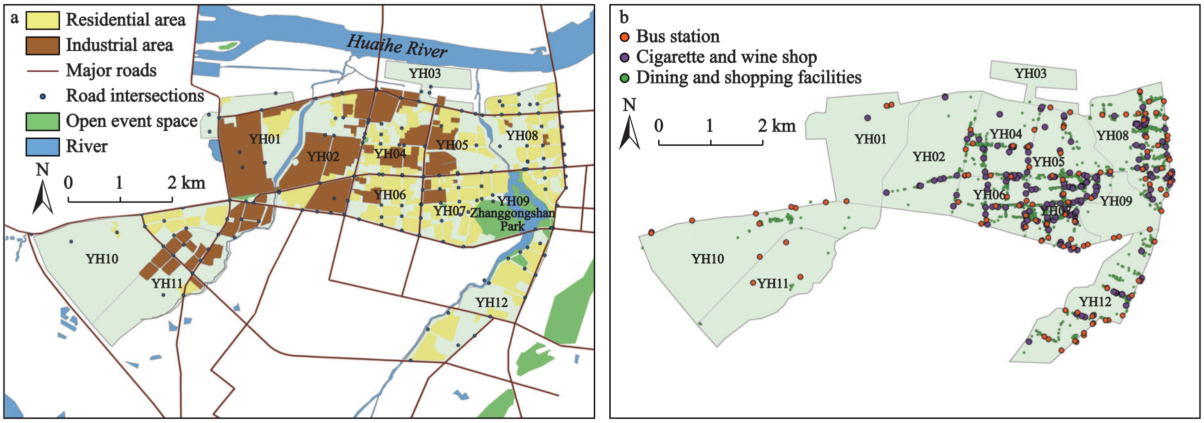

Fig. 2 Land uses categories (a) and POI (points of interest) type data (b) for 2019 in Yuhui District, Bengbu City, China

Table 1 Summary of environmental impact factors affecting lung cancer mortality in Yuhui District, Bengbu City, China

Environmental factor	Evaluation indicator	Impact factor	Scales and measurement method	Potential impact	Unit
Built environment	Land use	Residential density	Residential density; residential area/ total land area	Pollutant concentrations and open space (Frank et al., 2006)	%
		Commercial density	Catering facilities density; density of catering facilities in 500 m buffer zone	Motor vehicle emissions and environmental quality (Booth et al., 2005)	pcs/ha
			Alcohol and tobacco facilities density; density of alcohol and tobacco facilities in 500 m buffer zone	The effects of smoking and alcohol consumption on the body (Thun et al., 2006)	pcs/ha
	Road traffic	Road intersections density	Density of road intersections in 500 m buffer zone	Emissions of pollutants and noise impacts (Bidoliet al., 2016)	pcs/ha
		Bus stops density	Density of bus stops in 500 m buffer zone	Ease of travel and reduction of pollution emissions (Choi et al., 2018)	pcs/ha
	Spatial form	Building density	Building coverage ratio; the sum of the base area of buildings/ total planned construction land area	High density reduces ventilation corridors and increases exposure to pollutants (Wen and Malki-Epshtein, 2018)	%
		Volume ratio	Land use intensity, total building area/ total planned construction land area	High volume ratios reduce ventilation corridors and increase exposure to pollutants (Wen and Malki-Epshtein, 2018)	/
	Blue-green space	Vegetation cover	Normalized Difference Vegetation Index (NDVI)	Reduced air and noise pollution, high accessibility and pleasant mood (Nielsen and and Hansen, 2007)	/
		Distance to the river	Distance from the nearest river	Adsorption of airborne particulate matter by water bodies (Wang et al., 2018)	m
		Distance to the park	Distance from the nearest park	Accessibility, high openness (Tischer et al., 2017)	m
Natural environment	Air pollution	Particulate matter (PM) concentration	$PM_{2.5}$ and PM_{10} mean values, interpolated analysis	Air pollution exposure (Cao et al., 2018)	ug/m^3
		Gaseous pollutants concentration	SO_2, NO_2 and O_3 mean values, interpolation analysis	Air pollution exposure (Loomis et al., 2013)	ug/m^3
	Temperature	Surface temperature	Mean surface temperature, interpolation analysis	Cold winter temperatures increase the risk of disease and death (Hong et al., 2020)	°C

The global spatial auto-correlation of distribution (Liu et al., 2006; Mu and de Jong, 2012) is usually measured by Moran's I, with the value range of [–1, 1], and the higher value indicates the more remarkable spatial correlation, the lower value indicates the greater spatial difference, and the value 0 of global Moran's I

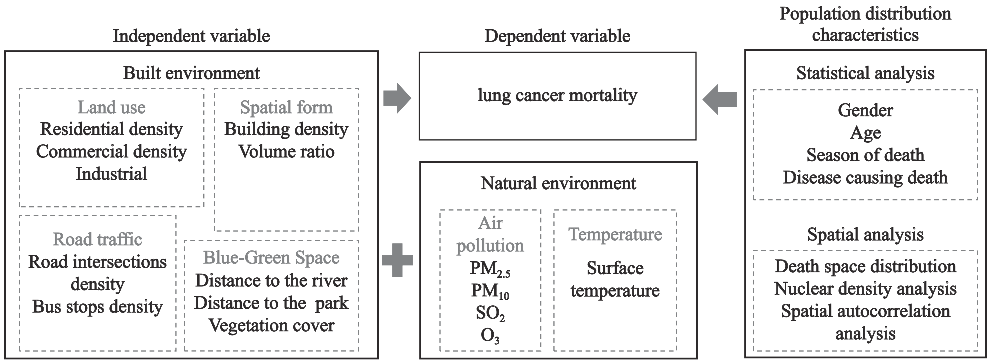

Fig. 3 Study framework of spatio-temporal distribution characteristics and environmental impact factors of lung cancer mortality analysis

indicates complete randomness (Hällfors et al., 2017; Li et al., 2018). The standardized statistic $Z(I)$ is usually used to test whether it is statistically significant after the Moran's I value is obtained. The null hypothesis was rejected when $Z > 1.96$ or $Z < -1.96$ and $P < 0.05$ at the significant level of spatial correlation $\alpha = 0.05$ of the statistical units (Pant et al., 2017), namely, there was spatial auto-correlation among the observed values of lung cancer mortality. The specific calculation formula is as follows:

$$\text{Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})\left(x_j-\bar{x}\right)}{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\sum_{i=1}^{n}(x_i-\bar{x})^2} (i \neq j) \tag{2}$$

where n represents the number of study units in the study area; x_i and x_j represent the lung cancer mortality in area i and area j, respectively; $\bar{x}$ represents the average mortality of lung cancer in the study area; W_{ij} represents the spatial weight matrix. An analysis of the spatial weight matrix illustrates the degree of positional association between each of the study units, $W_{ij} = 1$ means study area i and area j are 'neighbours', otherwise $W_{ij} = 0$. The auto-correlations may differ significantly based on the spatial weight matrix used. A value of $I > 0$ indicates that lung cancer mortality is positively correlated overall, with high (low) value study units clustering together. $I = 0$ indicates that lung cancer mortality is randomly distributed; A value of $I < 0$ indicates that lung cancer mortality is negatively correlated overall.

Local spatial auto-correlation can detect local spatial aggregation, and spatial heterogeneity determines which units have the observed values with larger impact, and identifies the spatial clustering positions of elements with high or low values for lung cancer mortality (Moore et al., 2017; Fu et al., 2017). The spatial difference of lung cancer mortality was measured by local indicators of spatial association (LISA) in this study, with the calculation formula shown as follows:

$$LISA_i = z_i \sum_{j} W_{ij} z_j \tag{3}$$

where z_i and z_j represent the standardized values of lung cancer mortality in area i and area j, respectively. W_{ij} represents the spatial weight matrix. LISA of local spatial auto-correlation identifies four spatial association patterns for lung cancer mortality: High-High clustering, high-value clustering; Low-Low clustering, low-value clustering; High-Low clustering, excluding high values and focusing primarily on low values; Low-High clustering, excluding low values and focusing primarily on high values (Liu et al., 2017b).

2.3.3 Spearman's rank correlation assessment

Lung cancer mortality data are not continuously equidistant, and their forms of correlation and patterns of distribution are unknown. If Pearson's rank correlation coefficient is directly used for analysis, the results may be inaccurate. Therefore, this paper uses Spearman's rank correlation analysis to improve the accuracy of the analysis. Spearman's rank correlation coefficient (Liu et al., 2015; Song et al., 2021) is a non-parametric correlation coefficient. This coefficient has no requirements regarding the selection of raw data, the form of the correlation, and the pattern of distribution. It is typically used to measure the strength of a monotonic relationship or rank correlation between variables.

In order to investigate the relationship between lung cancer and environmental influencing factors, the correlation between the mortality of lung cancer (dependent variable) and the values of various environmental factors (independent variables) was comprehensively measured by Spearman's rank correlation coefficient (Colditz et al., 1987). Lung cancer mortality and environmental influencing factors were subject to normalized processing (value range of [0, 1]), which was used to balance the dimensional gap between data, and enable different data to be counted under the same conditions, represented with the calculation formula:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{4}$$

where r_s represents Spearman's rank correlation coefficient, with the value range of [–1, 1], and the larger absolute value indicates the stronger correlation. n represents the number of lung cancer mortality studied units, and $i = 1 \ldots n$. d_i represents the rank difference between the dependent variable (lung cancer mortality) and the independent variable (environmental influencing factor values) (Cao et al., 2018).

2.3.4 Assessment of spatial stratified heterogeneity

A stratified heterogeneity (Wang et al., 2016b) can not only refer to a quantitative index whose intra-layer variance is smaller than the inter-layer variance, but also a significant difference between factors on the spatial distribution as measured by q statistics. The higher the q value is, the greater its effect on lung cancer mortality. Additionally, a q value of 0 indicates that there is no spatial differentiation. Geodetector software was used to conduct factor interaction detection in this study, with the calculation formula as follows:

$$q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2} = 1 - \frac{SSW}{SST} \tag{5}$$

where $SSW = \sum_{h=1}^{L} N_h \sigma_h^2$, $SST = N\sigma^2$, and the study areas are divided into h strata, $h = 1 \ldots L$; N_h and N represent the number of units in layer h and the study area, respectively. σ^2 represents the variance of lung cancer mortality, and σ_h represents the variance of intra-layer index. SST and SSW represent the total quadratic sum and the inner quadratic sum, respectively.

3 Results and Analysis

3.1 Spatio-temporal distribution characteristics of lung cancer deaths

3.1.1 Temporal distribution characteristics of lung cancer deaths

From January 2017 to December 2020, 343 cases of lung cancer deaths were studied in the study area, with an incidence rate of 0–0.8 (per 100 000 people). A seasonal pattern is evident in the time distribution of lung cancer mortality over the period 2017–2020 (Fig. 4). There are a large number of patients in winter (December to February) every year, on the other hand, there is a small difference in the number of patients in other seasons. In light of Spearman's rank correlation analysis between different seasons and mortality, it can be concluded that winter is strongly correlated with mortality (r_s = –0.690**, P= 0.000). Therefore, it shows that lung cancer death is vulnerable to climate conditions, mostly in winter (December to February). It can be inferred that the incidence trend based on time series may be closely related to temperature and humidity.

According to numerical statistical analysis, the mortality rate of male lung cancer patients was about 2.77:1 higher than that of female lung cancer patients. People over 80-year-old accounted for 27.12% of lung cancer deaths, while under 60 accounted for only 13.12% (Table 2). Thus, older patients have higher mortality.

3.1.2 Spatial distribution of lung cancer deaths

In the study area, lung cancer deaths occurred in a number of blocks from 2017 to 2020, with certain differences among the blocks. According to Fig. 5a, there is a significant difference in the distribution of lung cancer deaths, with 78.61% being attributed to YH07 and YH08. Based on the results of the analysis, lung cancer deaths were primarily concentrated around Unit YH09 in Zhanggongshan Park and north of Unit YH08 near the Huaihe River. Bengbu's old urban area, close to Unit YH09, is characterized by high population density and serious aging. The number of deaths is higher in the area surrounding the old urban area and the Huaihe River.

The normalized lung cancer mortality index showed spatial auto-correlation between 2017 and 2020 according to the global Moran's I index (Moran's I > 0, Z = 2.367, P < 0.05). The probability that the spatial distribution pattern of lung cancer mortality is random is less

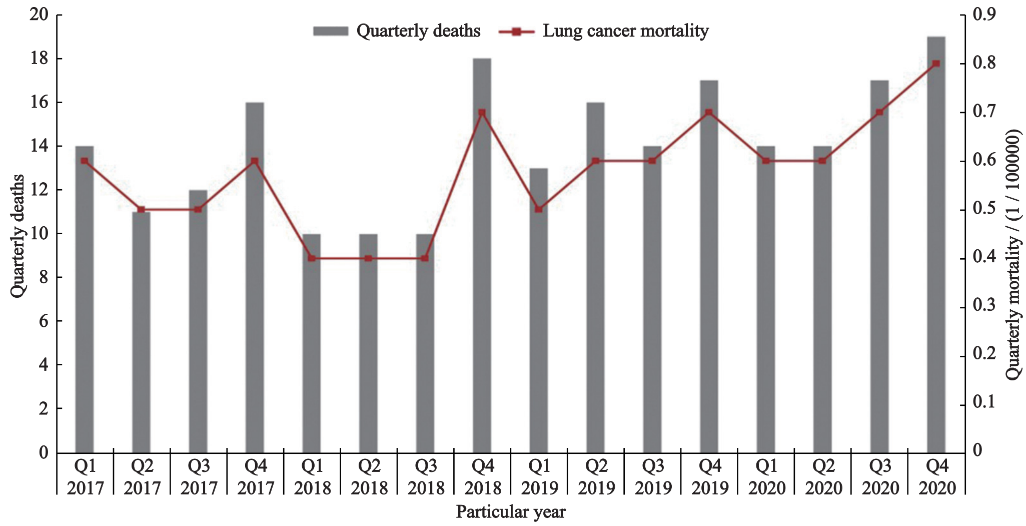

Fig. 4 Seasonal distribution characteristics of lung cancer deaths in Yuhui District, Bengbu City, China in 2017–2020; Q1 represents spring (March–May), Q2 represents summer (June–August), Q3 represents autumn (September–November), and Q4 represents winter (December to February)

Table 2 Descriptive statistics of lung cancer death cases of Yuhui District, Bengbu City, China in 2017–2020

Variable	Categories	Number of deaths	Proportion in deaths / %
Gender	Man	252	73.47
	Woman	91	26.53
Age	< 60	45	13.12
	60–69	87	25.36
	70–79	118	34.40
	≥ 80	93	27.12
Season	Spring (March–May)	77	22.45
	Summer (June–August)	90	26.24
	Autumn (September–November)	83	24.20
	Winter (December to February)	93	27.11

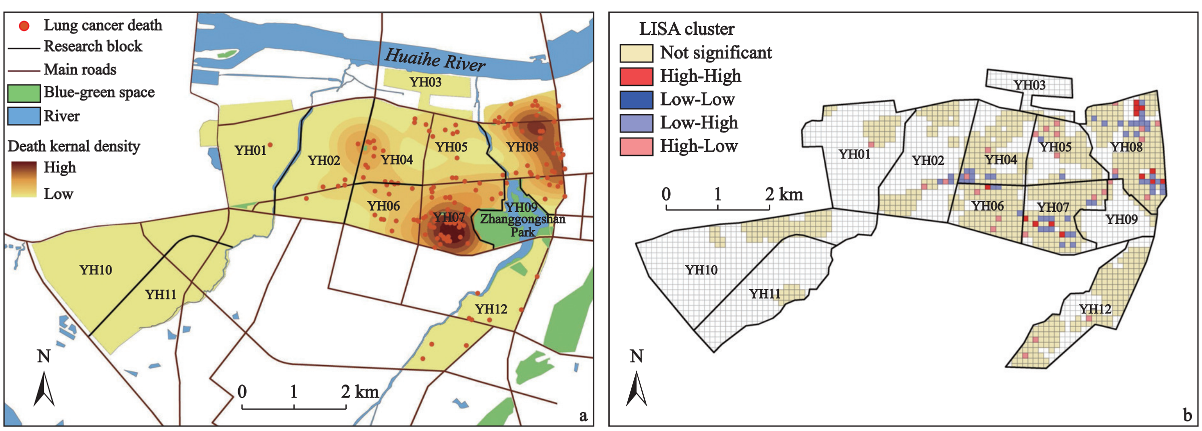

Fig. 5 Spatial distribution (a) and spatial auto-correlation (b) of lung cancer mortality in Yuhui District, Bengbu City, China in 2017–2020

than 0.01. If the probability of having a random distribution is significantly lower than that of spatial clustering, then the null hypothesis can be strongly rejected, which suggests that there is an obvious spatial clustering pattern and a positive spatial correlation for lung cancer mortality.

Furthermore, the normalized mortality index exhibited local spatial auto-correlation based on the clustering and outlier analysis of the LISA clustering spatial distribution (Fig. 5b), where Low-Low clusters (0) and High-High clusters (13) were primarily located in the block units YH07 and YH08. The analysis indicates that these two blocks were the areas with the highest risk of lung cancer death, and the blocks near the old urban area and Zhanggongshan Park, which were densely populated areas, were taken into account when determining the optimal strategy. Overall, the distribution of lung cancer mortality followed the spatial characteristics of geographical proximity and network proximity of each block.

3.2 Detection of the influencing factors of lung cancer death

3.2.1 Analysis of the relationship between environmental factors and lung cancer mortality

According to Table 3, 15 environmental factors have been identified with significant correlations and statistical significance ($P < 0.05$) that may affect lung cancer mortality. However, their correlation coefficients were different. The most significant environmental factor was the residential density. The other factors followed include alcohol and tobacco facilities density, catering facilities density, bus stops density, volume ratio, road intersections density, building density, and the distance to the river, PM_{10} (inhalable particulate matter), $PM_{2.5}$ (fine particulate matter), O_3, NO_2 successively, and a significant negative correlation was found among three environmental factors, namely the (ground) surface temperature, the distance to the park, and the vegetation cover (from high to low). No correlation between industry and lung cancer mortality was found in this study (P>0.05)basedonadifferenceanalysisofSO_2(sulfurdioxide). Fig. 6 illustrates the relationship between different death ①groups and environmental factors in the Yuhui District, Bengbu from 2017 to 2020.

(1) Built environment

Residencial density was significantly and positively associated with lung cancer mortality (r_s = 0.281).

Table 3 Spearman's rank correlation tests for the relationship between independent variables and lung cancer mortality in Yuhui District, Bengbu City, China

Environmental factor	Evaluation indicator	Impact factor	Scale	Correlation coefficient	Significance (two-tailed)
Built environment	Land use	Residential density	Residential density	0.281**	0.000
		Commercial density	Catering facilities density	0.240**	0.000
			Alcohol and tobacco facilities density	0.250**	0.000
	Road traffic	Road intersections density	Road intersections density	0.197**	0.000
		Bus stops density	Bus stops density	0.219**	0.000
	Spatial form	Building density	Building density (building coverage ratio)	0.179**	0.000
		Volume ratio	Volume ratio (land use intensity)	0.208**	0.000
	Blue-green space	Vegetation cover	Normalized Difference Vegetation Index (NDVI)	−0.152**	0.000
		Distance to the river	Distance from the nearest river	0.125**	0.000
		Distance to the park	Distance from the nearest park	−0.153**	0.000
Natural environment	Air pollution	Particulate matter (PM) concentration	$PM_{2.5}$ mean value	0.110**	0.000
			PM_{10} mean value	0.118**	0.000
		Gaseous pollutants concentration	SO_2 mean value	0.020	0.301
			NO_2 mean value	0.059**	0.002
			O_3 mean value	0.040*	0.039
	Temperature	Surface temperature	Mean surface temperature	−0.134**	0.000

Notes: *$P < 0.05$, **$P < 0.01$

① The death of lung cancer was divided into gender and age groups, of which gender was divided into male and female; the age group is divided into < 60, 60–69, 70–70, ≥ 80.

Therefore, the risk of death from lung cancer tends to increase when the residential density increases. There was a significant positive correlation between the density of catering facilities and alcohol and tobacco facilities and lung cancer mortality (r_s = 0.240 and r_s = 0.250, respectively), indicating that lung cancer mortality tends to increase when the density of catering facilities and alcohol and tobacco facilities increases.

In terms of road traffic, there was a significant positive correlation (r_s = 0.197) between the density of road intersections and lung cancer mortality. Therefore, lung cancer mortality tends to increase as road intersections increase. A significant positive correlation was observed between bus stop density and lung cancer mortality (r_s = 0.219). This indicates that lung cancer mortality tends to increase when the density of bus stops increases.

There was a significant positive correlation between building density and volume ratio and lung cancer mortality (r_s = 0.179, r_s = 0.208). This indicates that lung cancer mortality tends to increase when building density and volume ratio are higher.

Similar to blue-green space, vegetation cover was negatively correlated with lung cancer mortality (r_s = −0.152). Thus, when the number of green spaces increases, lung cancer mortality tends to decrease. Distance to the river was significantly correlated with lung cancer mortality (r_s= 0.125). This indicates that the risk of lung cancer mortality tends to decrease as one gets closer to the river. A statistically significant correlation was found between distance from a park and lung cancer mortality (r_s= −0.153). As a result, lung cancer mortality tends to decrease as one moves further away from the park.

(2) Natural environment

A significant positive correlation was found between PM_{10} and $PM_{2.5}$ concentrations and lung cancer mortality (r_s = 0.118 and r_s = 0.110, respectively). As a result, lung cancer mortality tends to increase when the concentration of particulate matter increases. In gaseous pollutants, NO_2 and O_3 concentrations were significantly positively related to lung cancer mortality (r_s = 0.059 and r_s = 0.040, respectively). The results indicate that the risk of lung cancer mortality tends to increase when the concentration of gaseous pollutants increases.

In terms of (ground) surface temperature, there was a significant negative correlation (r_s=−0.134) between (ground) surface temperature and lung cancer mortality. This indicates that lung cancer mortality tends to increase in colder winter months.

(3) Analysis of various lung cancer mortality

The correlation between lung cancer mortality among males and females and environmental factors was similar at bus stops density (r_s = 0.437, r_s = 0.416) and catering facilities density (r_s= 0.159, r_s= 0.306). As a result, lung cancer mortality tends to increase in old urban areas with more bus stops and catering facilities. In addition, there was a significant negative correlation between river distance and park distance. There is a lack of green space in older urban areas, resulting in a concentration of open space in the city's core area. Mortality tends to increase as people move closer to rivers and parks. Temperature and mortality had a significant negative relationship (r_s = −0.130, r_s = −0.442). As a result, lung cancer mortality tends to increase as the temperature decreases. Although there are some similarities between men and women, there are also some differences as well. A strong correlation exists between female mortality rate and SO_2 concentration. At higher concentrations, lung cancer mortality tends to increase.

People under 60-year-old had a weak correlation with environmental factors as a whole, whereas people over 60 had a strong positive correlation with bus stops density, from large to small in the age group (r_s = 0.492, r_s = 0.430, r_s = 0.447). Therefore, lung cancer mortality tends to increase when the density of bus stops increases. There was a significant negative relationship between temperature and mortality (r_s = −0.428, r_s = −0.330, r_s = −0.302), indicating that mortality tends to increase at lower temperatures. There are, however, some differences as well. A positive correlation existed between lung cancer mortality and catering facilities density (r_s = 0.390), while a negative correlation existed between lung cancer mortality and distance to the river (r_s = −0.329). As a result, the further away from the river, the lower the lung cancer mortality tends to be. The lung mortality among individuals aged 70 to 79 was negatively correlated with the density of road intersections, suggesting that the higher the density of road intersections, the lower the lung cancer mortality tends to be.

3.2.2 Analysis of spatial stratified heterogeneity of environmental impact factors

The spatial distribution of lung cancer mortality is af-

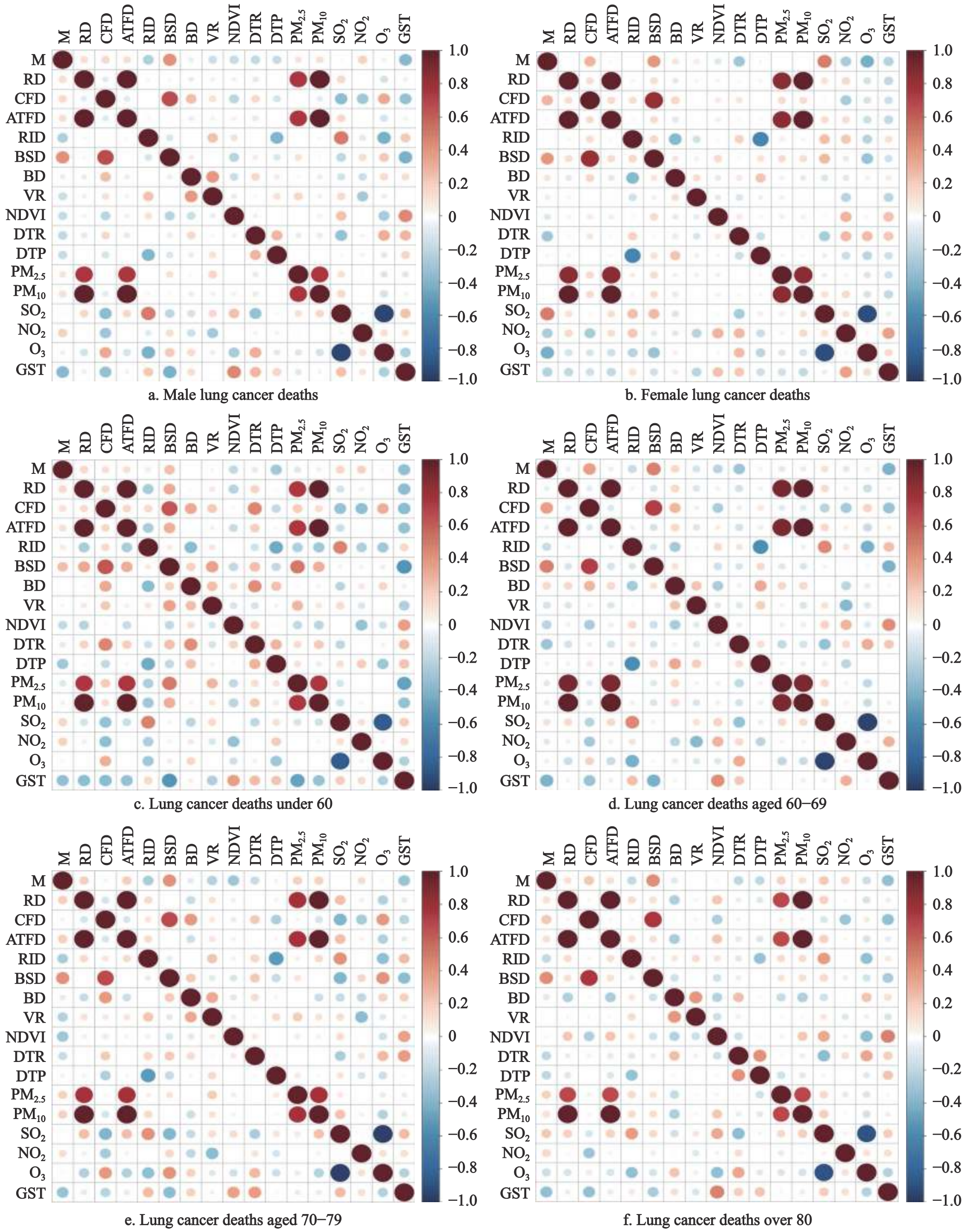

Fig. 6 Correlation coefficients between different lung cancer mortality and environmental factors in Yuhui District, Bengbu City, China in 2017–2020. M represents lung cancer mortality, RD represents residential density, CFD represents catering facilities density, ATFD represents alcohol and tobacco facilities density, RID represents road intersections density, BSD represents bus stops density, BD represents building density, VR represents volume ratio, NDVI represents the vegetation cover, DTR represents the distance to the river, DTP represents the distance to the park, $PM_{2.5}$ represents the concentration of $PM_{2.5}$, PM_{10} represents the concentration of PM_{10}, SO_2 represents the concentration of SO_2, NO_2 represents the concentration of NO_2, O_3 represents the concentration of O_3, GST represents the surface temperature

fected by different indices of spatial stratified heterogeneity. Geodetector's factor detection results indicate that all selected factors were statistically significant at $P < 0.05$. A detailed analysis of interactions between factors impacting lung cancer mortality was conducted using the interaction detector. The effect of building density alone on lung cancer mortality was weak (q = 0.005). As shown in Table 4, when combined with other factors, the interaction between two factors has an explanatory power of 0.152. As a result, the interaction between various influencing factors was greater than their individual effects.

4 Discussion

In order to prevent diseases, it is of great importance to evaluate the risk of death. The purpose of this study was to investigate the characteristics of the spatial and temporal distribution of lung cancer mortality in the study area and the effect of the environment. In this paper, the law of disease deaths was explored from a spatial perspective at the macro level using spatial auto-correlation and other methods. Through the analysis of spatial stratified heterogeneity, we can identify the key factors of the built environment and the geographical changes in their scale and direction. These methods not only offer a new way of looking at the health of the population, but also provide more efficiency and efficiency compared to traditional census data or social and economic statistics. Studies have shown that urban built environments can affect respiratory health by altering air quality and human behavior, such as physical activity (Gottlieb, 1983).

In terms of the built environment, 1) land use: there is evidence that both high building density and volume ratio, as well as the increased pollution exposure in high-density areas, have negative effects on lung cancer mortality, which supports our conclusion that the lung cancer mortality is positively correlated with density. It is possible to integrate industrial land with residential land in the future to provide job-housing balance, reduce local car trips (Xu and Wang, 2018), and increase walking and cycling commuting, thereby reducing pollution and human exposure. 2) Road traffic: combining multiple destinations within walking distance will reduce the use of motor vehicles, thereby reducing air pollution and carbon dioxide emissions (Chen et al., 2010). In addition, walking and cycling will be promoted. Our findings indicate that lung cancer deaths are positively correlated with high road density and traffic volume. Green belts planted 50−100 m away from low urban roads are recommended for dust control and to reduce residents' exposure to high levels of motor vehicle emissions. 3) Spatial form: as a result of low frontal density, particulate matter diffuses more rapidly and is less concentrated (Wen and Malki-Epshtein, 2018). The use of land that is conducive to air pollution should be minimised, with particular emphasis on unconventional uses, such as catering facilities. In order to improve physical fitness and enhance immunity, it is necessary to reduce the density of buildings, to improve the accessibility of housing, to improve natural ventilation and to improve the interior functions of housing. 4) Blue-green space: the presence of green space and the proximity of a river can reduce air pollution and reduce lung cancer mortality. Moreover, the layout of the green space is beneficial to the greates. In summer, the more green space patches, the lower the concentration of $PM_{2.5}$, and green spaces also purify the air and adsorb dust, thus reducing the risk of lung cancer.

From the natural environment point of view, the gradual increase in lung cancer mortality is attributed to

Table 4 Results of the interaction of environmental influences on lung cancer mortality inYuhui District, Bengbu City, China

Interaction factors	Building density	Surface temperature	Catering facilities density	Alcohol and tobacco facilities density	Bus stops density	Road intersections density
Building density	0.005					
Surface temperature	0.019	0.004				
Catering facilities density	0.031	0.013	0.008			
Alcohol and tobacco facilities density	0.152	0.022	0.018	0.011		
Bus stops density	0.070	0.026	0.036	0.034	0.018	
Road intersections density	0.098	0.026	0.044	0.054	0.055	0.012

Notes: After Geodetector model interactions, six factors were found to be statistically significant, namely building density, (ground) surface temperature, catering facilities density, alcohol and tobacco facilities density, bus stops density and road intersections density.

higher concentrations of NO_2 and total suspended particles in the air. There are a number of factors that affect the generation of fine particulate matter in the atmosphere, including geographic factors, climatic conditions, and human behavior. The built environment is closely related to air pollution (Wang et al., 2016b). Air pollution affects the concentration distribution of atmospheric particulate matters through urban form, land use, development intensity, traffic, green space, and open space, thereby affecting lung cancer mortality (Ma and Gui., 2017). Human respiratory systems are the most important target organs of air pollution and atmospheric fine particulate matter exposure, and prolonged excessive exposure may result in reduced lung function. Over time, long-term exposure to this chemical may decrease lung function, trigger an inflammatory response, cause oxidative stress, and damage DNA. These mechanisms can contribute to the increase in lung cancer mortality (Vineis et al., 2006; Ren et al., 2018). In conclusion, among the natural environmental factors, the air pollution and the environment influence the death rate of lung cancer. Ultimately, it causes systemic inflammation and increases the likelihood of death. This is consistent with the findings of the study.

The study is fine-tuned and innovative in terms of the research scale; in stead of the scales of counties, states, and states, we focused on smaller scales, like communities and streets. Furthermore, we have broken the traditional one-factor model, identified 16 influential factors, classified the influential factors according to the type, and explored the variety of factors affecting the mortality of lung cancer. Based on geographical detectors, the explanation of each environmental factor and its pairwise interaction on lung cancer mortality was quantified in the discussion of the impact mechanism. Yet, there are limitations in our study. Firstly, there is a lack of information regarding smoking, genetics, and individual habit factors. Secondly, the study area is located in the old city where lacks open space. Crowd activities are largely concentrated near Zhanggongshan Park in the study area. When deciding where to live, the elderly deliberately choose to live in an open space (Wang and Pan, 2015). As a result, middle-aged and elderly individuals are at a higher risk of lung cancer death. Consequently, the results of this experiment differed from those of general research. We found that the closer to the park, the greater the risk of lung cancer. Likewise, the greater the vegetation coverage, the greater the risk of lung cancer death.

5 Conclusions

Based on discussion on the spatial and temporal distribution characteristics of lung cancer mortality in the urban residents in Yuhui District, Bengbu City, China, we examined the environmental factors impacting lung cancer mortality and their interactions, as well as factors influencing the risk of death and their mechanisms. Several conclusions have been drawn:

(1) First, there is a significant correlation betweem lung cancer mortality and the season and temporal latitude. There are a large number of patients in winter (December to February) every year, and results have shown that lung cancer mortality is highly correlated with climatic conditions.

(2) Second, there is a strong spatial clustering pattern of lung cancer mortality, which is concentrated in the old urban area and the center of Bengbu, close to the Huaihe River

(3) Finally, the interaction and integration of several factors resulted in the spatial differentiation model of lung cancer mortality, which is closely related to the environment There is a complex relationship between the built and natural environments and lung cancer mortality. Key factors include land use, road traffic, spatial form, blue-green spaces, temperature, and the concentration of pollutants. According to the analysis of the specific effects of each proxy variable on lung cancer mortality, alcohol and tobacco facilities density, road intersections density, bus stops density, catering facilities density, and building density affected spatial differentiation of lung cancer. Single-factor effects had less explanatory power than two-factor interactions.

Based on the above findings, the mortality of lung cancer exhibits distinct spatial and temporal features and is strongly correlated with multiple environmental factors. The following measures can be adopted to reduce the death rate of lung cancer in the construction of a healthy city: increase open transportation space in residential areas, reduce building density and volume ratio, increase open space to reduce pollutant concentrations, and decentralize the layout of catering facilities and alcohol and tobacco facilities. To reduce traffic and vehicle emissions, public transportation investments should be increased in regional residential areas. The creation of networks, the systematization of layouts, and the intensification of blue-green spaces. As a result of these approaches, airborne particulate matter emissions will be significantly reduced, the urban climate will be improved, and policy advocacy will be strengthened to reduce particulate matter emissions and gaseous pollutants. Aside from smoking, genetics, and personal behavior are not the only factors that contribute to lung cancer incidence and mortality. Future studies should focus on the characteristics of the individual population.

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