Environmental Science and Pollution Research (2023) 30:126165–126177
https://doi.org/10.1007/s11356-023-31138-8

RESEARCH ARTICLE

Exploring the association of $PM_{2.5}$ with lung cancer incidence under different climate zones and socioeconomic conditions from 2006 to 2016 in China

Bin Guo[1] · Qian Gao[1] · Lin Pei[2] · Tengyue Guo[3] · Yan Wang[4] · Haojie Wu[1] · Wencai Zhang[5] · Miaoyi Chen[1]

Received: 4 August 2023 / Accepted: 16 November 2023 / Published online: 27 November 2023

Abstract

Air pollution generated by urbanization and industrialization poses a significant negative impact on public health. Particularly, fine particulate matter ($PM_{2.5}$) has become one of the leading causes of lung cancer mortality worldwide. The relationship between air pollutants and lung cancer has aroused global widespread concerns. Currently, the spatial agglomeration dynamic of lung cancer incidence (LCI) has been seldom discussed, and the spatial heterogeneity of lung cancer's influential factors has been ignored. Moreover, it is still unclear whether different socioeconomic levels and climate zones exhibit modification effects on the relationship between $PM_{2.5}$ and LCI. In the present work, spatial autocorrelation was adopted to reveal the spatial aggregation dynamic of LCI, the emerging hot spot analysis was introduced to indicate the hot spot changes of LCI, and the geographically and temporally weighted regression (GTWR) model was used to determine the affecting factors of LCI and their spatial heterogeneity. Then, the modification effects of $PM_{2.5}$ on the LCI under different socioeconomic levels and climatic zones were explored. Some findings were obtained. The LCI demonstrated a significant spatial autocorrelation, and the hot spots of LCI were mainly concentrated in eastern China. The affecting factors of LCI revealed an obvious spatial heterogeneity. $PM_{2.5}$ concentration, nighttime light data, 2 m temperature, and 10 m u-component of wind represented significant positive effects on LCI, while education-related POI exhibited significant negative effects on LCI. The LCI in areas with low urbanization rates, low education levels, and extreme climate conditions was more easily affected by $PM_{2.5}$ than in other areas. The results can provide a scientific basis for the prevention and control of lung cancer and related epidemics.

Keywords Lung cancer · $PM_{2.5}$ · Modification effects · Climate change · GTWR · GIS

Introduction

Lung cancer, ranked as the deadliest for men and the second deadliest for women, is one of the most severe malignancies worldwide (Hawrysz et al. 2022; Mattiuzzi and Lippi 2019). In 2018, the International Agency for Research on Cancer (IARC) released global cancer statistics showing that lung cancer accounted for 11.6% of cancer incidence and 18.4% of mortality; it ranks first in cancer incidence and mortality (Bray et al. 2020).

Lung cancer is possibly affected by the synergistic effects of many factors such as air pollution, meteorology, urbanization, industrialization, aging population, and lifestyles (Liu et al. 2023). In particular, the correlation between fine particulate matter ($PM_{2.5}$) and lung cancer is very significant (Feng et al. 2021; Hill et al. 2023; Zhang et al. 2023). $PM_{2.5}$ has become one of the prominent influential factors of lung cancer (Hvidtfeldt et al. 2021; Wu et al. 2023; Guo et al. 2023a).

Responsible Editor: Lotfi Aleya

Bin Guo and Qian Gao contributed equally to this work.

✉ Bin Guo
guobin12@xust.edu.cn

1 College of Geomatics, Xi'an University of Science and Technology, Xi'an 710054, Shaanxi, China

2 School of Exercise and Health Sciences, Xi'an Physical Education University, Xi'an 710068, Shaanxi, China

3 Department of Geological Engineering, Qinghai University, Xining 810016, Qinghai, China

4 School of Geography and Tourism, Shaanxi Normal University, Xi'an 710119, Shaanxi, China

5 College of Land Science and Technology, China Agricultural University, Beijing 100193, China

Severe air contamination in China caused by the acceleration of industrialization and urbanization, especially $PM_{2.5}$, has become an increasingly serious issue, leading to a rising risk of lung cancer (Luo et al. 2019; Wang et al. 2019a). In recent years, the Chinese government has launched and carried out a series of air pollutants control measures such as the " Ten Air Pollution Measures" and the " Blue Sky Protection Campaign." The average annual $PM_{2.5}$ concentration has reached or approached the lower limit of 35 μg/m^3 in most regions. However, there is still a significant gap compared with the annual average $PM_{2.5}$ concentration guideline of 5 μg/m^3 published by the World Health Organization (Wang et al. 2019b; Yin et al. 2020). Outdoor $PM_{2.5}$ exposure caused 145,600 lung cancer deaths in 2016 in China, accounting for 24.66% of the total lung cancer deaths (Zheng et al. 2021). Currently, previous studies have proved that the occurrence of lung cancer is not only related to genetic factors and smoking factors (Ni et al. 2020), but also correlated with social economy (Rosskamp et al. 2021), meteorology (Ansari and Ehrampoush 2019), green vegetation (Kayyal-Tarabeia et al. 2022), and terrain factors (Hawrysz et al. 2022). Therefore, it is urgent and necessary to determine the influencing factors of lung cancer.

Published research has revealed that the lung cancer incidence (LCI) of China represented spatial autocorrelation (Guo et al. 2016; Xing et al. 2019). However, most existing studies have analyzed the relationship between LCI and influencing factors from a global perspective (Guo et al. 2021c; Li et al. 2021), while the differences in influencing factors on LCI from a local perspective have been always ignored. Hence, it is important and valuable to explore the heterogeneity of influential factors on LCI for identifying the hot spots and spatiotemporal variation trend of LCI. A variety of statistical models have been used to study the relationship between different influencing factors and the LCI. However, most of the traditional statistical models are global linear models without considering the effects of affecting factors on LCI from a local perspective. To address the above issues, machine learning algorithms such as support vector regression (SVR) (Huang et al. 2023), geographically weighted regression model (GWR) (Al-Ahmadi and Al-Zahrani 2013; Chan et al. 2019), quantile regression (QR) (Momenyan et al. 2016), and ridge regression (RR) (Zhang 1986) have been introduced to LCI studies. SVR can effectively solve collinearity and depict the nonlinear relationship between influencing factors and LCI (Sekeroglu and Tuncal 2021); the spatial heterogeneity of influencing factors can be considered by GWR (Guo et al. 2021a, 2022b). However, the time correlation of LCI and its affecting factors were ignored by both SVR and GWR. Fortunately, the capability of the geographically and temporally weighted regression (GTWR) model in capturing the spatiotemporal heterogeneity of variables has been confirmed by existing studies (Guo et al. 2023b; Huang et al. 2021). Therefore, it is very necessary to verify the feasibility and reliability of the GTWR model in determining the quantitative relationship between LCI and influencing factors. Exploring the spatiotemporal heterogeneity of influencing factors of LCI can help form targeted prevention and intervention measures for lung cancer.

In addition, meteorological and socioeconomic factors are considered important factors for LCI besides $PM_{2.5}$. Although the significant effects of socioeconomic and meteorological factors on LCI have been confirmed, the modification effects of $PM_{2.5}$ on LCI under different socio-economic levels and climate zones have not been discussed up to now. So, it is necessary to detect the modification effects of $PM_{2.5}$ on LCI under different socioeconomic levels and climate zones.

Based on the above research dynamic, this study aims to explore the spatiotemporal agglomeration dynamic of LCI in China from 2006 to 2016, to indicate the spatial heterogeneity of influential factors on LCI, and to demonstrate the modification effects of $PM_{2.5}$ on LCI under different socioeconomic levels and climatic zones.

Materials and methods

Study area

The elevation of China decreases from west to east. The climate exhibits diverse types including monsoon climate, continental climate, and alpine climate. The temperature rises from north to south. The physical geography of each region represents significant heterogeneity.

In this paper, China was selected as the study area. Meanwhile, city and county (or district) were selected as the study scale. LCI in China ranks first in the world (Li et al. 2020), and $PM_{2.5}$ pollution is serious in East and Northwest China (He et al. 2019). To explore the modification effects of $PM_{2.5}$ on LCI under different climatic zones, according to the typical monsoon climatic zones of China, the study areas were divided into five climatic zones (Fig. 1).

Data collection and pretreatment

The data used in this study include epidemiological statistical dataset, $PM_{2.5}$ concentration dataset, socio-economic dataset, meteorological dataset, and auxiliary dataset (Table 1).

To eliminate the influence of age and gender, the age-standardized incidence of lung cancer (International Classification of Diseases (ICD) code: C33-34) of each city or county (or district) in China Annual Cancer Registry was chosen as the dependent variable. One important reminder needs to be stated. The number and location of tumor registration stations in China

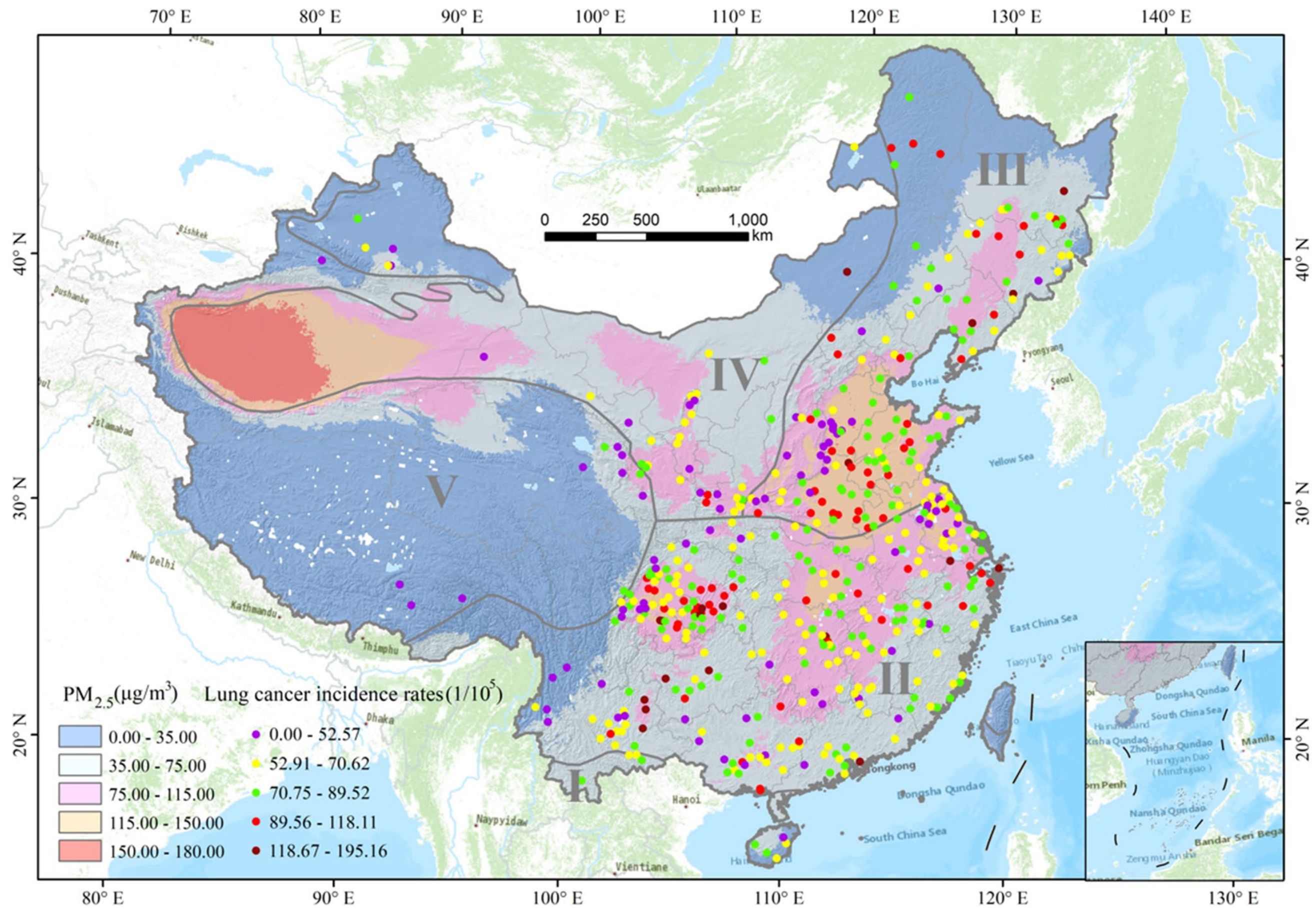


Fig. 1 The distribution map of annual mean $PM_{2.5}$ concentrations and LCI in China in 2016. Note: I, II, III, IV, and V represent tropical monsoon climate (Trmc), subtropical monsoon climate (Smc), temperate monsoon climate (Tmc), temperate continental climate (Tcc), and Alpine climate (Ac), respectively

Table 1 Data sources and descriptions

Data types	Indicators	Duration	Resolution	Sources
Lung cancer incidence (LCI)	Age-standardized rate	2006–2016	-	China Cancer Registry Annual Report
Particulate matter	$PM_{2.5}$ concentration ($PM_{2.5}$)	2006–2016	0.01°	https://search.earthdata.nasa.gov/
Socio-economic factors	Population density (POP)	2006–2016	1 km	https://www.worldpop.org/
	Nighttime light data (NTL)	2006–2016	500 m	https://dataverse.harvard.edu/
	Medical-related POI	2012	-	-
	Education-related POI (Edu POI)	2012		
	Potential pollution factories POI	2012		
Meteorological factors	2 m temperature (TEM)	2006–2016	0.25°	https://cds.climate.copernicus.eu/
	Total precipitation	2006–2016		
	Surface pressure	2006–2016		
	2 m dewpoint temperature	2006–2016		
	10 m v-component of wind	2006–2016		
	10 m u-component of wind (WIND)	2006–2016		
Auxiliary factors	Normalized difference vegetation index (NDVI)	2006–2016	1 km	https://www.resdc.cn/
	Digital elevation model (DEM)	2020	30 m	http://www.gscloud.cn

Unit: $PM_{2.5}$ (μg/m^3), 2 m temperature (K), total precipitation (m), surface pressure (Pa), 2 m dewpoint temperature (K), 10 m v-component of wind and 10 m u-component of wind (m/s), population density (Person/hm^2), NTL (W/cm^2/sr), NDVI (unitless), DEM (m) varied every year, and the number of stations increased from 34 in 2006 to 487 in 2016 (Table A.1). Moreover, the statistical scales of the age-standardized incidence of lung cancer were not constant. For example, the age-standardized incidence of lung cancer was available on both the city scale and county scale in one year, but there may be only the city scale remained in the next year. For statistical and mapping purposes, the statistical and mapping scales of age-standardized incidence of lung cancer in the year 2016 were set as the analysis scales. Additionally, some data on the county scale were deleted because they were not complete samples for delegating an entire city. The number and scale of tumor registration stations after deletion in China were listed in Table A.2 and Fig. A.1.

For $PM_{2.5}$ data, the city-level scale vector data was used to conduct zonal statistics to calculate the mean value of $PM_{2.5}$ concentration for each tumor registration point via ArcGIS 10.0.

This study selected population density, night light image DN value, and places of interest (POI) data of medical-related, education-related, and potential pollution factories as socioeconomic affecting factors for LCI. The city-level scale vector data were used to calculate the mean value and the total value of population density and night light images by zonal statistics. The kernel density was calculated to obtain 1 km × 1 km POI raster data.

Fifth Generation Reanalysis Meteorological data (ERA5), including 2 m temperature (K), total precipitation (m), surface pressure (Pa), 2 m dewpoint temperature (K), 10 m v-component of wind, and 10 m u-component of wind (m/s), were derived from the European Centre for Medium Range Weather Forecasts (ECMWF). The spatial and temporal resolutions of the ERA5 dataset are 0.25° and 1 h. The zonal statistics tool in ArcGIS10.0 was used to retrieve the mean value of the meteorological indicator for each tumor registration point.

In this study, NDVI data with a resolution of 1 km from 2006 to 2016 were obtained from the Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences. DEM data with a resolution of 30 m was obtained from the geospatial data cloud. The vector boundary data of the study area was used to cut the NDVI and DEM data for each year. The city-level scale vector data were used to calculate the mean value and the total value of population density and night light images by zonal statistics. The zonal statistics were used to retrieve the mean values of NDVI and DEM at each tumor registration point.

All data used in this study were unified to the China Geodetic Coordinate System 2000 (CGCS2000).

Methods

Global Moran's I index

Global Moran's I was used to characterize the degree of spatial autocorrelation of LCI and to diagnose whether the distribution of LCI has spatial agglomeration characteristics. The formula of global Moran's I was expressed below (Adegboye et al. 2021; Kulldorff et al. 2006):

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \overline{x}\right)\left(x_j - \overline{x}\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}\left(x_i - x\right)^2} \tag{1}$$

$$\overline{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

where n represents the number of tumor registration stations each year, and w_{ij} is the spatial weight coefficient between tumor registration points i and j. If the regions are adjacent, $w_{ij} = 1$. Otherwise, $w_{ij} = 0$. x_i and x_j are LCI at tumor registration sites i and j, respectively. $\overline{x}$ is the average LCI. Moran's I values can be converted to Z, when the $|Z| > 1.96$ (or $P < 0.05$), indicating that spatial autocorrelation was statistically significant at the 95% level (Wang et al. 2022b).

Emerging hot spot analysis

Hot spot analysis (Getis-Ord Gi*) was adopted to evaluate the hot spot and cold spot trends of LCI using the Mann–Kendall trend. Local statistics using Getis-Ord can be expressed as follows (Kim et al. 2023):

$$Gi^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \overline{x}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{3}$$

$$\overline{x} = \frac{\sum_{j=1}^{n} x_j}{n} \tag{4}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{x}\right)^2} \tag{5}$$

where n,w_{ij}, x_j, and $\overline{x}$ are the same as Eqs. (1) and (2), and S denotes the standard deviation of LCI. The Mann–Kendall trend analysis is a non-parametric statistical test method. The trend test statistics for time series with sample size n are as follows (Kuletz et al. 2015):

$$V = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n} sgn\left(x_j - x_i\right) \tag{6}$$

$$\mathrm{sgn}\left(x_j - x_i\right) = \begin{cases} 1 & x_j > x_i \\ 0 & x_j = x_i \\ -1 & x_j < x_i \end{cases} \tag{7}$$

When the statistics obey the normal distribution, the variance is as follows:

$$Var(V) = \frac{n(n-1)(2n+5)}{18} \tag{8}$$

$$Z = \begin{cases} \frac{V-1}{\sqrt{Var(V)}} V > 0 \\ 0 V = 0 \\ \frac{V+1}{\sqrt{Var(V)}} V < 0 \end{cases} \tag{9}$$

where n, w_{ij}, and x_j are the same as Eqs. (1) and (2), and corresponding Z and P values are obtained through the Mann–Kendall trend analysis. If the Z score is greater than 1.65, it indicates that the time series is in an upward trend. If the Z score is lower than − 1.65, the time series is in a downward trend. If the Z score is close to zero, it indicates that the time series does not change significantly. The significance level is determined according to the range of P-values ($P < 0.05$). According to the Z-score and P-value, the significance of cold spot and hot spot trends of lung cancer incidence was classified into eight patterns for cold and hot spots, including new, continuous, strengthening, continuing, gradually decreasing, dispersing, oscillating, and historical, respectively (Zhou et al. 2023).

GTWR model

The GTWR model is defined as follows:

$$\varphi_{LC} = \beta_0(\mu_i v_i t_i) + \beta_1(\mu_i v_i t_i) \times PM_{2.5i} + \beta_2(\mu_i v_i t_i) \times NTL_i + \beta_3(\mu_i v_i t_i) \times TEM_i + \beta_4(\mu_i v_i t_i) \times WIND_i + \beta_5(\mu_i v_i t_i) \times POI_i + \varepsilon_i \tag{10}$$

where φ_{LC} is the LCI in t_i year at (μ_i, v_i) position, and β_0 is the intercept of a specific position (μ_i, v_i) and time t_i. $\beta_1, \beta_2, \beta_3, \beta_4$, and$\beta_5$ are the slopes of $PM_{2.5}$, NTL, TEM, WIND, and Edu POI at the specific position (μ_i, v_i) and the specific time t_i, respectively. (μ_i, v_i) represents the location of each tumor registry, t_i represents the period from 2006 to 2016, and ε_i represents the error term in sample I (Wang et al. 2022c). Variance inflation factor (VIF) was used for variable screening to determine whether there was collinearity among explanatory variables (Guo et al. 2021b). $PM_{2.5}$, socioeconomic factors, meteorological factors, and terrain were all tested as independent variables to determine whether there was obvious collinearity in the results. According to the collinearity diagnosis in the least square model (OLS) in ArcGIS 10.0, the VIF of $PM_{2.5}$, NTL, Edu POI, TEM, and WIND are all less than 7.5 and have passed the significance test (Guo et al. 2022a). The significance level was determined by the P-value ($P < 0.05$).

Definition of modification effects

The modification effect analysis was introduced to reveal the difference in the impact of $PM_{2.5}$ on LCI under different socioeconomic levels and climate zones (Guo et al. 2019). The modification effects of $PM_{2.5}$ on the LCI under different economic levels and climatic zones were explored by stratification of socio-economic levels and climatic zones. The socioeconomic level was measured by values of nighttime light remotely sensed images and Edu POI, and climate zones were defined by the typical monsoon zones in China (Fig. 1). The modification effects of $PM_{2.5}$ on the LCI were determined by the average coefficient of $PM_{2.5}$ at different socioeconomic levels and climate zones from the GTWR model. The ArcGIS 10.0 geometric discontinuity method was used to divide the nighttime light value and Edu POI into three levels (Elmore et al. 2017): namely, high urbanization, medium urbanization, and low urbanization, and low education level, medium education level, and high education level, respectively. The significance level was determined by the P-value ($P < 0.05$).

Workflow of this study

The workflow of this study is shown in Fig. 2. Firstly, data from independent variables and dependent variables were collected and preprocessed, and a database of LCI and its influencing factors was constructed. Secondly, the collinearity test using the least square model was conducted to screen independent variables, and the spatial correlation diagnosis and hot spot analysis of LCI were carried out via ArcGIS 10.0 and ArcGIS Pro, respectively. Step 3 established a GTWR model with the LCI as the dependent variable and the screened influencing factors as independent variables to determine the relationship between influencing factors and the LCI. The modification effects of $PM_{2.5}$ on the LCI under different socioeconomic levels and climatic zones were explored in step 4.

Results and discussion

Descriptive statistics

A total of 3654 samples of LCI from city and county tumor registration stations were recorded from 2006 to 2016 in

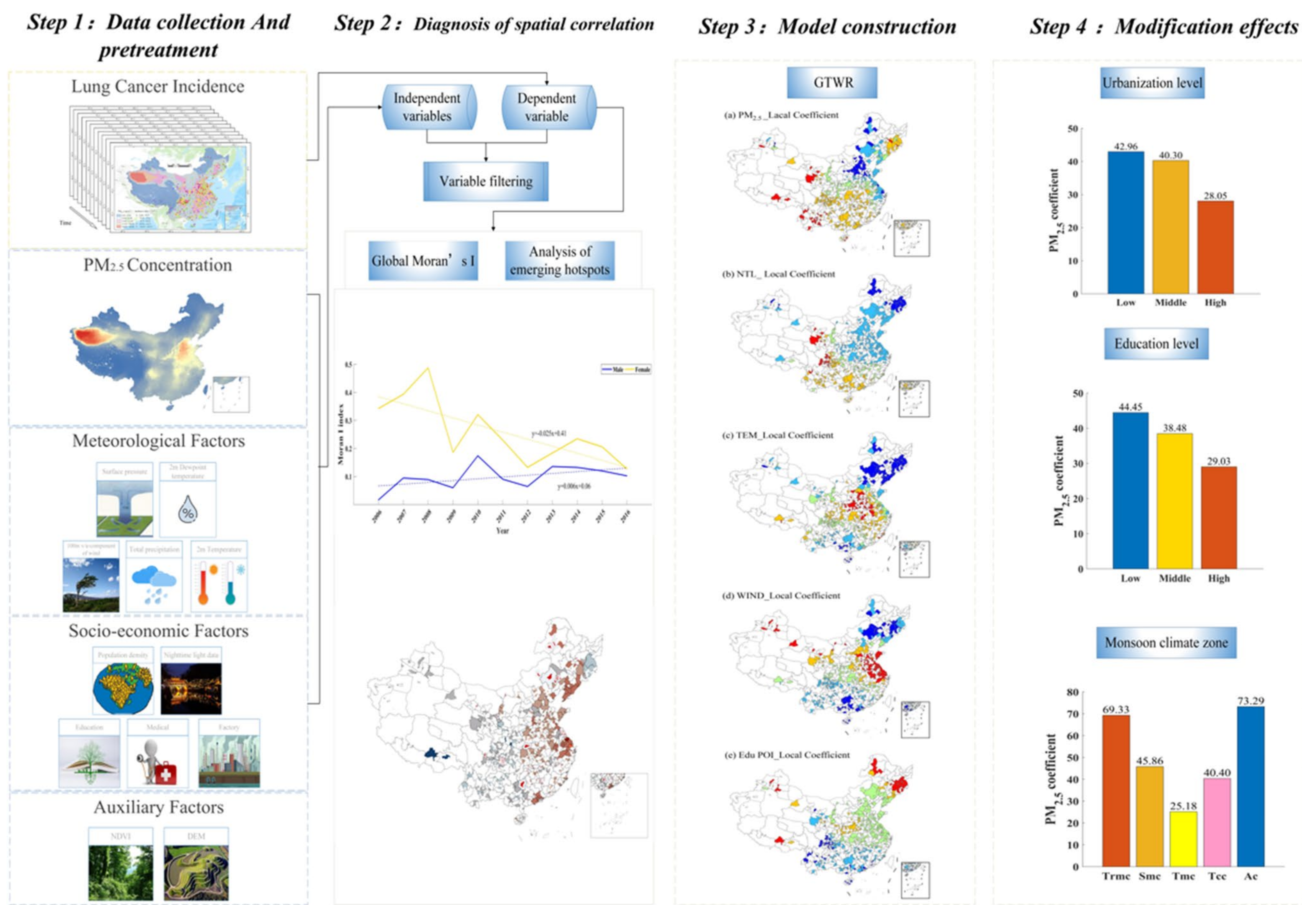


Fig. 2 Workflow of this study

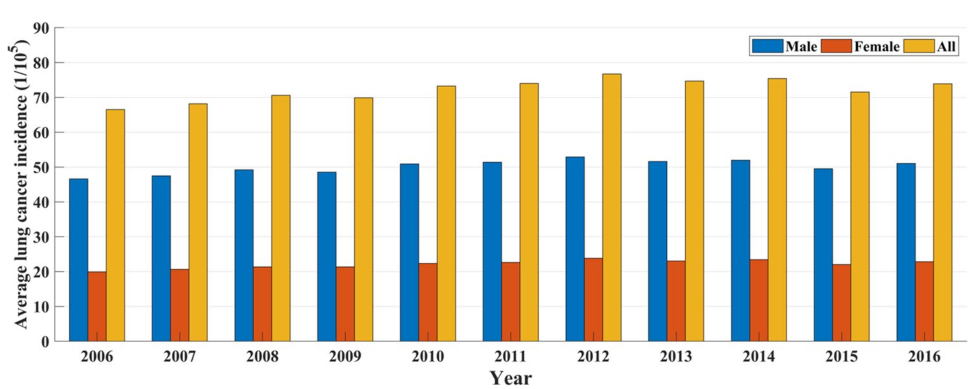
China. Figure 3 illustrates the average male LCI, female LCI, and the whole LCI in the study area. The LCI for males raised gradually, but an obvious downward trend was detected in 2009, 2013, and 2015. LCI of females increased steadily during the first 7 years; then, it began to decline in 2013 and 2015. Obviously, the LCI was overall increased and the male LCI was always much higher than the female.

Spatial correlation diagnosis for LCI from 2006 to 2016 in China

Auto-correlation for LCI via global Moran's *I* index

Moran's *I* index is larger than zero for both males and females, which indicates the distribution of LCI is not

Fig. 3 Descriptive statistics for LCI in China during 2006–2016



random but exhibits concentrated patterns possibly due to environmental and geographical factors. Most global Moran's *I* index passed the significance test except for the years 2006, 2007, 2008, and 2009 due to the small number of tumor registration stations in the mentioned years (Table 2). Furthermore, the global Moran's *I* index for men demonstrated an upward trend probably for the external environmental conditions posed more significant impacts on the male LCI. On the contrary, though the global Moran's *I* index for females showed an obvious downward trend, all values were larger than zero, indicating that the LCI for females still represented a certain spatial autocorrelation. In conclusion, the distribution of LCI is not random, but presents certain spatial clustering characteristics, indicating that the LCI may be influenced by geographical environment and other factors (Goss et al. 2014) (Fig. 4). Therefore, the traditional epidemic methods tend to ignore the temporal and spatial correlation of variables, and models with the capability of spatial–temporal correlation detection are very desired.

Table 2 Non-stationarity of parameters from the global Moran's *I*

	Male		Female	
Year	*Z*-value	*P*-value	*Z*-value	*P*-value
2006	0.475192	0.634650	0.475192	0.634650
2007	1.286810	0.198160	1.286810	0.198160
2008	1.210305	0.226162	1.210305	0.226162
2009	2.049357	0.040427	2.049357	0.040427
2010	4.360695	0.000013	4.360695	0.000013
2011	3.425287	0.000614	3.425287	0.000614
2012	4.459648	0.000008	4.459648	0.000008
2013	7.048950	0.000000	7.048950	0.000000
2014	7.458269	0.000000	7.458269	0.000000
2015	9.787201	0.000000	9.787201	0.000000
2016	10.301979	0.000000	10.301979	0.000000

Emerging hot spot analysis for LCI from 2006 to 2016 in China

Hot spots of LCI were concentrated in eastern China, including the urban agglomeration of the Yangtze River Delta and the Pearl River Delta along the eastern coast, while cold spots were mostly distributed in western China, such as Lhasa and Shannan of the Tibet Autonomous Region. Compared with the West, Eastern China has a faster population growth and a developed economy, which leads to a more prominent pollution issue and a higher LCI than the Western part of China (Wen et al. 2022) (Fig. 5).

At the same time, the hot spots of new LCI were dispersed, mainly in some counties and cities in Sichuan and Chongqing. Moreover, the distribution of continuous hot spots in the eastern coastal areas indicates that the high LCI has been maintained in these areas for a long time. In particular, enhanced hot spots of LCI were identified in Nantong City of Jiangsu Province, Shanghai, Anshan, and Yingkou City of Liaoning Province. The developed economy and dense population of Shanghai may lead to lots of air pollutants emissions, so the risk of lung cancer was promoted. Anshan and Yingkou cities are typical heavy industry cities in Northeast China, and industrial pollution increases health risks, leading to a high incidence of lung cancer (Lee et al. 2022).

The oscillating hot spot of LCI was detected in Beijing-Tianjin-Hebei, Luoyang, Yichang, Hefei, and Xuzhou. These regions are the key areas of LCI in China. Continuous cold spots were mostly distributed in western China. In conclusion, the hot and cold spots of LCI indicated significant spatial–temporal dynamics in China (Fig. A.2). The hot spots of LCI change frequently and were accompanied by the emergence of new areas, while the cold spots were relatively stable and often present in the form of aggregation and dispersion.

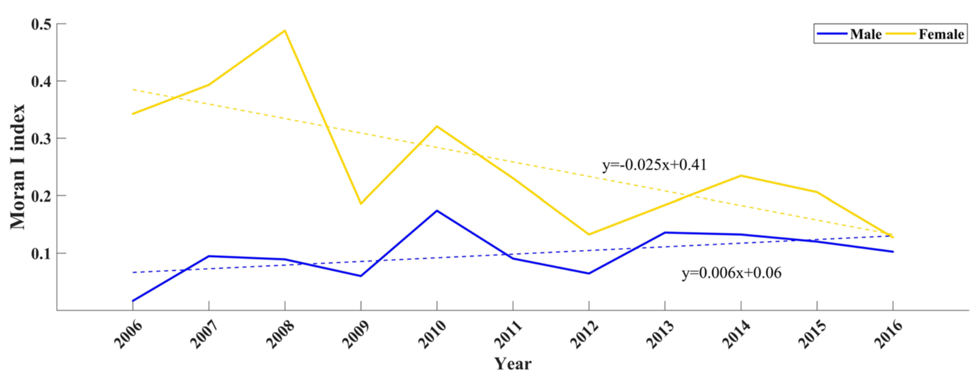


Fig. 4 Global autocorrelation of LCI in China from 2006 to 2016

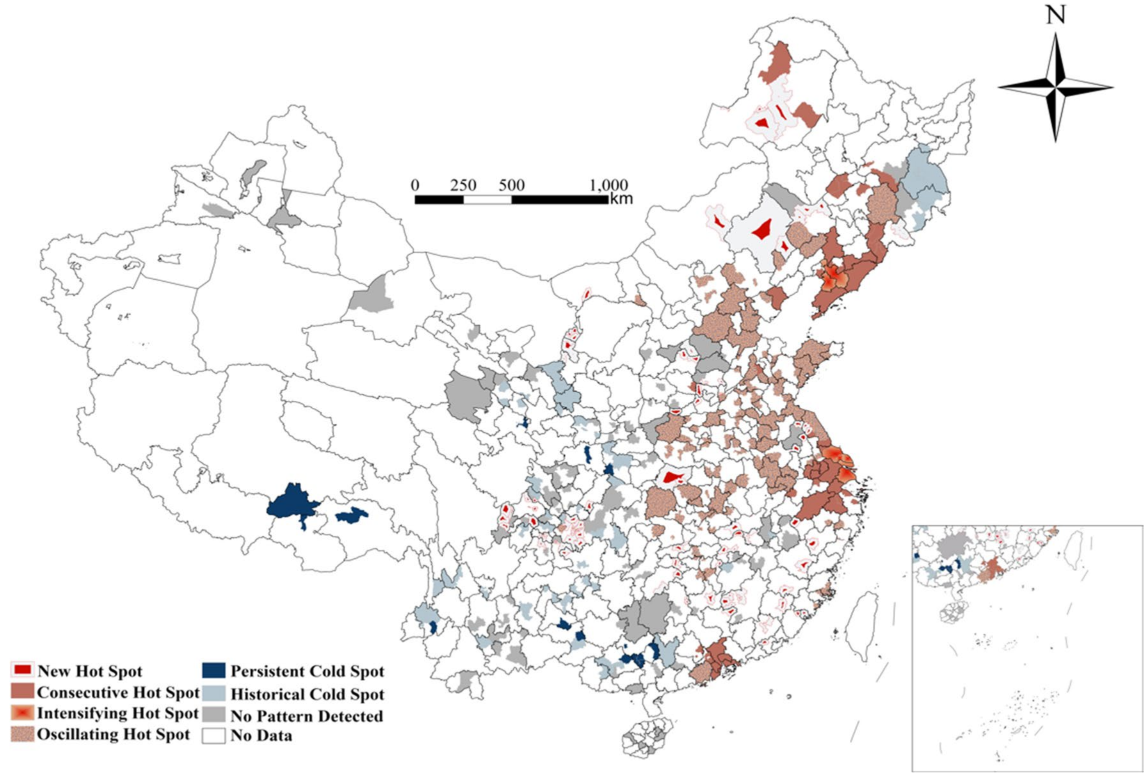


Fig. 5 Hot spots and cold spots of LCI across China from 2006 to 2016

Table 3 Evaluation of the performance of the GTWR model

Group	R^2	R^2 adjusted	Sigma
All	0.2935	0.2916	19.4818
Male	0.2746	0.2726	13.9956
Female	0.3570	0.3552	6.9280

Table 4 Coefficients and intercepts for each independent variable of LCI

Variable	ALL	Male	Female
Intercept	45.13	24.03	21.10
$PM_{2.5}$	39.23**	31.62**	7.61**
NTL	28.67**	15.76**	12.91**
TEM	18.95**	22.15**	− 3.20**
WIND	2.09**	0.51**	1.58**
Edu POI	− 18.13**	− 11.90**	− 6.23**
Residual	0.23	0.25	− 0.01

$^{**}P < 0.01$

Spatial heterogeneity of influencing factors for LCI

Performance and stability test of GTWR model

R^2, adjusted R^2, and root mean square error (RMSE) were used to evaluate the performance of the GTWR model. The results showed that the accuracy of the GTWR model for females was better than for males (Table 3). The performance of the GTWR in estimating LCI may be restrained to some extent due to some unconsidered factors such as lifestyles.

The influences of independent variables on LCI from a global perspective

The effects of independent variables on LCI exhibited significantly heterogeneous. The residuals of the total group and males were 0.23 and 0.25, indicating the LCI in these two groups was underestimated, while the females' group was − 0.01, showing that the LCI in females was overestimated (Table 4).

For the total group, $PM_{2.5}$, NTL, and WIND represented positive effects on the LCI. $PM_{2.5}$ exhibited the most significant effect on the LCI for males, and NTL indicated the most significant effect on the LCI for females.

Previous studies demonstrated that $PM_{2.5}$ can be absorbed by the body into the bronchus, thus interfering with air exchange in the lungs, leading to diseases including asthma, COPD, lung cancer, and cardiovascular diseases (Chu et al. 2021). Moreover, epidemiological studies from Asia, Europe, and North America consistently indicated a positive correlation between lung cancer and $PM_{2.5}$. The current findings are completely consistent with published studies (Hvidtfeldt et al. 2021; Loomis et al. 2014).

According to existing research, NTL can reflect the urbanization level of a region to some extent (Zhang et al. 2022b). A series of urban ecological environmental problems may lead to LCI raising. Previous studies also confirmed that the level of urbanization was positively associated with an increased risk of cardiovascular disease (Wang et al. 2022a), cancer (Cote-Lussier et al. 2020), and obesity (Khan et al. 2023). Similarly, a positive relationship between nighttime light and LCI was obtained in the present study.

On the contrary, education level posed a negative effect on LCI, especially the effect on the LCI for females was more significant than temperature (Table 4). Previous studies have shown that education level has a negative impact on the relationship between PM1 (or SO_2) and male LCI (Guo et al. 2021c). Moreover, some scholars have studied that education was negatively correlated with ambient air quality, and the lower the education level, the lower the ability to protect oneself from potential health risks (Long et al. 2001; Walker et al. 2022).

Interestingly, TEM posed a negative effect on females' LCI but a positive effect on males. Studies have confirmed that low temperatures may exacerbate surface air pollution by influencing the diffusion and dilution of air pollutants and increasing the risk of lung cancer. The outdoor activities for males were often more frequent than for females, and the cold climate may restrict outdoor activities for corresponding people, reducing their exposure risk to air pollution, and reducing the risk of morbidity (Guo et al. 2020).

Additionally, vertical wind shear and wind speed may also influence particulate matter pollution (Zhang et al. 2020b). The larger wind speed and complex urban form may lead to the accumulation of pollutants and form eddy currents that are not easy to diffuse, which may pose an impact on health and further cause lung cancer (Abril et al. 2022).

The influence of independent variables on LCI via a local perspective

The coefficients of each independent variable for LCI obtained from the GTWR model varied according to location and time (Fig. 6).

Obviously, $PM_{2.5}$ posed a significant positive effect on LCI in most regions and showed an upward trend from east to west. NTL indicated a significant negative effect on LCI in the eastern and western regions and a significant positive effect in the central and western regions.

The influence of temperature on the LCI was relatively scattered. Temperature posed a significant negative impact on the LCI in extremely high and low-temperature areas.

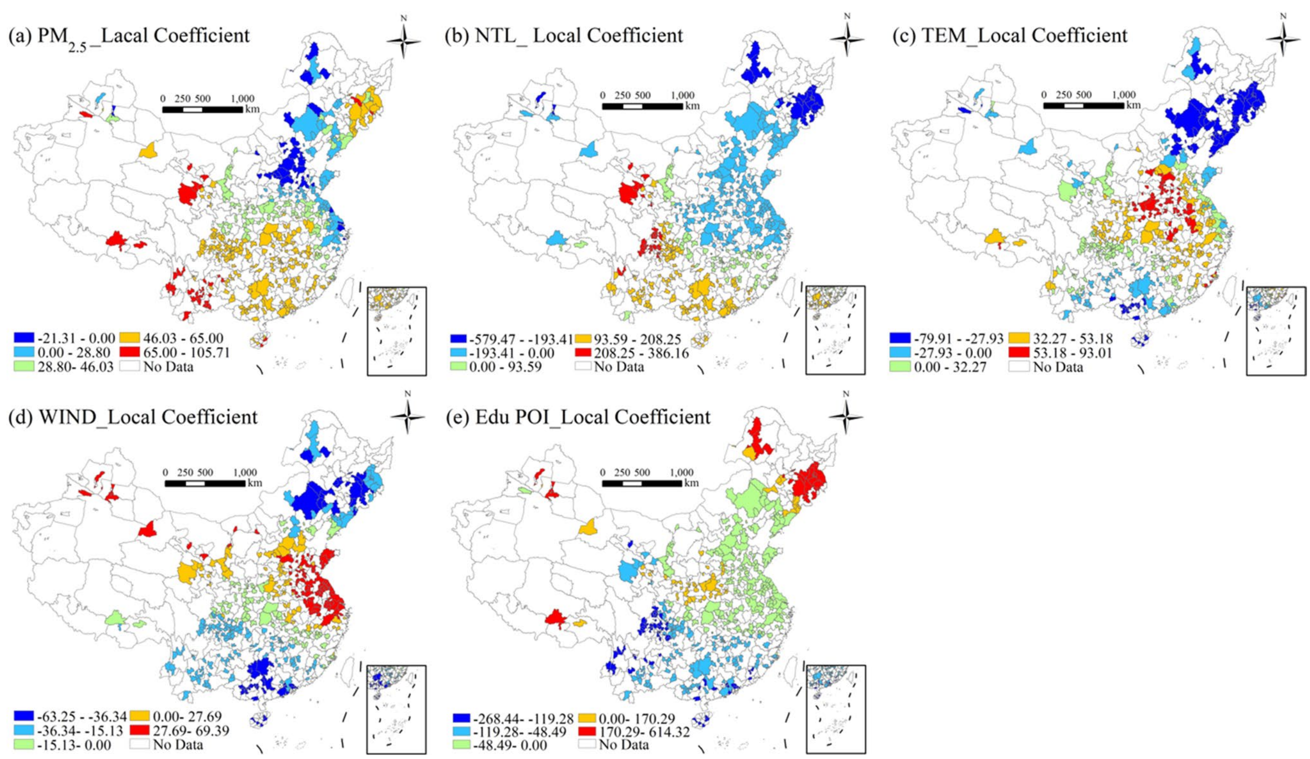


Fig. 6 Spatial distribution maps for standard coefficients of LCI influential factors from 2006 to 2016. Note: Spatial distribution maps for standard coefficients of females (Fig. A.3) and males (Fig. A.4) LCI influential factors from 2006 to 2016 were presented in supplementary materials

Female LCI was high in northeast China mainly owing to serious $PM_{2.5}$ pollution and extremely low temperature (Zhang et al. 2022a). A previous study confirmed that life expectancy and lung cancer mortality exhibited differences in northern and southern China (Chen et al. 2013). Additionally, the local cold climate, unhealthy lifestyle, and habits induced lung cancer in western Heilongjiang Province and eastern Inner Mongolia (Xing et al. 2019).

The effect of wind on the LCI was scattered. When the wind speed increased in high-temperature areas, the LCI decreased. When the wind speed decreased in low-temperature areas, the LCI increased. The wind speed in the central region showed a significant positive effect on the LCI, and gradually increased from inland to coastal areas. For the northwest, the higher the wind speed was, the higher the LCI. The vegetation coverage was less in the northwest, but the wind sand was strong. The dust particles mixed into the atmosphere may offset the favorable effect of wind diffusion. Wind speed posed limited influence on the dissipation and sedimentation of pollutants, leading to a higher incidence of lung cancer in areas with severe air pollution such as Hotan, Kashgar, Kezhou, and Aksu in Xinjiang (Han et al. 2020). Therefore, there was a positive correlation between wind speed and LCI in the northwest and eastern coastal areas of China.

The negative effect of education level on the LCI was significant in the southern region. The effect of education level posed a positive impact on the LCI in a few northeast and western areas. Diet and living habits posed a significant impact on the LCI in these areas, resulting in education level expressing a relatively low effect on LCI.

Modification effects of $PM_{2.5}$ on LCI at different urbanization levels, education levels, and climatic zones

According to published papers, night lights can reflect both social economy and urbanization levels. So, the urbanization level was divided into low, medium, and high levels according to nighttime light values in the present study for identifying the modification effects of $PM_{2.5}$ on LCI at different urbanization levels (Fig. 7a). Obviously, the LCI was most susceptible to being influenced by $PM_{2.5}$ in the low urbanization level, followed by the medium and high levels. Studies have shown that urbanization can increase resistance to the adverse effects of air pollution by improving the quality of health services and collective awareness of healthy lifestyles (Liang et al. 2021). The results of this study also confirmed that people from low urbanization levels were more easily influenced by $PM_{2.5}$.

For education level, $PM_{2.5}$ showed a more significant positive modification effect on the LCI in areas with lower education levels (Fig. 7b). Previous studies have proved that education was negatively correlated with ambient air quality. Residents with low income and education levels are hardly to protect themselves from potential health risks, especially from serious air pollution city (Huang et al. 2019). Contrarily, people with higher income and education levels tend to be more aware of the potential impact of air pollutants on health (Zhang et al. 2020a). These results were consistent with our study that people in areas with lower education levels were more easily influenced by $PM_{2.5}$, and the LCI was larger than in high education level areas.

The influence of $PM_{2.5}$ on the LCI was positive in different climatic zones, and the influence of $PM_{2.5}$ on the LCI in tropical monsoon and plateau mountain climates was more obvious than that in other climatic zones (Fig. 7c). Extreme temperature and altitude may be the reasons for the above phenomenon. Relevant studies have indicated that high temperatures lose appetite and decreased nutrition intake of the human body, which can influence health and further pose a more significant impact of $PM_{2.5}$ on lung cancer under high temperatures (Sunyer 2010). Low temperature may cause vasoconstriction on the human body surface and then increase

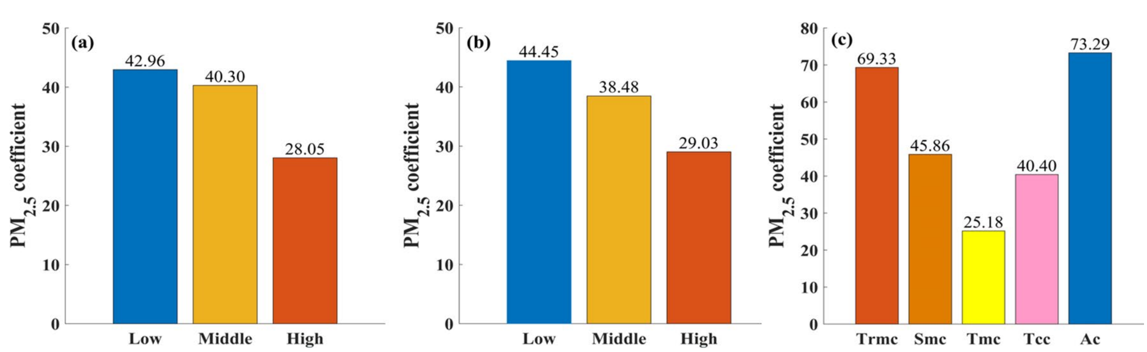


Fig. 7 Stratified analysis of modification effects of $PM_{2.5}$ on LCI at different urbanization levels (**a**), education levels (**b**), and climate zones (**c**). Note: All modification effects of $PM_{2.5}$ on LCI at different urbanization levels, education levels, and climatic zones were significant at $P<0.01$ level; please see Table A.3 in supplementary materials. Moreover, modification effects of urbanization levels, temperature, wind, and education levels on LCI at different $PM_{2.5}$ exposure levels are shown in Fig. A.5

the cardiopulmonary burden and the LCI (Fan et al. 2023). Therefore, people living in plateau areas should improve their ability to prevent air pollution, which will benefit not only chronic lung health, but also other $PM_{2.5}$-related diseases such as ischemic heart disease, cerebrovascular disease, lung cancer, and lower respiratory tract infections.

Limitations and plans

Although some findings have been achieved in the work, some issues need to be further addressed (Raaf et al. 2023). First of all, some other influential factors for LCI such as physical fitness, lifestyle, living habits, and family history of diseases have been proven to be closely related to the LCI. However, these factors were ignored due to the data availability. Secondly, the lag effects of $PM_{2.5}$ on the LCI were not considered, and the unknown incubation period of cancer may cause certain uncertainties for the research results. Thirdly, the population LCI data only recorded the household registration population; the inconsistency of workplaces and household registration may lead to wrong estimations. As the pathogenesis of lung cancer is the result of multiple factors, more comprehensive consideration is needed in the future. Finally, this study only discussed the LCI at the regional scale, and the research results have certain limitations. In the future, the relationship between LCI and completely related influencing factors should be discussed on a global scale.

Conclusions

In this study, novel datasets such as NPP-VIIRS night light remotely sensed images, worldpop population density datasets, and new data collection methods such as places of interest (POI) extraction technical were introduced to represent different socioeconomic levels. The spatial autocorrelation was adopted to reveal the spatial aggregation dynamic of LCI, the emerging hot spot analysis was introduced to indicate the hot spot changes of LCI, the geographically and temporally weighted regression (GTWR) model was used to determine the influential factors of LCI and their spatial heterogeneity, and the modification effects of $PM_{2.5}$ on the LCI under different socioeconomic levels and climatic zones were explored. Some outcomes were achieved. Firstly, the LCI for both males and females showed significant differentiation and agglomeration from 2006 to 2016 in China. This finding reminds us that the relationship between LCI and anthropic activities needs to be paid more attention. Secondly, the effects of various factors on the LCI exhibited spatiotemporal heterogeneity. $PM_{2.5}$, NTL, and WIND posed a positive effect on the LCI, while education level had a negative effect on the LCI. Finally, this study proved that the LCI in lowly urbanized areas was more easily influenced by $PM_{2.5}$ than that in more urbanized areas in China. This result suggests that improving urbanization levels may enhance resistance to the adverse effects of $PM_{2.5}$ on LCI. People in areas with low levels of education were more significantly influenced by $PM_{2.5}$, which suggests that people should promote their education levels for improving awareness of environmental control and prevention. $PM_{2.5}$ has a much more obvious impact on the LCI than other climatic conditions under extreme temperature conditions. This outcome reminds us that lung cancer-related studies should be paid more attention under extreme temperature conditions. The current findings suggest that measures should be taken, and people should be encouraged to raise environmental awareness to reduce the risk of lung cancer. This work provides a scientific basis for the study of related diseases from the perspective of spatial epidemiology.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-023-31138-8.

Acknowledgements We are deeply grateful for comments from editors and reviewers.

Author contribution Bin Guo: conceptualization, writing—original draft, supervision. Qian Gao: writing—original draft, data preparation, visualization. Tengyue Guo: editing. Lin Pei: data curation. Yan Wang: methodology. Haojie Wu: software. Wencai Zhang: investigation. Miaoyi Chen: revision.

Funding This work was supported by the open foundation of Shaanxi Key Laboratory of Environmental Monitoring and Forewarning of Trace Pollutants.

Declarations

Ethical approval The authors declare that all data used in the present study were approved.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

Abril GA, Amarillo AC, Mateos AC, et al. (2022) Exposure to atmospheric particle-bound polycyclic aromatic hydrocarbons in the vicinity of two cement plants in Cordoba, Argentina. Microchem J 177. https://doi.org/10.1016/j.microc.2022.107271

Adegboye OA, Adekunle AI, Pak A, et al. (2021) Change in outbreak epicentre and its impact on the importation risks of COVID-19 progression: a modelling study. Travel Med Infect Dis 40. https://doi.org/10.1016/j.tmaid.2021.101988

Al-Ahmadi K, Al-Zahrani A (2013) Spatial autocorrelation of cancer incidence in Saudi Arabia. Int J Environ Res Public Health 10:7207–7228. https://doi.org/10.3390/ijerph10127207

Ansari M, Ehrampoush MH (2019) Meteorological correlates and AirQ(+) health risk assessment of ambient fine particulate matter in Tehran, Iran. Environ Res 170:141–150. https://doi.org/10.1016/j.envres.2018.11.046

Bray F, Ferlay J, Soerjomataram I et al (2020) Global cancer statistics 2018: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries (vol 68, pg 394, 2018). CA-A Cancer J Clin 70:313–313. https://doi.org/10.3322/caac.21609

Chan J, Polo A, Zubizarreta E et al (2019) Access to radiotherapy and its association with cancer outcomes in a high-income country: addressing the inequity in Canada. Radiother Oncol 141:48–55. https://doi.org/10.1016/j.radonc.2019.09.009

Chen Y, Ebenstein A, Greenstone M et al (2013) Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. Proc Natl Acad Sci USA 110:12936–12941. https://doi.org/10.1073/pnas.1300018110

Chu H, Xin J, Yuan Q, et al. (2021) A prospective study of the associations among fine particulate matter, variants, and the risk of colorectal cancer. Environ Int 147. https://doi.org/10.1016/j.envint.2020.106309

Cote-Lussier C, Knudby A, Barnett TA. (2020) A novel low-cost method for assessing intra-urban variation in night time light and applications to public health. Soc Sci Med 248. https://doi.org/10.1016/j.socscimed.2020.112820

Elmore PA, Petry FE, Yager RR (2017) Geospatial modeling using Dempster-Shafer theory. Ieee Trans Cybern 47:1551–1561. https://doi.org/10.1109/tcyb.2016.2551979

Fan Z, Li Y, Wei J, et al. (2023) Long-term exposure to fine particulate matter and site-specific cancer mortality: a difference-in-differences analysis in Jiangsu province, China. Environ Res 222. https://doi.org/10.1016/j.envres.2023.115405

Feng R, Xu H, Wang Z, et al. (2021) Quantifying air pollutant variations during COVID-19 lockdown in a capital city in Northwest China. Atmosphere 12. https://doi.org/10.3390/atmos12060788

Goss PE, Strasser-Weippl K, Lee-Bychkovsky BL et al (2014) Challenges to effective cancer control in China, India, and Russia. Lancet Oncol 15:489–538. https://doi.org/10.1016/s1470-2045(14)70029-4

Guo Y, Zeng H, Zheng R et al (2016) The association between lung cancer incidence and ambient air pollution in China: a spatiotemporal analysis. Environ Res 144:60–65. https://doi.org/10.1016/j.envres.2015.11.004

Guo H, Chang Z, Wu J, et al. (2019) Air pollution and lung cancer incidence in China: who are faced with a greater effect?. Environ Int 132. https://doi.org/10.1016/j.envint.2019.105077

Guo H, Li W, Wu J (2020) Ambient PM2.5 and annual lung cancer incidence: a nationwide study in 295 Chinese counties. Int J Environ Res Public Health 17. https://doi.org/10.3390/ijerph17051481

Guo B, Wang Y, Pei L, et al. (2021a) Determining the effects of socioeconomic and environmental determinants on chronic obstructive pulmonary disease (COPD) mortality using geographically and temporally weighted regression model across Xi'an during 2014–2016. Sci Total Environ 756. https://doi.org/10.1016/j.scitotenv.2020.143869

Guo B, Zhang D, Pei L, et al. (2021b) Estimating PM2.5 concentrations via random forest method using satellite, auxiliary, and ground-level station dataset at multiple temporal scales across China in 2017. Sci Total Environ 778. https://doi.org/10.1016/j.scitotenv.2021.146288

Guo H, Wei J, Li X, et al. (2021c) Do socioeconomic factors modify the effects of PM1 and SO2 on lung cancer incidence in China?. Sci Total Environ 756. https://doi.org/10.1016/j.scitotenv.2020.143998

Guo B, Wu H, Pei L, et al. (2022a) Study on the spatiotemporal dynamic of ground-level ozone concentrations on multiple scales across China during the blue sky protection campaign. Environ Int 170. https://doi.org/10.1016/j.envint.2022.107606

Guo B, Zhang W, Pei L, et al. (2022b) Remote sensing evidence for significant variations in the global gross domestic product during the COVID-19 epidemic. Sustainability 14. https://doi.org/10.3390/su142215201

Guo B, Wang Z, Pei L, et al. (2023a) Reconstructing MODIS aerosol optical depth and exploring dynamic and influential factors of AOD via random forest at the global scale. Atmospheric Environment. 120159. https://doi.org/10.1016/j.atmosenv.2023.120159.

Guo B, Xie T, Zhang W, et al. (2023b) Rasterizing CO2 emissions and characterizing their trends via an enhanced population-light index at multiple scales in China during 2013–2019. Sci Total Environ 167309–167309. https://doi.org/10.1016/j.scitotenv.2023.167309

Han X, Fang W, Li H, et al. (2020) Heterogeneity of influential factors across the entire air quality spectrum in Chinese cities: a spatial quantile regression analysis. Environ Pollut 262. https://doi.org/10.1016/j.envpol.2020.114259

Hawrysz I, Wadolowska L, Slowinska MA, et al. (2022) Lung cancer risk in men and compliance with the 2018 WCRF/AICR Cancer Prevention recommendations. Nutrients 14. https://doi.org/10.3390/nu14204295

He J, Christakos G, Jankowski P (2019) Comparative performance of the LUR, ANN, and BME techniques in the multiscale spatiotemporal mapping of PM2.5 concentrations in North China. Ieee J Sel Top Appl Earth Obs Remote Sens 12:1734–1747. https://doi.org/10.1109/jstars.2019.2913380

Hill W, Lim EL, Weeden CE et al (2023) Lung adenocarcinoma promotion by air pollutants. Nature 616:159–167. https://doi.org/10.1038/s41586-023-05874-3

Huang G, Zhou W, Qian Y et al (2019) Breathing the same air? Socioeconomic disparities in PM2.5 exposure and the potential benefits from air filtration. Sci Total Environ 657:619–626. https://doi.org/10.1016/j.scitotenv.2018.11.428

Huang B, Wang J, Cai J et al (2021) Integrated vaccination and physical distancing interventions to prevent future COVID-19 waves in Chinese cities. Nat Hum Behav 5:695-+. https://doi.org/10.1038/s41562-021-01063-2

Huang S, Yang J, Shen N et al (2023) Artificial intelligence in lung cancer diagnosis and prognosis: current application and future perspective. Semin Cancer Biol 89:30–37. https://doi.org/10.1016/j.semcancer.2023.01.006

Hvidtfeldt UA, Severi G, Andersen ZJ, et al. (2021) Long-term low-level ambient air pollution exposure and risk of lung cancer - a pooled analysis of 7 European cohorts. Environ Int 146. https://doi.org/10.1016/j.envint.2020.106249

Kayyal-Tarabeia I, Michael Y, Lensky IM, et al. (2022) Residential greenness and site-specific cancer: a registry based cohort of 144,427 participants with a 21-years of follow-up, Tel-Aviv district, Israel. Environ Res 212. https://doi.org/10.1016/j.envres.2022.113460

Khan JR, Islam MM, Faisal ASM et al (2023) Quantification of urbanization using night-time light intensity in relation to women's overnutrition in Bangladesh. J Urban Health-Bull New York Acad Med. https://doi.org/10.1007/s11524-023-00728-9

Kim J, Hong K, Yoo D, et al. (2023) Spatiotemporal clusters of Kawasaki disease in South Korea from 2008 to 2017: a municipal-level ecological study. Front Pediatr 10. https://doi.org/10.3389/fped.2022.1054985

Kuletz KJ, Ferguson MC, Hurley B et al (2015) Seasonal spatial patterns in seabird and marine mammal distribution in the eastern Chukchi and western Beaufort seas: identifying biologically important pelagic areas. Prog Oceanogr 136:175–200. https://doi.org/10.1016/j.pocean.2015.05.012

Kulldorff M, Song C, Gregorio D et al (2006) Cancer map patterns: are they random or not? Am J Prev Med 30:S37-49. https://doi.org/10.1016/j.amepre.2005.09.009

Lee N-W, Wang H-Y, Du C-L, et al. (2022) Air-polluted environmental heavy metal exposure increase lung cancer incidence and mortality: a population-based longitudinal cohort study. Sci Total Environ 810. https://doi.org/10.1016/j.scitotenv.2021.152186

Li J, Lu X, Liu F et al (2020) Chronic effects of high fine particulate matter exposure on lung cancer in China. Am J Respir Crit Care Med 202:1551–1559. https://doi.org/10.1164/rccm.202001-0002OC

Li P, Jing J, Guo W, et al. (2021) The associations of air pollution and socioeconomic factors with esophageal cancer in China based on a

spatiotemporal analysis. Environ Res 196. https://doi.org/10.1016/j.envres.2020.110415
Liang Z, Wang W, Wang Y, et al. (2021) Urbanization, ambient air pollution, and prevalence of chronic kidney disease: a nationwide cross-sectional study. Environ Int 156. https://doi.org/10.1016/j.envint.2021.106752
Liu Y, Xu Y, Li Y et al (2023) Identifying the environmental determinants of lung cancer: a case study of Henan, China. GeoHealth 7:e2023GH000794-e2023GH000794. https://doi.org/10.1029/2023gh000794
Long CM, Suh HH, Catalano PJ et al (2001) Using time- and size-resolved particulate data to quantify indoor penetration and deposition behavior. Environ Sci Technol 35:2089–2099. https://doi.org/10.1021/es001477d
Loomis D, Huang W, Chen G (2014) The International Agency for Research on Cancer (IARC) evaluation of the carcinogenicity of outdoor air pollution: focus on China. Chin J Cancer 33:189–196. https://doi.org/10.5732/cjc.014.10028
Luo Y, Teng M, Yang K, et al. (2019) Research on PM2.5 estimation and prediction method and changing characteristics analysis under long temporal and large spatial scale - a case study in China typical regions. Sci Total Environ 696. https://doi.org/10.1016/j.scitotenv.2019.133983
Mattiuzzi C, Lippi G (2019) Current cancer epidemiology. J Epidemiol Global Health 9:217–222. https://doi.org/10.2991/jegh.k.191008.001
Momenyan S, Sadeghifar M, Sarvi F et al (2016) Relationship between urbanization and cancer incidence in Iran using quantile regression. Asian Pac J Cancer Prev: APJCP 17:113–117
Ni Y, Shi G, Qu J (2020) Indoor PM2.5, tobacco smoking and chronic lung diseases: a narrative review. Environ Res 181. https://doi.org/10.1016/j.envres.2019.108910
Raaf CL, Tondel M, Isaksson M, et al. (2023) Average uranium bedrock concentration in Swedish municipalities predicts male lung cancer incidence rate when adjusted for smoking prevalence: indication of a cumulative radon induced detriment?. Sci Total Environ 855. https://doi.org/10.1016/j.scitotenv.2022.158899
Rosskamp M, Verbeeck J, Gadeyne S, et al. (2021) Socio-economic position, cancer incidence and stage at diagnosis: a nationwide cohort study in Belgium. Cancers 13. https://doi.org/10.3390/cancers13050933
Sekeroglu B, Tuncal K (2021) Prediction of cancer incidence rates for the European continent using machine learning models. Health Inform J 27. https://doi.org/10.1177/1460458220983878
Sunyer J (2010) Geographical differences on the mortality impact of heat waves in Europe. Environ Health : A Glob Access Sci Source 9:38–38. https://doi.org/10.1186/1476-069x-9-38
Walker ES, Noonan CW, Belcourt A, et al. (2022) Efficacy of air filtration and education interventions on fine particulate matter among rural Native American homes heated with wood stoves: results from the EldersAIR randomized trial. Sci Total Environ 843. https://doi.org/10.1016/j.scitotenv.2022.157029
Wang Y, Guo B, Pei L et al (2022b) The influence of socioeconomic and environmental determinants on acute myocardial infarction (AMI) mortality from the spatial epidemiological perspective. Environ Sci Pollut Res 29:63494–63511. https://doi.org/10.1007/s11356-022-19825-4
Wang Z, Liu L, Yang K (2022) Geographical and temporal weighted regression model and its application in epidemiology: a review. Zhongguo xue xi chong bing fang zhi za zhi = Chinese journal of schistosomiasis control 35:199–205. https://doi.org/10.16250/j.32.1374.2022086
Wang N, Mengersen K, Tong S, et al. (2019a) Short-term association between ambient air pollution and lung cancer mortality. Environ Res 179. https://doi.org/10.1016/j.envres.2019.108748
Wang Y, Duan X, Wang L, (2019b) Spatial-temporal evolution of PM2.5 concentration and its socioeconomic influence factors in Chinese cities in 2014–2017. Int J Environ Res Public Health 16. https://doi.org/10.3390/ijerph16060985
Wang W, Li J, Liu Y, et al. (2022a) Spatiotemporal trends and ecological determinants of cardiovascular mortality among 2844 counties in mainland China, 2006–2020: a Bayesian modeling study of national mortality registries. Bmc Med 20. https://doi.org/10.1186/s12916-022-02613-9
Wen J, Chuai X, Gao R, et al. (2022) Regional interaction of lung cancer incidence influenced by PM2.5 in China. Sci Total Environ 803. https://doi.org/10.1016/j.scitotenv.2021.149979
Wu H, Guo B, Guo T, et al. (2023) A study on identifying synergistic prevention and control regions for PM2.5 and O3 and exploring their spatiotemporal dynamic in China. Environ Pollut 122880. https://doi.org/10.1016/j.envpol.2023.122880
Xing DF, Xu CD, Liao XY, et al. (2019) Spatial association between outdoor air pollution and lung cancer incidence in China. Bmc Public Health 19. https://doi.org/10.1186/s12889-019-7740-y
Yin P, Brauer M, Cohen AJ et al (2020) The effect of air pollution on deaths, disease burden, and life expectancy across China and its provinces, 1990–2017: an analysis for the Global Burden of Disease Study 2017. Lancet Planet Health 4:E386–E398. https://doi.org/10.1016/s2542-5196(20)30161-3
Zhang FM (1986) The analysis of ridge regression about occupational factors of lung cancer in Yunnan tin miners. Zhonghua Yu Fang Yi Xue Za Zhi [chinese Journal of Preventive Medicine] 20:151–153
Zhang X, Chen X, Yue Y et al (2023) Ecological study on global health effects due to source-specific ambient fine particulate matter exposure. Environ Sci Technol. https://doi.org/10.1021/acs.est.2c06752
Zhang B, Wu B, Liu J, (2020a) PM2.5 pollution-related health effects and willingness to pay for improved air quality: evidence from China's prefecture-level cities. J Clean Prod 273. https://doi.org/10.1016/j.jclepro.2020.122876
Zhang Y, Guo J, Yang Y, et al. (2020b) Vertica wind shear modulates particulate matter pollutions: a perspective from radar wind profiler observations in Beijing, China. Remote Sens 12. https://doi.org/10.3390/rs12030546
Zhang L, Wan X, Shi R, et al. (2022a) Comparing spatial patterns of 11 common cancers in Mainland China. Bmc Public Health 22. https://doi.org/10.1186/s12889-022-13926-y
Zhang W, Wang J, Xu Y, et al. (2022b) Analyzing the spatio-temporal variation of the CO2 emissions from district heating systems with "coal-to-gas" transition: evidence from GTWR model and satellite data in China. Sci Total Environ 803. https://doi.org/10.1016/j.scitotenv.2021.150083
Zheng S, Schlink U, Ho K-F, et al. (2021) Spatial distribution of PM2.(5)-related premature mortality in China. Geohealth 5. https://doi.org/10.1029/2021gh000532
Zhou Y, He X, Zikirya B, (2023) Boba shop, coffee shop, and urban vitality and development-a spatial association and temporal analysis of major cities in China from the standpoint of nighttime light. Remote Sens 15. https://doi.org/10.3390/rs15040903