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Spatial and moderating effects of greenspace on the association between air pollution and lung cancer incidence

Abstract

Lung cancer remains the primary cause of death globally. Studies have increasingly explored the role of greenspace in mitigating lung cancer risks, yet research gaps persist. First, while the direct spatial effect of greenspace has received attention, its potential spillover effects, driven by human mobility and air pollution dispersion, remain underexamined. Second, despite prevalent assertions of greenspace as an air purifier, the extent to which it moderates the air pollution-lung cancer association has yet to be fully understood. Third, the evaluation of greenspace's effects, predominately analyzed linearly *a priori*, demands exploration into their potential nonlinearity. We utilize three-year lung cancer datasets from 228 counties in China, to investigate greenspace's spatial, moderating, and threshold effects on lung cancer incidence in relation to air pollution. Employing spatial econometric and threshold models, our findings indicate that greenspace reduces lung cancer incidence in both local and neighboring counties. We also observe a diminution in the detrimental impact of air pollution on lung cancer incidence in areas with higher greenspace, especially when the Normalized Difference Vegetation Index surpasses a given threshold (0.38). These insights contribute to an enhanced understanding of greenspace's role in lung cancer prevention and could inform policies on greenspace expansion prioritization.

Keywords: greenspace; air pollution; lung cancer; spatial effect; moderating effect

1 Introduction

Lung cancer, the leading cause of death worldwide, necessitates an intensified focus on its preventive measures, underscoring its importance as a critical health priority. In 2018, it accounted for 1.8 million deaths and 2.1 million new cases globally (WHO., 2020). China, as the most populous nation, contributes over 20% of new global lung cancer cases and approximately 40% of deaths (Cao, Chen, Yu, Li, & Chen, 2021; Y. Guo, et al., 2016; S. He, et al., 2020). This significant burden is further compounded by rapid urban development; the country's swift urbanization in recent decades has led to several environmental and lifestyle issues, including air pollution, environmental degradation, and decreased physical activity (Chung, et al., 2021; Sun, Bao, Zhao, Tang, & Wang, 2021; L. Wang, et al., 2022; L. Wang, Zhao, Xu, Tang, & Jiang, 2016). As a consequence, projections suggest a rising lung cancer burden in China within the coming two decades (Cao, et al., 2021).

Lung cancer risk factors include individual behaviors like smoking and alcohol consumption, lifestyle factors such as unhealthy dietary choices and physical inactivity, as well as the influence of socioeconomic status and environmental exposure to air pollution (Barta, Powell, & Wisnivesky, 2019; Chung, et al., 2021; Sun, et al., 2021; L. Wang, et al., 2022; L. Wang, et al., 2016). Notably, among these, ambient air pollutants are recognized as one of the most critical determinants (Y. Guo, et al., 2016). Biologically, these pollutants introduce viruses, bacteria, and harmful gases into the lungs, triggering chronic low-grade inflammation and oxidative stress, thereby heightening lung cancer susceptibility (Loomis, et al., 2013; Turner, et al., 2020). Numerous large-scale epidemiological studies consistently link ambient air pollution with increased lung cancer incidence and mortality (Yuming Guo, et al., 2015;

Raaschou-Nielsen, et al., 2013; L. Yang, et al., 2020). For example, a comprehensive 12-year cohort study in northern China associated long-term exposure to PM_{10}, SO_2, and NO_2 with higher lung cancer mortality (Chen, et al., 2016). Another study across 75 Chinese communities found that $PM_{2.5}$ and ozone exposure correlated with increased lung cancer incidence (Y. Guo, et al., 2016).

The established link between ambient air pollution and increased lung cancer risk has prompted investigations into mitigating factors of air pollution, notably greenspaces. These areas, encompassing parks and forests, act as natural filters, efficiently capturing airborne particulate matter (PM), dust, and pollen. Specific tree species, such as the London plane tree, demonstrate a capacity for absorbing nitrogen dioxide (NO_2) (Buccolieri et al. 2018), while broader vegetation effectively neutralizes sulfur dioxide (SO_2) (Sarker et al. 2016). Greenspaces' shading effect also reduces high temperatures, curbing the formation of ground-level ozone (O_3) in warm conditions (Knight et al. 2021). Empirically, the Normalized Difference Vegetation Index (NDVI), a metric assessing vegetation density, is widely employed to measure greenspace exposure; a close linkage between increased NDVI and air pollution reduction has been observed in the existing literature (Yu et al. 2021; Thiering et al. 2016). Within this context, the formulation of health-oriented interventions aimed at augmenting residential greenspace exposure is gaining recognition in mitigating lung cancer risks and lessening its associated health burdens (Loomis, et al., 2013).

Greenspaces, which facilitate physical activities (B. Xie, Lu, Wu, & An, 2021; Yu, et al., 2023) and offer physical and mental health benefits (Lachowycz & Jones, 2013; Bo Xie, Lu, & Zheng, 2022), have attracted considerable attention from scholars and public health officials. In light of their potential as environmental interventions, a growing body of research has explored the relationship between greenspace exposure and lung cancer incidence (Markevych, et al., 2017; L. Wang, et al., 2022; Zare Sakhvidi, et al., 2022). While some suggest a protective role of greenspaces (Huang, et al., 2022; Lei Yang, et al., 2021), others, including a comprehensive meta-analysis (Coleman, et al., 2021), along with several case studies (Shao, et al., 2019; Sun, et al., 2021; Xu, Ren, Yuan, Nichol, & Goggins, 2017; Zare Sakhvidi, et al., 2021), report no significant impact on lung cancer incidence or mortality. Despite these insights, critical research gaps persist, which may contribute to such inconsistencies and hinder an in-depth understanding of this complex relationship.

First, research has predominately concentrated on the direct impact of greenspace exposure, examining its correlation with lung cancer incidence within specific spatial areas (L. Wang, et al., 2016; Lei Yang, et al., 2021). However, the potential spillover effects of greenspace exposure—its influence beyond immediate geographical boundaries due to human mobility and the diffusion of air pollution—remain largely underexplored. This lack of attention to spatial spillover effects hampers the development of a more comprehensive understanding of the overall health implications of greenspaces, potentially leading to biased research outcomes (Elhorst, 2010).

Second, the majority of existing literature has viewed greenspace exposure as an air purifier, suggesting that it may reduce lung cancer risks through lowered levels of air pollution. However, beyond this mediating linkage, there is limited understanding of how greenspace moderates the relationship between air pollution and lung cancer risks. In essence, how air pollution affects lung cancer may vary with the amount of greenspace exposure. For example, studies have suggested that increased greenspace exposure may enhance lung function and immune response, thus bolstering resilience against air pollutants (Zhang et al. 2023; Sun et al. 2023), which consequently affects lung cancer risk. Evidence also suggests that greenspaces serve as communal areas, fostering social interactions and community engagement (Lund 2003). Strong community ties and collective efficacy enhance health information dissemination, shaping individual responses to air pollution, such as increased awareness of its adverse health effects and informed health choices to mitigate exposure like reducing outdoor activities during periods of high pollution (see Ward et al. (2022) for a review). In practice, investigating such moderating effect of greenspace helps inform targeted greenspace planning to mitigate health disparities driven by variations in air pollution exposure.

Third, while the existing research often assumed a linear relationship between greenspace and lung cancer risks *a priori* (E. A. Richardson & Mitchell, 2010; E. A. Richardson, et al., 2012), this assumption lacks comprehensive validation. Empirically, recent studies suggest a more complex, nonlinear association not only between greenspace and lung cancer risk factors but also with various other health outcomes. For example, Ai et al. (2023)'s study revealed that the expansion of greenspace (measured by NDVI) only starts to reduce PM2.5 concentrations after exceeding a specific threshold. Once this point is surpassed, the pollution-reducing impact intensifies with additional greenspace, up until it reaches another threshold, where the effects then plateau and remain relatively constant. Similar nonlinearity has also been observed in the relationship between greenspace exposure and levels of physical activity (Klompmaker et al. 2018). Moreover, empirical evidence has revealed non-linear relationships between greenspace exposure and various other health outcomes, such as general health (Huang et. al 2018), hypertension (Wensu, Wenjuan, Fenfen, Wen, & Li, 2022), and obesity (Ghimire et al. 2017). Therefore, it is reasonable to explore the association between greenspace and lung cancer incidence within a nonlinear analytical framework. Against this backdrop, determining the presence and nature of threshold effects is crucial for implementing greenspace planning that is both effective and cost-efficient in mitigating lung cancer risks.

This study aims to examine the comprehensive effects of greenspace exposure on lung cancer incidence, utilizing panel data from 228 counties in China between 2013 and 2015. It seeks to examine: (1) the direct, spatial, and overall spillover effects of greenspaces on lung cancer incidence; (2) the moderating role of greenspaces in the relationship between air pollution and lung cancer incidence; and (3) the presence of a threshold effect in the greenspace-lung cancer incidence association. A conceptual framework was developed to elucidate the interactions between greenspaces and lung cancer incidence (Fig. 1). Our findings could provide in-depth insights into the intricate dynamics among greenspace, air pollution, and lung cancer incidence, serving as a foundation for developing effective health-promoting greenspace strategies in developing countries.

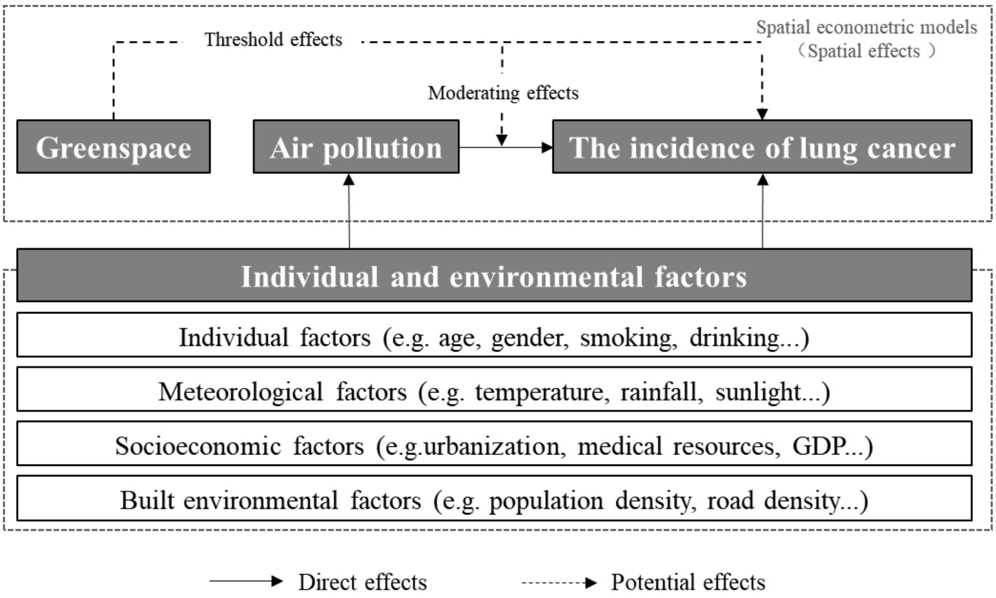


Fig.1. Conceptual framework.

2 Methods

2.1 Study area

County-level administrative regions (counties or county-equivalent areas), which are fundamental urban administrative units in China, served as the study area. Considering the availability of data for all variables, we selected 228 sample counties distributed across 30 municipalities, autonomous regions, and provinces (Fig. 2). On average, new lung cancer cases reported in these selected counties covered approximately 20% of the total new cases diagnosed in China from 2013 to 2015. Such large case sizes in the study area ensured the generalizability of the findings. Moreover, these sample counties consisted of 53% low-income counties and 47% high-income counties with a balanced distribution of economic levels, which avoided biased results caused by economic variation.

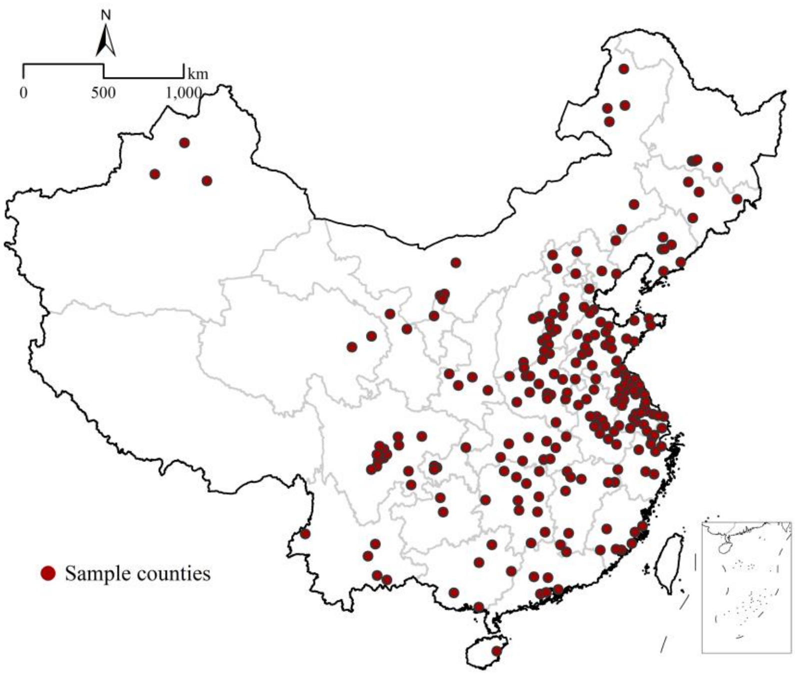


Fig. 2. Locations of the 228 sample counties in China.

2.2 Data collection

Four types of panel data over 3 years were used in this study: lung cancer incidence, air pollution ($PM_{2.5}$) exposure, greenspace exposure, and covariates. The summary and definition for all variables are presented in Table 1.

2.2.1 Incidence of lung cancer

The accurate medical information on lung cancer was gathered from the China Cancer Registry Annual Report. Cancer registries in 31 provinces submit cancer registration data to the National Cancer Center Registry of China (NCCR) annually. These data are collected using active methods (registry personnel investigating the sources of data) and passive methods (medical institution notification forms forwarded to the registry, copies of abstracts for studies containing the necessary data). The NCCR ensures the integrity and credibility of the submitted data by reviewing them against the Guidelines for Chinese Cancer Registration and the applicable data quality criteria outlined in the Cancer Incidence in Five Continents Volume published by IARC/IACR. Quality problems were timely feedback to registries, who then revised and re-submitted the data to the NCCR, forming a cancer reporting database. The database included the registry's name and the number of newly diagnosed cancer cases categorized by the International Classification of Diseases (ICD-10) code at the county or equivalent geographic unit level. Registries lacking complete lung cancer data for 2013 to 2015 were omitted. Consequently, 228 county-level cancer registries were incorporated into the final analysis. From this dataset, we extracted data on the number of newly diagnosed lung cancer cases, as defined by the ICD-10 code for lung cancer (C33-C34), for each county or equivalent geographic unit. The incidence rate of lung cancer in each of these areas was determined by dividing the new cases by the total population.

2.2.2 Air pollution exposure assessment

Research indicates PM2.5 as a key risk factor for non-communicable diseases, notably lung cancer (Song, et al., 2017). The Global Burden of Disease (GBD) 2017 report (GBD Risk Factor Collaborators, 2018) shows that ambient $PM_{2.5}$ air pollution is estimated to account for 14.1% of global lung cancer deaths, second only to tobacco smoking. East Asia bore the heaviest regional burden of PM2.5 on lung cancer, contributing to over 50% of the global disability-adjusted life years (DALYs) attributed to PM2.5-induced lung cancer, with China being the most affected country (Yang et al. 2022). Therefore, the average annual $PM_{2.5}$ was employed as a surrogate for assessing air pollution exposure in this study. Other research suggests that exposure to other ambient air pollutants such as SO_2, NO_2, and O_3 may also significantly contribute to lung cancer risks (Yang et al. 2016). Therefore, we included SO_2 and NO_2 in our sensitivity analyses as adjustments to our model to ensure the robustness of our findings (see, subsection 2.4.3). $PM_{2.5}$ data were collected from the China High Air Pollutants (CHAP) dataset (https://weijing-rs.github.io/product.html). These data are derived and estimated using the Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle implementation of Atmospheric Correction (MAIAC) algorithm and Space-Time Extra-Trees (STET) model, which achieved a cross-validation coefficient of determination ranging from 0.80 to 0.92 (Wei, et al., 2020; Wei, et al., 2021). The $PM_{2.5}$ data, with a spatial resolution of 1 km, have been extensively utilized in studies related to air pollution and public health (Feng, et al., 2023; D. He, Lu, Xie, & Helbich, 2022).

2.2.3 Greenspace assessment

Greenspace exposure estimates were based on the NDVI. We obtained NDVI from Terra MODIS of the National Aeronautics and Space Administration (NASA); the dataset provided comprehensive coverage of China, capturing spatial details at a resolution of 250 m and temporal variations over 16 days from 2013 to 2015. The NDVI values vary between −1 and 1, with higher positive values indicating greater vegetation coverage and negative values corresponding to areas covered by clouds, water, or snow. According to Kayyal-Tarabeia, Michael, Lensky, Blank, and Agay-Shay (2022), we calculated the NDVI values for different months of the year to maximize NDVI contrast and selected August, the greenest month, as the greenspace exposure.

2.2.4 Covariates

Four types of covariates were selected in this study: individual behavioral covariates, meteorological covariates, socioeconomic covariates, and built environment covariates (Table 1). The individual behavioral covariates used in this study were obtained from The China Health and Retirement Longitudinal Study (CHARLS) (http://charls.pku.edu.cn/index.htm), published by the Institute of Social Science Survey of Peking University, Beijing, China. CHARLS is a well-regarded longitudinal survey capturing a broad range of data, from socioeconomic factors to health conditions of individuals aged 45 and above in mainland China (Zhao, Hu, Smith, Strauss, & Yang, 2014). Launched in 2011 with biennial or triennial follow-ups, CHARLS has been instrumental in lung cancer research, especially in integrating representative individual health-related behavioral characteristics as covariates, enhancing the validity of research findings (H. Guo, Chang, Wu, & Li, 2019; Huagui Guo, et al., 2021). In our research, we extracted smoking and drinking rates from the CHARLS Wave 3 survey as covariates. This survey, conducted in 2015, encompassed 150 cities across 28 of the 30 province-level administrative units in China, involving approximately 21,000 individuals (H. Guo, et al., 2019; Liu, Xu, & Yang, 2018). The data on smoking and alcohol consumption were obtained from the health status and function module of the survey. As CHARLS provides data at the prefectural city level, we assigned the same smoking and drinking information to all sample counties within the same prefectural city. We applied the provincial information to the counties for those sample prefecture-level cities not covered by the target prefectural cities in CHARLS.

While CHARLS focused on individuals aged 45 and above, we argue that this may not significantly undermine the robustness of our findings. The reason is that lung cancer incidence in China predominantly increases after age 40 (S. Liu, et al., 2018), with individuals between 50-69 and over 70 accounting for over 80% of cases (Long, et al., 2023). This age distribution aligns closely with the CHARLS cohort, making it an ideal source for extracting representative covariates like smoking and drinking rates from its third wave in 2015.

Rainfall, temperature, and sunshine duration were included as meteorological covariates in this study. Data were obtained from the National Meteorological Data Center (http://data.cma.cn/site).

Socioeconomic covariates such as urbanization, gross domestic product (GDP), proportion of industrial production, and medical supply beds were included as covariates. These variables were selected to control the impact factors of lung cancer based on the urban development level, economic status, and medical conditions. Drawing on prior epidemiological studies (Ge, et al., 2021), we employed annual average nighttime light as a proxy to assess urbanization. These data were obtained from the Visible Infrared Imaging Radiometer Suite (https://ladsweb.modaps.eosdis.nasa.gov/), with higher values indicating higher levels of urbanization. Data on the GDP, proportion of industrial production, and medical supply beds were extracted from the China City Statistical Yearbook.

Built environments have significant effects on air pollution (Ferm & Sjoberg, 2015; Pant & Harrison, 2013) and can potentially affect the incidence of chronic non-communicable diseases (Bo Xie, Jiao, An, Zheng, & Li, 2019). We selected population density and road density as built environment covariates; data were obtained from the China Statistical Yearbook at the county level.

2.3 Examination of spatial dependency

To avoid endogeneity bias in area-level estimations, we employed the Global Moran's I statistic to assess the spatial autocorrelation of lung cancer incidence within counties across the study area. The Global Moran's I value were 0.587, 0.636, and 0.663 in 2013, 2014, and 2015, respectively, illustrating that the incidence of lung cancer in a county presents a significant and strong spatial autocorrelation with that in adjacent counties.

Table 1

Summary statistics for all variables (N=228).

Variable	Description	Unit	Min	Max	Mean	SD
The incidence of lung cancer	Newly diagnosed lung cancer cases /the total population in each county	New cases per 100,000 person	0.715	23.114	5.137	2.137
Air pollution	Annual average $PM_{2.5}$ concentration	μg/m^3	16.424	112.094	69.102	19.672
Greenspace	Average NDVI value in August	——	0.096	0.734	0.444	0.122

Individual factors						
Smoking	Smokers/total number of population in each county	%	25.800	58.333	39.585	0.053
Alcohol drinking	The number of people who drink more than once a month/ total population in each county	%	4.918	56.493	35.586	0.075
Meteorological factors						
Rainfall	Annual average rainfall	mm	712.604	3422.926	1989.772	513.397
Temperature	Annual average temperature	℃	1.910	32.67	16.89	4.50

				5	0	9
Sunshine duration	Annual average sunshine hours	hour	1.140	12.652	5.761	1.984
Social-economic factors						
Urbanization	Annual average nighttime light intensity	——	0.041	73.121	11.236	14.544
GDP	Per capita GDP per year	10 thousand yuan per person	0.808	46.775	5.652	3.978
Proportion of industrial production	The proportion of industrial output in total output per year	%	0.061	5.595	1.662	0.810

Medical supply beds	Medical bed number per 1,000 person	counts per 1,000 person	11.897	241.662	49.911	26.229
Built environment factors						
Population density	Population/total area of the counties	Person per km^2	79.000	13971.000	3710.722	2616.363
Road density	Road length/total area of the counties	km/km^2	0.002	3.902	0.346	0.532

263 Note: Min = minimum; Max = maximum; SD = standard deviation

2.4 Statistical analysis

2.4.1 Spatial econometric models for panel data

The existence of spatial dependence and autocorrelation violates the hypothesis that variables are independent of each other (LeSage & Pace, 2009). Therefore, we constructed spatial econometric models for the panel data to correct the biased and inconsistent estimations caused by the spatial spillover effect. A general spatial nesting model was constructed as follows:

$$Y_{it} = \rho W Y_{it} + \alpha I_n + \beta X_{it} + u, u = \lambda W_{\mu} + \varepsilon \quad (1)$$

where, for county i in year t, Y_{it} is the n $\times$ 1 vector of lung cancer incidence; X_{it} is the explanatory variable; β is the corresponding coefficients; W is an n $\times$ n spatial weight matrix; I_n is an N × 1 vector which is associated with the constant term parameter α; ρ denotes the spatial autoregressive coefficient; λ denotes the spatial autocorrelation coefficient; ε denotes a vector of disturbance terms; and W_{μ} denotes the interaction effects arising from the disturbance terms across different spatial units.

Based on Eq. (1), when $\lambda = 0$, the model was transformed into a spatial Durbin model (SDM) containing the spatial lag terms of the dependent and independent variables:

$$Y_{it} = \rho W Y_{it} + \alpha I_n + \beta X_{it} + \theta W X_{it} + \varepsilon \quad (2)$$

Based on Eq. (2), when $\theta = 0$, the SDM could be simplified to a spatial lag model (SLM) containing the spatial lag terms of the dependent variable. If $\theta = -\rho\beta$, then $\lambda = \rho$, and we obtained the spatial error model (SEM), which only contained the spatial lag terms of the error term. To determine which model is more appropriate for describing data, the Lagrange multiplier (LM) test, robust Lagrange multiplier (robust LM) test, and likelihood ratio (LR) test were used (for specific model selection methods, see Elhorst (2012)). The Hausman test examined fixed effects when individual or time effects were correlated with regressors (Lee & Yu, 2012).

The advantages of employing spatial econometric models are as follows. First, the spatially lagged terms WY_{it} and WX_{it} can help explicitly reduce the endogeneity bias caused by spatial dependence and spatial autocorrelation. Two main approaches are commonly employed when constructing the spatial weight matrix: neighboring and distance-based. As there were distances between some sample counties, the diffusion of air pollutants was not confined by administrative boundaries. Therefore, to account for possible bias, the reciprocal of the Euclidean distance among counties was used as an element in our distance weight matrix, according to the equation:

$$W = \begin{cases} \frac{1}{d} & i \neq j \\ 0 & i = j \end{cases} \tag{3}$$

where d represents the distance of the geometric center between county i and county j.

Second, spatial econometric models can be employed to calculate the spatial spillover effects of greenspaces on lung cancer incidence. LeSage and Pace (2009) defined every average diagonal element of the WX_{it} matrix of WX_{it} as a direct effect. This term refers to the influence of changes in the independent variable on the dependent variable of local areas. Moreover, every non-diagonal average element is defined as the spillover effect, which is interpreted as the impact of the independent variable on the dependent variable of neighboring areas. Finally, the total effect includes both the average direct and spillover effects.

2.4.2 Panel threshold model

To explore the threshold effect of greenspace on lung cancer incidence, the panel threshold model, which can automatically identify the endogenous features of data, was employed in this study (Hansen, 1999).

The threshold model is expressed by Eq. (4) and Eq. (5) as follows:

$$Y_{it} = \mu_i + \beta_1 X_{it} + \varepsilon_{it}, \quad q_{it} \leq \gamma \tag{4}$$

$$Y_{it} = \mu_i + \beta_2 X_{it} + \varepsilon_{it}, \quad q_{it} > \gamma$$

(5)

For county i in year t, Y_{it} is lung cancer incidence, X_{it} is the independent variable, and q_{it} denotes the threshold variable; μ_i represents the individual effect. Depending on the threshold γ, the observations are categorized into two stages. Each stage represents a distinct regime with its regression slope, either β_1 or β_2.

2.4.3 Sensitivity analysis

To enhance the robustness of our findings, we performed two types of sensitivity analyses. First, we employed an alternative weight matrix structure, specifically the queen contiguity matrix, to ascertain the stability of our model given its distinct weight matrix configuration. Second, we recalibrated the primary model, incorporating adjustments for SO2 and NO2 concentrations, to explore the potential confounding effects of these gaseous pollutants on lung cancer incidence. The data for these pollutants, with a 10km resolution, were sourced from the Comprehensive Air-quality Prediction (CHAP) dataset (https://weijing-rs.github.io/product.html).

3 Results

3.1 Descriptive analysis

According to the data presented in Table 2, there was no significant variation in the incidence of lung cancer from 2013 to 2015, whereas the variations in $PM_{2.5}$ and NDVI differed significantly. The mean $PM_{2.5}$ concentration significantly decreased by 36 μg/m^3 in absolute terms and 41.2% in percentage terms. The mean NDVI value in 2015 were slightly higher than those in 2013 (0.46 vs. 0.42).

In terms of spatial distribution, a higher incidence of lung cancer was observed in counties in the eastern region (Fig. 3). Moreover, the concentration of $PM_{2.5}$ was found to be higher in the eastern region when compared to both the central and western regions within the study area (Fig. 4). Fig. 5 shows that the distribution of the NDVI differed significantly among the three regions in China, with the central region holding the highest level, followed by the eastern and western regions.

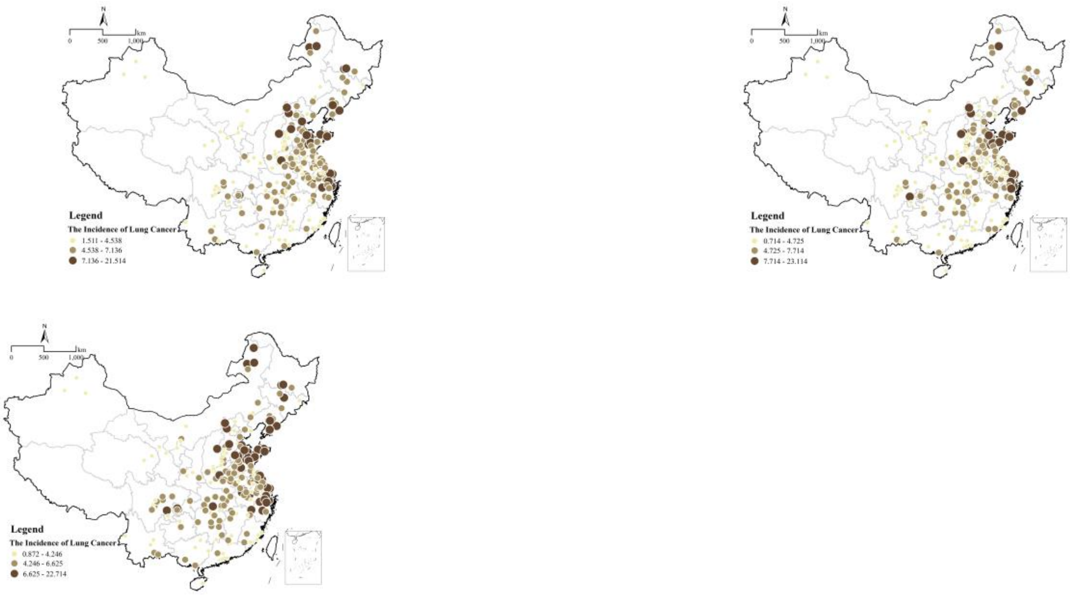
Table 2

The temporal variations of lung cancer incidence, $PM_{2.5}$ concentration, and the NDVI.

Incidence of lung cancer			$PM_{2.5}$			NDVI		
2014-2013	2015-2013	2015-2014	2014-2013	2015-2013	2015-2014	2014-2013	2015-2013	2015-2014

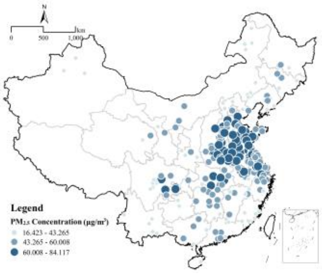
Z value	-1.074^b	-1.489^b	-.601^b	-11.887^c	-13.083^c	-13.067^c	-9.012^b	-10.101^b	-2.194^b
P value	0.283	0.136	0.548	0.000	0.000	0.000	0.000	0.000	0.028

Note: The *Wilcoxon signed-rank test* was used to examine the temporal variations of variables in each county from 2013 to 2015. b was based on negative ranks. c was based on positive ranks.



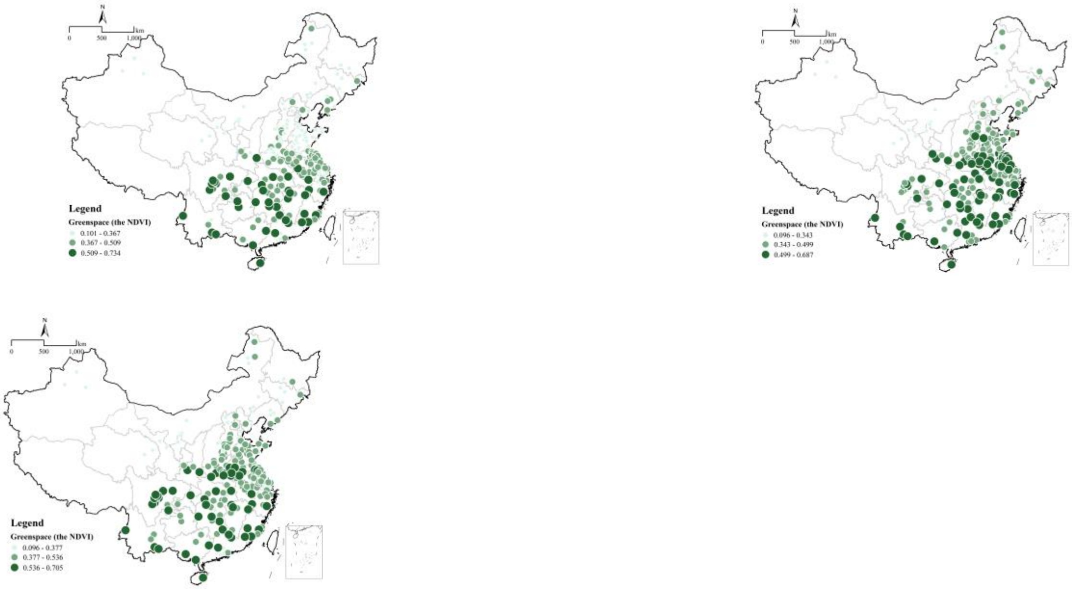
a. 2013 b. 2014 c. 2015

Fig. 3. Spatial distribution of the incidence of lung cancer in 2013-2015.



a. 2013 b. 2014 c. 2015

Fig. 4. Spatial distribution of $PM_{2.5}$ concentrations in 2013-2015.



a. 2013 b. 2014 c. 2015

Fig. 5. Spatial distribution of the NDVI in 2013-2015.

3.2 Results of basic models

Table 3 presents the estimated results of greenspaces' effects on lung cancer incidence. The statistical values of the LM and LR tests indicated that the SDM was deemed more suitable compared to the SLM and SEM in the present study. Furthermore, according to the Hausman test, fixed effects were more suitable for our research. Therefore, all models employed in our study incorporate the time-fixed effect.

The results showed that the direct effect of the NDVI on the incidence of lung cancer was significantly negative at the 5% significance level. A one-unit increase in NDVI caused a 2.793% decrease in the incidence of lung cancer. Furthermore, we found a negative spatial spillover effect of NDVI on the incidence of lung cancer. Every one-unit increase in NDVI decreased the incidence of lung cancer in the surrounding counties by 0.593%.

Regarding covariates, the incidence of lung cancer was significantly influenced by higher rates of smoking and alcohol consumption in counties. Moreover, rainfall and the proportion of industrial production had direct and spatial spillover effects on lung cancer incidence. We also found that road density was negatively related to lung cancer incidence in both local and nearby counties.

Table 3

Spatial econometric models result.

Dependent Variable：Incidence of lung cancer	SDM				
	Main	Wx	Direct effect	Indirect effect	Total effect
NDVI	-2.805** (1.0918)	-3.350* (1.8930)	-2.793** (1.1331)	-0.593* (0.3191)	-3.386** (1.4002)

Smoking	7.730*** (1.5155)	5.317** (2.7472)	7.748*** (1.4460)	1.631*** (0.5937)	9.379*** (1.8203)
Alcohol drinking	5.573*** (1.0795)	6.899*** (2.1194)	5.738*** (1.1568)	1.218** (0.4759)	6.956*** (1.4908)
Rainfall	0.455* (0.2391)	0.711* (0.4024)	0.449** (0.2410)	0.096* (0.0636)	0.545** (0.2975)
Sunshine duration	0.390 (0.3881)	1.263 (0.6237)	0.403 (0.3853)	0.087 (0.0921)	0.490 (0.4717)
Temperature	-0.397 (0.3050)	-0.464 (0.4310)	-0.390 (0.2987)	-0.080 (0.0673)	-0.470 (0.3598)

GDP	0.003	0.008	0.004	0.001	0.005
	(0.0242)	(0.0453)	(0.0261)	(0.0059)	(0.0318)
Urbanization	-0.001	-0.018	-0.001	-0.001	-0.002
	(0.0060)	(0.0112)	(0.0057)	(0.0013)	(0.0069)
Proportion of industrial production	0.475***	0.049*	0.485***	0.103**	0.588***
	(0.1006)	(0.1887)	(0.1002)	(0.0400)	(0.1278)
Medical supply-beds	-0.001	-0.001	-0.001	-0.001	-0.002
	(0.0005)	(0.0015)	(0.0005)	(0.0001)	(0.0006)
Population density	0.200	0.747	0.200	0.043	0.243
	(0.3995)	(0.7266)	(0.4060)	(0.0929)	(0.4945)
Road density	-	-0.396	-	-0.074*	-

	0.355** (0.1702)	(0.2859)	0.350** (0.1799)	(0.0452)	0.424** (0.2192)
ρ	0.195***				
σ	3.805***				
R^2	0.128				
N	228				
SEM-LM	0.009*				
SEM-Robust LM	2.158*				
LR test (SDM & SEM)	20.790**				
SLM-LM	2.191***				
SLM-Robust LM	4.340				
LR test (SDM &	21.330				

SLM)	*
Hausman test	40.010 ***

Note：*p <0.1; **p <0.05; ***p <0.01. In parentheses denotes the standard error. “Main” refers to the non-spatial regression coefficient; “Wx” refers to the spatial regression coefficient. “Direct effect” represents the impacts of variables on the incidence of lung cancer in local areas; “Indirect effect” represents the impacts of variables on the incidence of lung cancer in nearby areas. The spatial correlation coefficient of the dependent variable is denoted as ρ, and the standard error is defined as σ.

3.3 Moderating effect of greenspace

To examine the moderating effect of greenspace on the relationship between $PM_{2.5}$ and lung cancer incidence, we added $PM_{2.5}$ and the interaction term ($PM_{2.5}$ × NDVI) into the basic model. Table 4 shows that the negative direct and spatial spillover effects of NDVI remained significant after controlling for covariates. In addition, there was a positive direct and spillover effect of $PM_{2.5}$ on the incidence of lung cancer. Furthermore, we observed that the interaction term of $PM_{2.5}$ and NDVI had a significant negative direct effect on the incidence of lung cancer. That is, a one-unit increase in the NDVI is associated with a 0.050% decrease in the impact of $PM_{2.5}$ on the incidence of lung cancer. However, no spillover effect of the interaction term was observed in this model. Our sensitivity analyses revealed that after recalibrating the model with the queen contiguity matrix and incorporating adjustments for SO_2 and NO_2, the results demonstrated substantial consistency (Table S1 in Supplementary Material).

Table 4

Tests for the moderating effect of greenspace.

Dependent Variable：Incidence of lung cancer	SDM				
	Main	Wx	Direct effect	Indirect effect	Total effect
NDVI	-3.056*** (1.0908)	-3.587* (1.9299)	-3.047** (1.1322)	-0.646* (0.3266)	-3.693** (1.4021)
$PM_{2.5}$	0.020*** (0.0068)	0.002** (0.0105)	0.020*** (0.0066)	0.004** (0.0019)	0.024*** (0.0081)
$PM_{2.5}$×NDVI	-0.053* (0.0344)	-0.034 (0.0678)	-0.050* (0.0332)	-0.010 (0.0077)	-0.060* (0.0401)

Covariates	√
ρ	0.194***
σ	3.755***
R^2	0.169
N	228
SEM-LM	0.035*
SEM-Robust LM	2.838*
LR test (SDM & SEM)	21.180*
SLM-LM	3.215*
SLM-Robust LM	6.018**
LR test (SDM & SLM)	21.360*

Hausman test	31.940***

Note：*p <0.1; **p <0.05; ***p <0.01. In parentheses denotes the standard error.

3.4 Threshold of moderating effects

We developed two models to examine whether there was a significant threshold effect on the incidence of lung cancer. Model 1 in Table 5 shows that the total effect of the NDVI did not exhibit a significant threshold. However, the single and double thresholds in Model 2 passed the 5% significance test, suggesting significant double thresholds for NDVI's moderating effect.

The NDVI moderated the relationship between $PM_{2.5}$ and the incidence of lung cancer in the three stages (Table 6). When the NDVI value was less than 0.38, the interaction term did not significantly impact lung cancer incidence. When the NDVI was between threshold values of 0.38 and 0.4, the interaction term was negatively associated with the incidence of lung cancer. Specifically, with a one-unit increase in NDVI, the positive effect of $PM_{2.5}$ on lung cancer incidence decreased by 0.139%. Finally, when the NDVI was higher than a threshold value of 0.4, the negative effect of the interaction term on lung cancer incidence remained significant. However, the extent of the moderating effect decreased significantly compared with that in the second stage.

Table 5

Tests for the threshold effect of the NDVI.

Threshold	F statistic	P value	10%	5%	1%
Threshold test of the total effect (model 1)					
Single	14.870	0.150	16.521	18.559	24.455
Double	6.770	0.586	14.636	16.160	19.967
Triple	4.820	0.830	16.105	19.747	25.136
Threshold test of the moderating effect (model 2)					
Single	13.140*	0.070	11.730	15.018	19.044
Double	17.540**	0.026	12.277	15.589	19.727
Triple	14.100	0.253	20.787	29.958	32.980

Note: *p <0.1; **p <0.05; ***p <0.01.

Table 6

The threshold value and parameter estimation of the moderating effects of greenspace.

Dependent Variable: Incidence of lung cancer	Threshold	Coefficient	T statistic
	NDVI⩽0.38	0.002	0.260
$PM_{2.5}$×NDVI	0.38＜NDVI ⩽0.4	-0.139***	-4.080
	NDVI＞0.4	-0.013***	-2.820

Note: *p <0.1; **p <0.05; ***p <0.01.

4 Discussion

4.1 Associations between greenspace, $PM_{2.5}$, and lung cancer

This study found that greenspace exposure is a protective factor against lung cancer. To date, only a few studies have reported the preventive effects of greenspace on lung cancer. A cohort study from Taiwan, China, revealed a significant relationship between an increment of 0.1 units in NDVI and a hazard ratio (HR) of 0.95 in lung cancer risks (Huang, et al., 2022). Another cohort study conducted in Tel Aviv, Israel, over a 21-year follow-up period, involving 144,427 participants, revealed a beneficial correlation between higher residential greenness and lower incidence of lung cancer (Kayyal-Tarabeia, et al., 2022). We obtained consistent results at the national scale, as noted in previous studies. This finding provides evidence that greenspace intervention is a useful avenue for reducing the incidence of lung cancer.

The effects of greenspace on health outcomes in previous ecological studies are often simplified to a direct one-to-one relationship at the area level, which might report biased findings. For example, a comprehensive ecological study from the United Kingdom found no relationship between greenspace and lung cancer mortality (E. A. Richardson & Mitchell, 2010). Similarly, an urban study conducted in New Zealand failed to provide evidence that greenspace influences lung cancer mortality (E. Richardson, Pearce, Mitchell, Day, & Kingham, 2010). Although these studies observed consistent results at the local level across different countries, they do not fully capture the comprehensive health impact of greenspace, especially when considering the presence of spillover effects that align with the direction of the direct effects (Benjamin-Chung, et al., 2018). In our study, we go beyond previous studies that typically consider the direct effects of greenspace on lung cancer and adopt spatial econometric models to investigate the presence and extent of spatial spillover effects. The results from the SDM showed that the total protective effect of greenspace involved both direct and indirect effects (i.e., spatial spillover effect). These findings reveal that exposure to greenspaces can mitigate the risk of lung cancer not only in local counties but also in neighboring ones. Remarkably, the protective effects of greenspace from nearby counties account for 20% of the benefits derived from local greenspace. Increasing greenspace not only provides health benefits to residents who lived in local counties but also extends its impact to individuals who do not directly receive the greenspace intervention. Our findings highlight the importance of synergistically scaling up or subsidizing greenspace interventions nationally.

Two potential reasons have been proposed in this study to explain the spatial effects of greenspace on lung cancer incidence. A plausible explanation is that greenspaces in local counties may deposit and filter $PM_{2.5}$ diffused from adjacent counties by chemical, biological, and physical effects (Markevych, et al., 2017; Zare Sakhvidi, et al., 2022), thereby decreasing the harmful effects of $PM_{2.5}$. Moreover, most existing studies on cancer incidence failed to consider the greenspace exposure changes caused by human mobility across the geographical boundary (Gailey, McElroy, Benmarhnia, & Bruckner, 2021; Namin, Zhou, Neuner, & Beyer, 2021). In China, straddle and circle mobility among counties (such as inter-city commuting and hukou-based migrant) is widespread. This large-scale individual mobility involving approximately 18% of the country's total population may lead to continuous variations in residents' exposure to greenspace (Mai & Wang, 2022; Namin, et al., 2021). Under this scenario, the health benefits derived from greenspace may not solely originate from the local area but should encompass the cumulative effect of local and nearby counties. Our findings on spatial spillover effects emphasize the need for future studies to estimate greenspace exposure using the mobility-based approach in similar countries with high internal mobility levels to provide more comprehensive insights into the health effects of greenspace.

Second, recent epidemiological studies have shown that greenspace may moderate the effect of $PM_{2.5}$ on health outcomes. For example, a nationwide modeling study from China suggested that areas with higher levels of greenspace exhibited stronger protective effects against tuberculosis in the presence of $PM_{2.5}$ compared to areas with lower levels of greenspace (Zhu, et al., 2022). Similarly, an ecological study conducted in Greece reported that areas with greater greenness had lower $PM_{2.5}$ effects on cardiovascular mortality (Kasdagli, Katsouyanni, de Hoogh, Lagiou, & Samoli, 2021). Our estimated results suggest that greenspace can moderate the relationship between $PM_{2.5}$ and lung cancer incidence, which is in accordance with previous studies (Coleman, et al., 2021; Kasdagli, et al., 2021). In other words, the positive effects of $PM_{2.5}$ on the incidence of lung cancer decreased in greener counties.

However, a moderating greenspace effect was observed only after the NDVI exceeded a certain threshold. According to Table 6, when the NDVI exceeded 0.38, greenspace was conducive to reducing the positive effect of $PM_{2.5}$ on the incidence of lung cancer. Furthermore, when the NDVI increased to 0.4, the strength of the moderating effect decreased. Recent studies conducted in developed countries have observed similar nonlinear effect trends. For example, evidence from a national cohort of Canadian adults showed no significant relationship between $PM_{2.5}$ and non-accidental and cardiovascular mortality in the two greenest quintiles (Crouse, et al., 2019). Research comprising 5.5 million cancer patients and survivors across 14 states and metropolitan regions in the United States has found that an increase in county-level $PM_{2.5}$ is associated with a heightened risk of cardiopulmonary mortality in regions with low levels of NDVI. In contrast, areas with high levels of greenness were almost immune to any variations in $PM_{2.5}$ levels and did not pose any relative risk (Coleman, et al., 2021). Our findings differed slightly from those of previous studies. Results in our study emphasize the existence of a certain threshold value that may trigger the potential emergence of the moderating effect of greenspace. This finding implies that compared to developed countries, local governments in developing countries need to prioritize policy interventions focusing on expanding greenspaces to generate positive health effects even in counties with high air pollution.

Third, we comprehensively controlled for individual, meteorological, socioeconomic, and built environment factors, thus avoiding potential biases and giving more realistic results. Smoking and alcohol consumption were seldom incorporated in previous ecological studies, although they are crucial contributors to respiratory diseases like lung cancer (Lin, Murray, Cohen, Colijn, & Ezzati, 2008). In our research, these two factors based on data derived from CHARLS were introduced to the models. The results showed that they were positively correlated with the incidence of lung cancer, which is consistent with the results of previous studies (WHO., 2020). Regarding meteorological factors, we found that rainfall was positively related to the incidence of lung cancer, perhaps owing to condensation nuclei in microdroplets of rainfall water that carried air pollutants and damaged human lungs (Clauss, Mayes, Hilton, & Lawrenson, 2005; Javorac, et al., 2021). Furthermore, our findings indicate a positive correlation between the proportion of industrial production and the incidence of lung cancer, which is consistent with previous studies (López-Cima, et al., 2013; Lopez-Cima, et al., 2011). For built environment factors, the results suggest a negative correlation between road density and the incidence of lung cancer, which is inconsistent with the findings of other studies (Bechle, Millet, & Marshall, 2011; Chawinska, Tukiendorf, & Miszczyk, 2014; Sun, et al., 2021). A plausible explanation is that high road density in Chinese counties may decrease per capita emissions by discouraging car usage and promoting walking as a mode of transportation (Brownstone & Golob, 2009), thereby reducing the risk of lung cancer.

4.2 Policy implications

This study has several policy implications that can facilitate greenspace construction and lung cancer prevention in China and other developing countries. First, urban planners should note the strong spillover effects of greenspace, which can reap the health benefits that transcend the local population. Consequently, there is a pressing need to prioritize and allocate resources to support the expansion of greenspace at a national level, aiming to optimize health outcomes for a broader population.

Second, we found a moderating effect of greenspaces on the association between $PM_{2.5}$ and lung cancer incidence, providing new evidence and insights for central and local governments to enhance the understanding of greenspace-related health benefits. Although the government has taken proactive measures to control air pollution, $PM_{2.5}$ will likely continue to contribute significantly to the high burden of lung cancer. Therefore, policymakers and urban planners should pay attention to the mitigating function of greenspaces in lung cancer associated with air pollution. Specifically, policymakers can use NDVI as a crucial quantitative indicator and incorporate it into lung cancer resilience strategies and urban planning policies. The critical greenspace value, where the moderating effect was significant, could be considered the basic requirement for regional greenspace construction.

Third, to improve our understanding of the threshold value of the moderating effect of greenspace, we calculated the proportion of counties in which the NDVI value was less than 0.38, even in the greenest season, and presented their spatial distribution (see Fig. S1 and Table S2). In over 20% of the counties, NDVI was found to have no moderating effect on the relationship between $PM_{2.5}$ and lung cancer incidence. Therefore, the policymakers should provide more resources (e.g., financial investment to expand greenspace and mitigate air pollution) for these counties to reduce lung cancer risks at both the local and national levels.

4.3 Strengths and limitations

This study makes three contributions to the existing literature. First, this study considered greenspaces' direct and spatial spillover effects simultaneously, avoiding the estimated bias caused by ignoring spatial autocorrelation in previous studies. More importantly, our study provides insights for policymakers to develop broader regional policies to improve greenspaces. Second, we explored the moderating impact of greenspace on the link between $PM_{2.5}$ and lung cancer incidence after controlling for drinking and alcohol drinking factors, extending our knowledge of how residing in greener areas may contribute to better health outcomes. In most developing countries, people are simultaneously exposed to greenspaces and high levels of air pollution. Given this widespread issue, our findings can help local governments in China and similar developing countries realize that greenspace intervention effectively prevents health problems caused by high air pollution concentrations. Third, this study examined the nonlinear trend in the health effects of greenspaces, which could guide the implementation of greenspace interventions to improve health outcomes.

This study is subject to several limitations. First, due to data constraints and privacy laws in China, we did not include detailed sociodemographic details such as age and sex for individuals with lung cancer. Second, while our reliance on smoking and alcohol consumption rates from the CHARLS datasets, targeting those aged 45 and above, aligns with the age bracket most affected by lung cancer in China, it may not fully represent younger demographics, potentially affecting the generalizability of our findings. Also, our method of assigning uniform health-related behavior information to counties within the same prefectural cities or provinces might not account for local behavioral differences. Third, although we investigated the relationship between $PM_{2.5}$, greenspace exposure, and lung cancer, and enhanced our findings by adjusting for SO_2 and NO_2, our approach might not capture all air pollutant factors influencing lung cancer. Addressing these data limitations in future studies would be beneficial. Fourth, our study did not account for the cumulative effects of greenspace and $PM_{2.5}$ exposure on lung cancer incidence, potentially introducing uncertainty regarding threshold levels. It is advisable for future research to re-examine our findings using longitudinal data over an extended period, which would better facilitate the modeling of cumulative exposure to greenspace and $PM_{2.5}$.

5 Conclusions

This study provides robust evidence to explore the spatial effect of greenspaces on the incidence of lung cancer in developing countries, using panel data from 2013 to 2015. The results of spatial econometric models showed that greenspace has a negative direct effect and a spatial spillover effect on the incidence of lung cancer. Moreover, a negative moderating effect of greenspace on the relationship between $PM_{2.5}$ and the incidence of lung cancer was identified. Furthermore, the moderating effect of greenspaces became significant when it was greater than 0.38. This study suggests that investment in greenspaces can be an effective intervention strategy for reducing the incidence of lung cancer in China.

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