

Article

Spatial Analysis of Lung Cancer Patients and Associated Influencing Factors from the Perspective of Urban Sustainable Development: A Case Study of Jiangsu Province, China

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Abstract: With global environmental changes, lung cancer has become one of the most common types of cancer worldwide, posing a significant public health challenge. Jiangsu Province, located in the eastern part of China, is an economically and socially developed region. According to the latest cancer registration data in Jiangsu Province, lung cancer ranks first in both incidence and mortality of cancer in the province. Thus, studying the spatiotemporal distribution of lung cancer cases and analyzing the influence of various factors on this distribution are crucial for the effective prevention and control of the disease in Jiangsu Province. This study takes the statistical data of lung cancer patients in Jiangsu Province in 2020 as the research object, uses Geographic Information System (GIS) visualization and spatial analysis to study the spatial distribution characteristics of lung cancer patients in Jiangsu Province, and employs the geographical detector to numerically express the impact of various environmental factors on the distribution of lung cancer patients in Jiangsu Province. The results reveal a notable spatial clustering of lung cancer cases, with high-incidence areas concentrated in Suzhou, Nanjing, and Xuzhou cities. Among the seven environmental factors examined, PM_{2.5}, SO₂, and PM₁₀ concentration exert the most significant influence. This study employs multifactorial spatial analysis to elucidate the intricate relationships between people's health and air quality, medical resource distribution, and lung cancer incidence in the process of pursuing sustainable development in cities and provides an important reference for the improvement in lung cancer prevention and control strategies.

Keywords: lung cancer; spatial-temporal distribution; environmental factors; urban sustainable development; influencing factors; geographic detectors; Jiangsu Province



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1. Introduction

Lung Cancer is regarded as the most common cancer in the world and displays a higher possibility in more developed regions [1]. With the increasing number of lung cancer cases reported, it is already one of the major public health problems [2]. As reported by the World Health Organization, there were approximately 14 million cancer cases all over the world in 2012, among which 12% were caused by lung cancer, and the total cancer case number is expected to reach 24 million by 2035 [3]. With the rapid economic development trend in China over the last decades, people have been faced with more potential risks that may increase the incidence of cancer, such as over-populated communities, air pollution, indoor second-hand smoke, lack of physical exercise, and so on [4]. It is traditionally believed that there are more cancer cases in less developed rural areas than in urban areas as the rural area is usually poor with limited medical services. However, this situation seems to change due to the comprehensive risk factors, especially with respect to lung cancer [5–7]. Thus, it has received growing attention from both domestic and foreign

researchers to study the spatiotemporal patterns of lung cancer incidence [8–10]. Such analyses will help to improve the efficiency of public health planning and the preparedness of cancer management.

Numerous studies on lung cancer have already been reported [11–14]. Based on the medical statistical yearbook data, Shen conducted a statistical study on the distribution of lung cancer patients in China from 1973 to 2013 at a municipal spatial scale [11]. From the perspective of environmental research, Wang summarized the potential environmental factors that trigger lung cancer through literature knowledge induction and explored the influence mechanism of various air quality indicators on the spatiotemporal distribution characteristics of lung cancer patients. The study results showed that the concentration of PM_{2.5} is highly correlated with an increase in the number of lung cancer patients [12]. From the perspective of public health management, some studies have used geographical methods to study the spatiotemporal distribution characteristics of patients, including the use of geographically weighted regression models, global autocorrelation models, hot spot analysis models, Bayesian spatiotemporal models, and geographical detector models, etc. [13–15]. Geographic Information System (GIS) technology has been widely used in the field of public health, especially in the study of medical event characteristics, spatiotemporal distribution of patients, and research on ecological environmental influencing factors, and has been proven to be effective.

Environmental factors refer to various influential social and environmental factors present in the space where people live, and which have a certain impact on people's lives and development. These influential social and environmental factors affecting the incidence of lung cancer have been discussed in many current studies. The International Agency for Research on Cancer (IARC) has explicitly listed outdoor air pollution and PMs as highly relevant human carcinogens in its research reports [16]. Some scholars have linked atmospheric pollution, per capita GDP of countries and regions, medical conditions, and other factors to lung cancer, exploring the impact of such factors on the distribution of lung cancer [17,18]. For instance, Liu et al. discussed the impact of pollutant exposure on people's health and analyzed the relationship between the high incidence of lung cancer in Henan Province, China, and the concentration of various air pollutants. The study results indicated that different pollutants have varying degrees of impact on the triggering of lung cancer [19,20]. However, most studies only consider the impact of individual factors and lack an examination of the comprehensive impact of multiple factors combined on the distribution of lung cancer. Therefore, this study will combine multiple environmental factors to explore their comprehensive impact on the distribution of lung cancer.

Exploring the spatial distribution patterns of lung cancer patients and their related environmental impact factors is of significant importance for public health management and urban sustainability decision-making. In this study, GIS spatiotemporal analysis models will be used to extract the spatial distribution characteristics of lung cancer patients in Jiangsu Province and analyze their spatial distribution patterns. Global autocorrelation models will be employed to explore the spatial heterogeneity among patient spatial distributions. Finally, the geographical detector model will be utilized to detect the interactive effects of relevant environmental influencing factors. This study provides theoretical insights into sustainable urban governance. It emphasizes the need to integrate socioeconomic development, environmental protection, and public health within the framework of sustainable development. By conducting quantitative analysis, the study aims to propose public health management strategies that balance ecological health and human well-being, particularly in reducing lung cancer incidence. These findings offer sustainable policy recommendations for urban governance, ensuring a more holistic approach to improving public health outcomes while maintaining environmental integrity. And it will propose specific improvement measures for air pollution control, optimal allocation of medical resources, and an improvement in the living environment so as to provide an important reference for the prevention and control of lung cancer in Jiangsu Province and its coordination with sustainable urban development.

2. Materials and Methods

2.1. Study Area

Jiangsu Province is located in eastern China, which spans from longitude 116°60' E to 121°67' E and latitude 31°53' N to 34°89' N (Figure 1). The province is to the west of the East China Sea and at the lower reaches of the Yangtze River. The capital city of Jiangsu Province is Nanjing. The province covers a total area of 102,600 km² [21].

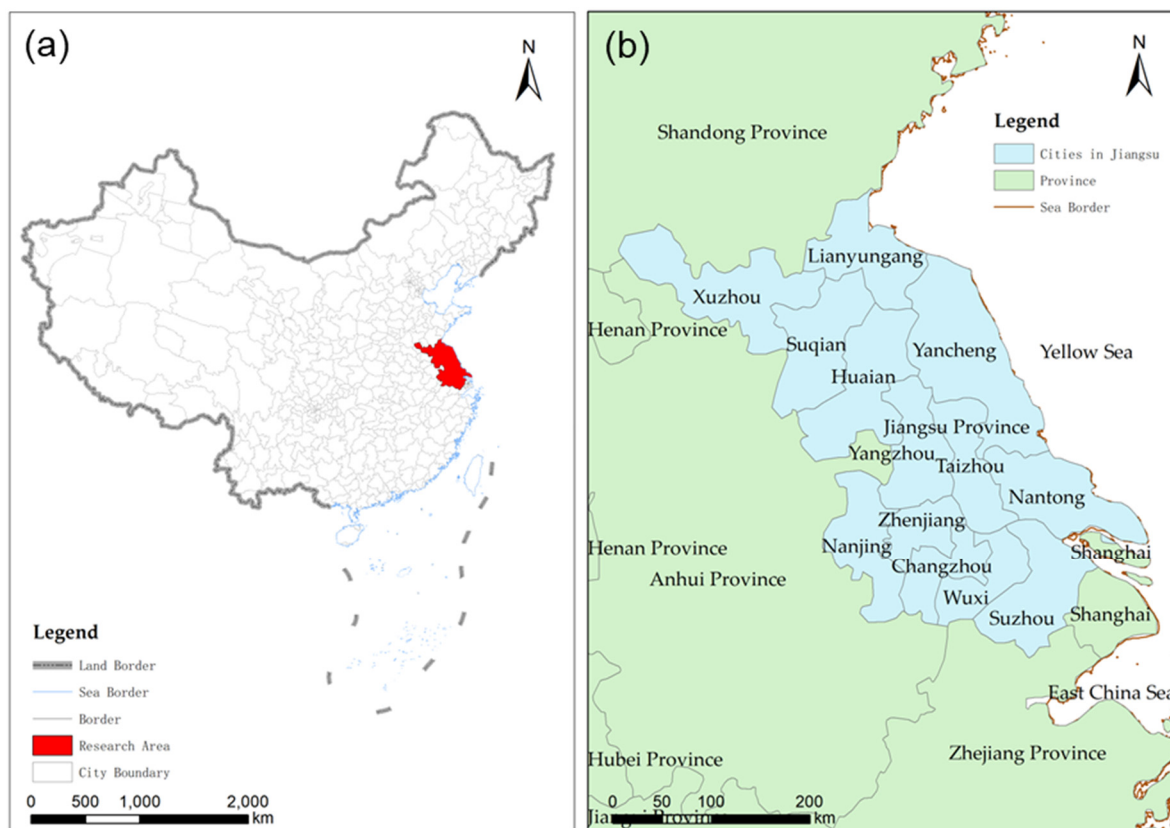


Figure 1. Distribution map of the research area: (a) Distribution of Jiangsu Province at the country level map; (b) Distribution map of the cities in Jiangsu Province.

Jiangsu Province, as one of the more economically prosperous regions in China, boasts a significant gross economic volume, a high per capita disposable income among its residents, and extensive public service resources in terms of social infrastructure. In the domain of healthcare, the province is well-endowed with various health institutions, positioning its medical resources at the forefront nationally. By the year 2020, the permanent resident population aged 60 and above in Jiangsu Province had reached 18.5 million, constituting 21.84% of the total population. This demographic marker signifies that the province has transitioned into a phase of moderate aging. The persistent intensification of this aging trend is anticipated to present considerable challenges to the social security system and the sustainability of medical resource provisioning [21–23].

2.2. Data

• Lung Cancer Data and Hospital Data

To explore the spatial patterns of lung cancer, we investigated lung cancer and reported hospital data provided by the National Health Commission of the People's Republic of China. These data were processed using STATA 17 statistical software to generate an Excel attribute table, which reflected the spatial distribution of lung cancer patients and the distribution of medical resources in Jiangsu Province in 2020. These data have undergone de-identification processing, and the content of the attribute table includes only

the longitude and latitude information of the distribution locations (Figure 2). This dataset was published by the National Science and Technology Sharing Service Platform and the National Earth System Science Data Center.

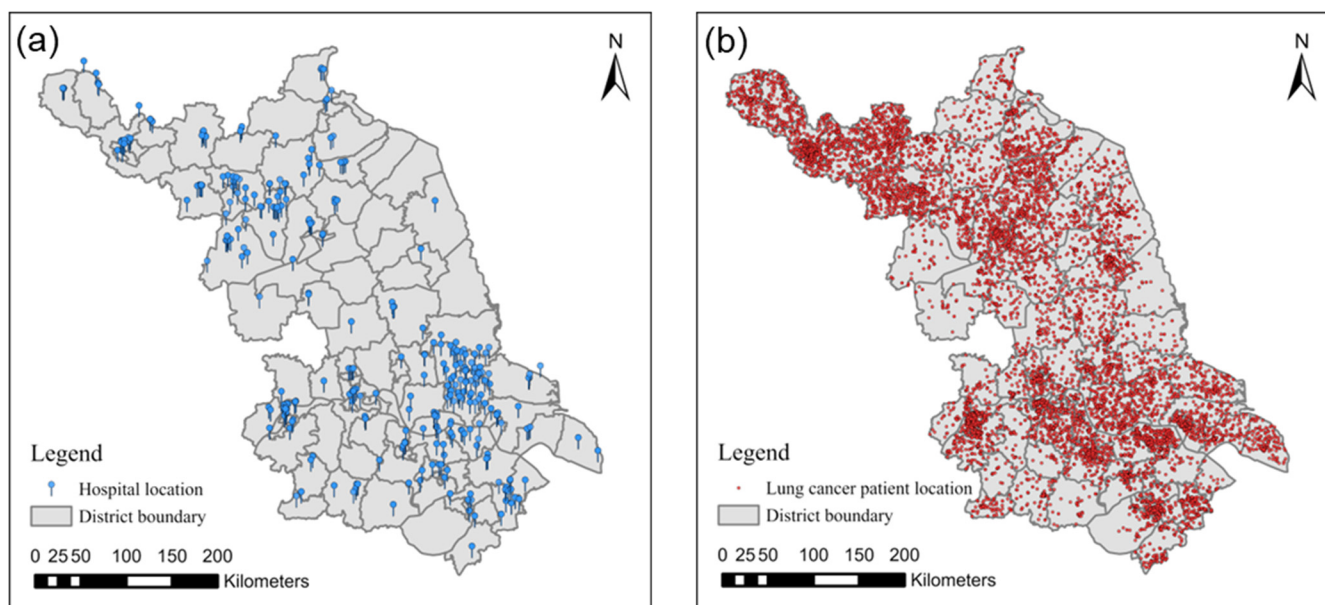


Figure 2. (a) Distribution map of hospitals in 2020; (b) Distribution map of lung cancer patients in 2020.

- **Basic Data on the City**

The basic data on the city, including the district boundary, city name, capital city, road network, urban center, etc., was provided by the Yangtze River Delta Science Data Center, National Science and Technology Infrastructure of China, and National Earth System Science Data Sharing Infrastructure (<http://nnu.geodata.cn/>, accessed on 1 January 2023) [24]. These data were stored in a shape file format.

- **Socioeconomic and Environmental Factors Data**

The environmental factors data used in this study were derived from the Statistics Bureau of Jiangsu Province. The dataset provided information on the air pollution density of 13 cities in Jiangsu Province. Also, the socioeconomic-related issues of Jiangsu Province included population, GDP of three industries, retail, residents' living conditions, industry, agriculture, investment in fixed assets, energy consumption, construction, etc. [23]. This dataset was stored in the Excel file format.

2.3. Methods

2.3.1. Statistical Analysis

Statistical analysis is a scientific method for revealing patterns within data through collection, organization, computation, and interpretation [25]. By employing statistical analysis, valuable information can be extracted from a vast array of data, allowing for reasonable inferences to be made. This discipline encompasses a variety of techniques, including mean, standard deviation, and regression analysis, among others [26]. In this study, statistical analysis tools were utilized to quantitatively examine socioeconomic data, the number of lung cancer patients, and the quantity and distribution of medical resources, as provided by the statistical yearbook.

2.3.2. Kernel Density Estimation Model

Kernel density estimation (KDE) is a non-parametric statistical method used to estimate the density distribution of spatial point features [27]. This method applies a kernel

function to each point feature, creating a smooth density surface that visually displays the spatial distribution of the points [28]. KDE not only reveals the local clustering characteristics of the points but also identifies potential hotspot areas in the space. In this paper, a kernel density estimation model was employed to analyze the spatial distribution of lung cancer patients in Jiangsu Province. By identifying areas with a high density of lung cancer patients, an in-depth analysis of the geographical distribution pattern of lung cancer was conducted, providing a scientific basis for public health planning and resource allocation. The mathematical model is as follows:

$$f(x) = \frac{1}{nh} \sum_{i=1}^n K\left(\frac{x - x_i}{h}\right) \quad (1)$$

where $f(x)$ is the density estimate at point x ; n is the number of point features; h is the bandwidth parameter; K is the kernel function; x_i is the position for the point i .

2.3.3. Global Spatial Autocorrelation Analysis

Global spatial autocorrelation analysis is utilized to measure the interrelationship among spatial data within a given area [29]. It assesses whether these data exhibit significant spatial patterns by calculating the degree of clustering or dispersion of these spatial data across the entire region [30]. In this study, we employed Moran's I from global spatial autocorrelation analysis to evaluate the overall spatial distribution of lung cancer patients across various regions in Jiangsu Province. The formula of Moran's I index is expressed as follows:

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (2)$$

where I is the Moran's I index; n is the total number of the observations; x_i is the value of these spatial data for observation i and the x_j is the value of these spatial data for observation j ; $\bar{x}$ is the mean value; W is the sum of all spatial weights of i and j . The range of Moran's I index is from -1 to 1 . When the value is close to 1 , this case has strong positive spatial autocorrelation. Otherwise, when the value is close to -1 , this case has strong negative spatial autocorrelation. When the value is close to 0 , these spatial data are randomly distributed without obvious spatial autocorrelation.

2.3.4. Local Spatial Autocorrelation Analysis

In global spatial autocorrelation analysis, the major focus is on the overall pattern of spatial data across an entire region, while local spatial autocorrelation analysis emphasizes the identification of local clusters or dispersions within the data, thereby revealing the spatial heterogeneity within the area. This method effectively complements the shortcomings of global spatial autocorrelation analysis in detecting local spatial patterns [31]. Common indicators of local spatial autocorrelation include Local Moran's I and the Getis-Ord G_i^* statistic [32]. In this paper, the Getis-Ord G_i^* statistic was employed to identify hotspots and cold spots of lung cancer patients in Jiangsu Province in order to investigate whether there was a significant spatial clustering or dispersion of lung cancer patients within specific regions. The calculation formula for the Getis-Ord G_i^* statistic is as follows:

$$G_i^* = \frac{\sum_{j=1}^n w_{ij} x_j - \bar{X} \sum_{j=1}^n w_{ij}}{S \sqrt{\left[n \sum_{j=1}^n w_{ij}^2 - \left(\sum_{j=1}^n w_{ij} \right)^2 \right] / (n-1)}} \quad (3)$$

$$\bar{X} = \left(\sum_{j=1}^n x_j \right) / n \quad (4)$$

$$S = \sqrt{\left(\sum_{j=1}^n x_j^2\right)/n - (\bar{X})^2} \quad (5)$$

where G_i^* is the G_i^* statistical result for observation i ; $\bar{X}$ is the mean value and S is the standard deviation value; n is the total number of the observations; x_i is the value of these spatial data for observation i and the x_j is the value of these spatial data for observation j ; W is the sum of all spatial weights of i and j . G_i^* statistical result is the Z-score. A high Z-score indicates that the area is a hotspot in spatial terms, while a low Z-score indicates that the area is a cold spot in spatial terms.

2.3.5. Geodetector Model

The geographical detector is a statistical method used to analyze spatial heterogeneity, capable of quantitatively assessing the explanatory power of different factors on geographical phenomena [33]. By calculating the explanatory power of various influencing factors, the geographical detector can detect the correlations among variables and their impact on spatial patterns [34]. In this study, the geographical detector was employed to analyze the impact of air pollutants, GDP, and medical resources on the spatial distribution of lung cancer patients in Jiangsu Province. Through the geographical detector, the explanatory power of these factors on the distribution of lung cancer patients can be quantified, providing a scientific basis for the formulation of public health policies. The calculation formula for the statistical measure of the geographical detector is as follows:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} \quad (6)$$

where q is the q statistic; L is the number of subregions; N_h is the number of samples in the subregion h ; σ_h^2 is the variance of that subregion; N is the total number of samples; σ^2 is the overall variance. The range of q statistic is $[0, 1]$. A higher value of the q statistic indicates a stronger explanatory power of the factor, while a lower value indicates a weaker explanatory power.

3. Results

3.1. Statistical Analysis

The utilization of Geographic Information Systems (GIS) technology for the visualization of the spatial distribution of lung cancer patients and hospitals in Jiangsu Province illustrated a spectrum of coloration, with increasing intensity from light to dark, corresponding to a gradient of patient density from sparse to dense within the designated research areas (Figure 3). This visual representation allowed for an intuitive and efficient apprehension of the spatial attributes of patient prevalence. Cumulatively, the city of Xuzhou exhibited the highest incidence of lung cancer patients, succeeded by a cluster of cities in Southern Jiangsu, notably Nanjing and Suzhou. The subsequent echelon of patient density was identified in Huai'an, Nantong, and Yancheng. Then, with Suqian, Yangzhou, and Zhenjiang. Wuxi records a minimal patient count. The distribution of medical facilities mirrors this disparity, with the more affluent southern Jiangsu region boasting a denser array of healthcare institutions, in contrast to the northern Jiangsu region, which is characterized by a relative paucity of hospitals. The aggregate distribution of healthcare resources evinces a pronounced tendency toward spatial agglomeration.

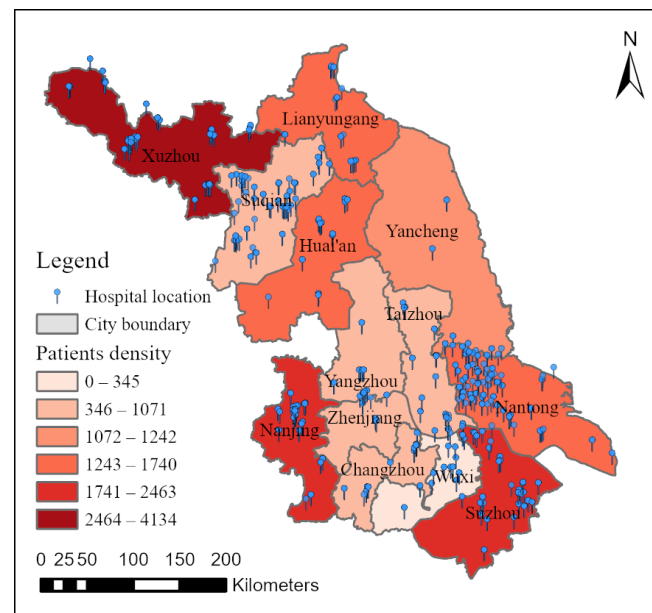


Figure 3. The distribution map of hospitals and lung cancer patients' density in Jiangsu Province in 2020.

3.2. Spatial Patterns Recognition

The kernel density model can make inferences based on samples, more realistically reflecting the actual situation of the data, and is applicable to a variety of different scenarios. This study employed the kernel density model to model the spatial distribution of lung cancer patients. Compared to the statistical analysis in the previous subsection, kernel density analysis modeling can more clearly reveal the distribution characteristics. According to the analysis results (Figure 4), the distribution of lung cancer patients in Jiangsu Province showed a clear clustering feature, with clustering characteristics observed in both the southern and northern regions of the province. Notably, the cities of Xuzhou and Lianyungang in the northern part exhibited areas of high density, while the southern part, including Nanjing, Suzhou, Changzhou, and Zhenjiang, showed distinct high-density areas. The distribution in the central and eastern coastal areas of Jiangsu Province was comparatively sparse.

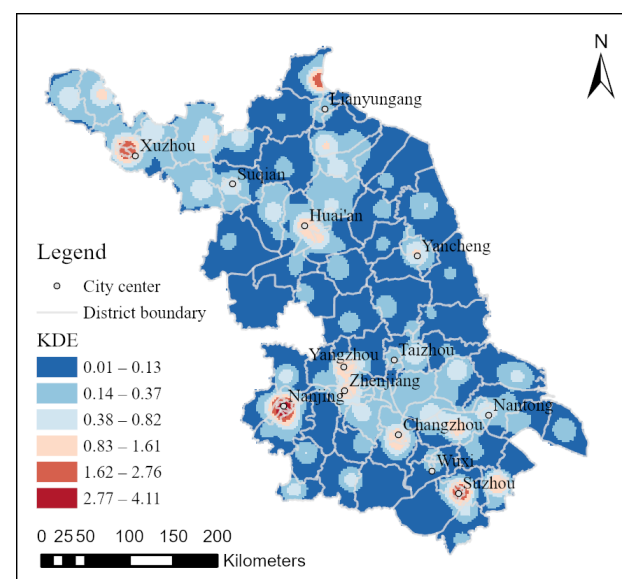


Figure 4. Spatial patterns of the distribution of lung cancer patients in Jiangsu Province.

3.3. Spatial Autocorrelation Analysis

In this study, the Global Moran's I index was utilized to assess the spatial autocorrelation of lung cancer patients in Jiangsu Province. The analysis revealed that the Global Moran's I index for lung cancer patients in Jiangsu Province was 0.14, and the p -value met the 1% level of significance, indicating a significant spatial autocorrelation in their distribution. To further investigate the spatial autocorrelation and clustering characteristics of lung cancer patients across different regions within the province, this study conducted an in-depth examination of the patients' distribution patterns using Local Moran's I and hotspot analysis from local spatial autocorrelation analysis. The Z-scores of the Local Moran's I are depicted in Figure 5, and the distribution of cold and hot spots is illustrated in Figure 6.

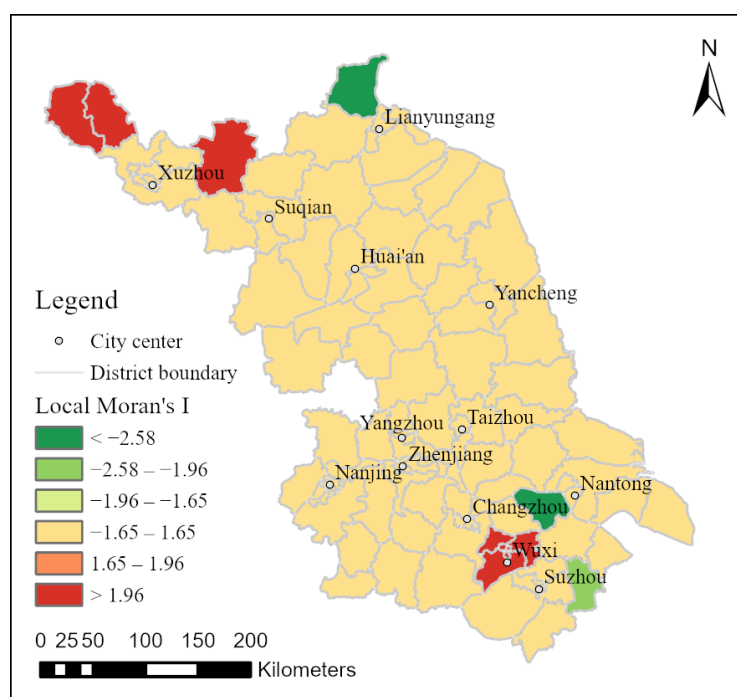


Figure 5. LMi Z score of analysis of autocorrelation of lung cancer patients in Jiangsu Province.

The results from the Local Moran's I index indicated that the northwestern city of Xuzhou and the southern Jiangsu cities of the Suzhou–Wuxi–Changzhou metropolitan area demonstrated positive spatial autocorrelation, suggesting that the distribution of lung cancer patients in these regions was similar, with potential clustering of hotspots for high values or cold spots for low values (Figure 5). Furthermore, certain areas in Lianyungang, Suzhou, and Nantong exhibited negative spatial autocorrelation, signifying a considerable disparity in patient distribution relative to surrounding areas, indicative of pronounced spatial heterogeneity.

The hotspot analysis results indicated that the hotspots for lung cancer patients were predominantly located in the northwestern region of Jiangsu Province, specifically in Xuzhou City, particularly in the Jiawang District and Pizhou District (Figure 6). These areas were identified as hotspots with a significance level of 99%, where the aggregation of patients was notably intensified. Conversely, the cold spots were concentrated in the southern part of Jiangsu Province, within the Suzhou–Wuxi–Changzhou metropolitan area, with a significance exceeding 95%, suggesting a significantly lower prevalence of lung cancer patients in this region. Apart from these areas, no other regions exhibited clear hotspot or cold spot characteristics.

Overall, there was a significant spatial correlation in the distribution of lung cancer patients in Jiangsu Province. Jiawang District and Pizhou District in Xuzhou were recognized

as the primary hotspots for lung cancer patients, while the Suzhou–Wuxi–Changzhou metropolitan area was characterized as a cold spot region.

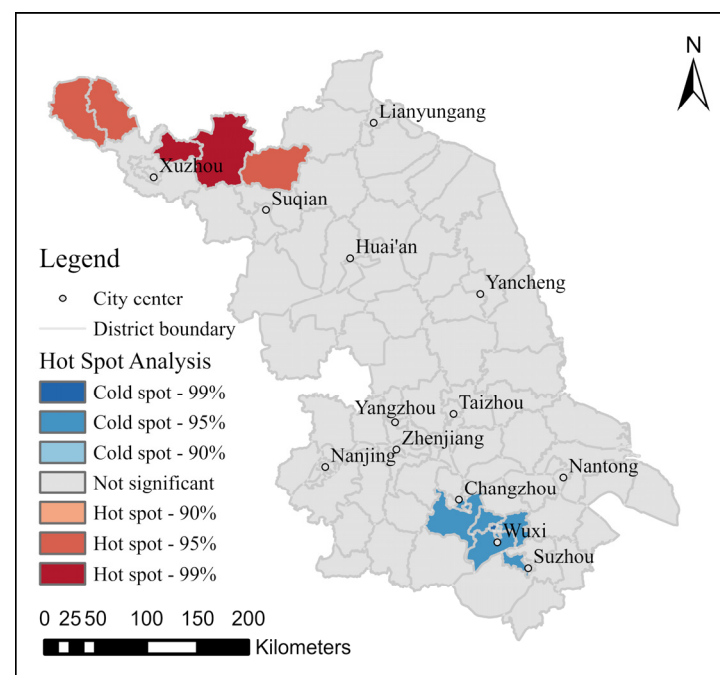


Figure 6. Hot spot analysis of lung cancer patients in Jiangsu Province in 2020.

3.4. Geodetector Analysis of Influencing Factors

In this study, the interactive detection model within the geographical detector was utilized to investigate the influence of numerous air pollutants, hospital availability, and GDP on the spatial distribution disparities of lung cancer patients in Jiangsu Province. The outcomes of the interactive detection model are delineated in Table 1, while the distribution patterns of certain influential factors are illustrated in Figures 7 and 8.

Table 1. The results of interaction detector.

Factors	PM _{2.5}	Hospital	GDP	PM ₁₀	NO ₂	O ₃	SO ₂
PM _{2.5}	0.822						
Hospital	0.977	0.450					
GDP	0.999	0.997	0.201				
PM ₁₀	0.932	0.919	0.985	0.725			
NO ₂	0.982	0.961	0.740	0.909	0.216		
O ₃	0.914	0.557	0.802	0.923	0.383	0.121	
SO ₂	0.910	0.909	0.990	1.000	0.981	0.989	0.747

In the context of individual factor impact, particulate matter (PM_{2.5}), sulfur dioxide (SO₂), and particulate matter with a diameter of less than 10 µm (PM₁₀) emerged as the air pollutants with the most significant explanatory power regarding the spatial distribution disparities of lung cancer patients. The influence of healthcare facilities followed in significance, while the explanatory power of gross domestic product (GDP), nitrogen dioxide (NO₂), and ozone (O₃) was comparatively weaker. This suggests a notable correlation between air pollutants and the spatial distribution of lung cancer patients, with varying impacts from different pollutants. Among the five air quality indicators considered in this study, PM_{2.5}, SO₂, and PM₁₀ exhibited a pronounced correlation with the distribution of lung cancer patients, with PM_{2.5} being particularly influential. PM_{2.5}, characterized by fine particulate matter with a diameter of 2.5 µm or less, is small enough to penetrate the

respiratory tract, reaching the lungs and potentially entering the bloodstream. Its larger surface area facilitates the adherence of harmful substances, thereby increasing the risk of cancer. Consequently, in regions with higher $PM_{2.5}$ concentrations, the distribution of lung cancer patients tended to be more concentrated. Furthermore, medical conditions also play a crucial role in the distribution of lung cancer patients. Areas with a greater number of healthcare facilities and abundant medical resources enable earlier diagnosis and treatment, leading to a concentrated distribution of lung cancer patients. Conversely, in regions where medical resources are scarce, patients may seek treatment in cities with better medical conditions, and this cross-regional flow further influences the spatial distribution of lung cancer patients.

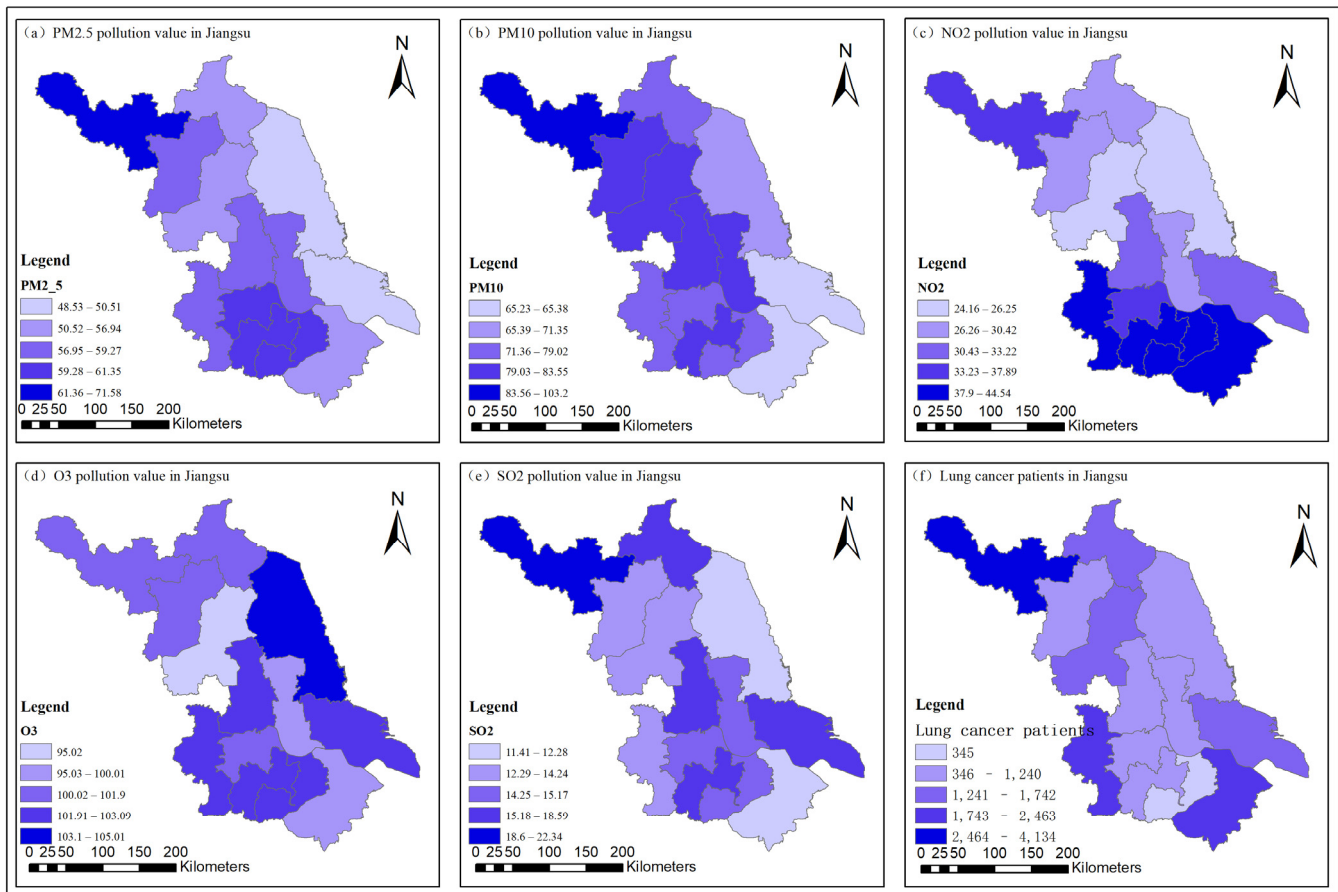


Figure 7. Distribution map of environmental influencing factors' density in Jiangsu Province: (a) $PM_{2.5}$ pollution value in Jiangsu; (b) PM_{10} pollution value in Jiangsu; (c) NO_2 pollution value in Jiangsu; (d) O_3 pollution value in Jiangsu; (e) SO_2 pollution value in Jiangsu; (f) Lung cancer patients in Jiangsu.

From the perspective of the interactive effects of multiple factors, first, the combined impact of various air pollutants had a more significant influence on the distribution disparities of lung cancer patients. The synergistic effects of air pollutants not only exacerbate the deterioration of air quality but may also produce more harmful secondary pollutants through chemical reactions, further aggravating pulmonary damage to residents and increasing the incidence of lung cancer, leading to the aggregation of patients in specific areas. Second, although hospitals and air pollutants each have a strong explanatory power for the spatial distribution disparities of lung cancer patients, their impact is somewhat diminished when they act in concert. This is because the presence of hospitals typically signifies better medical services, and even in the face of severe air pollution, timely diagnosis and

treatment can still mitigate the incidence of lung cancer to some extent, weakening the influence of air pollution on the distribution of patients in these areas.

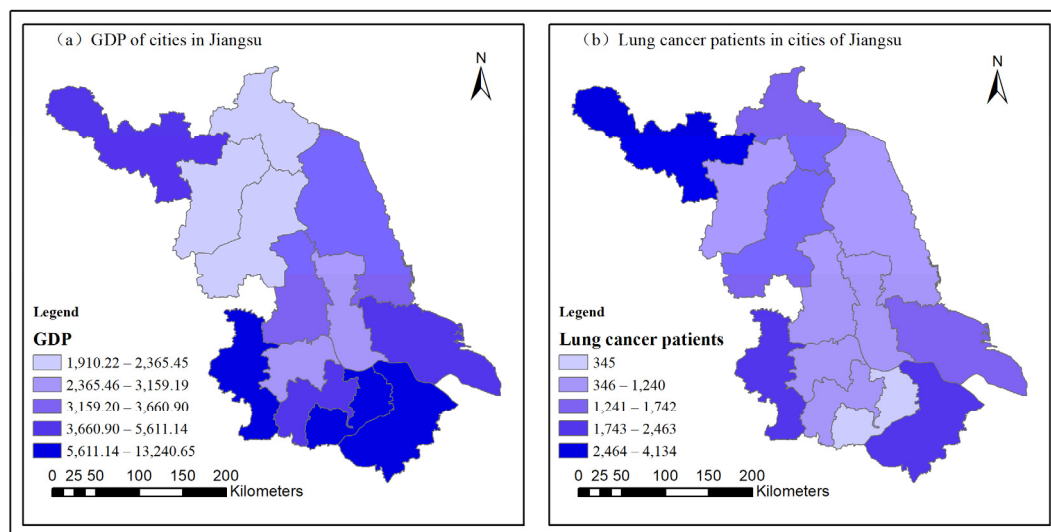


Figure 8. Distribution map of economic influencing factors' density in Jiangsu Province: (a) GDP of cities in Jiangsu; (b) Lung cancer patients in cities of Jiangsu.

The combined effect of hospital quantity and GDP substantially improves the explanatory power regarding the spatial distribution of patients. Although regional economic development is accompanied by an abundance of medical resources, areas with high GDP and rapid economic growth are often characterized by high population density, advanced urbanization, and accelerated industrial processes, which increase the risk of exposure to lung cancer [35,36]. Additionally, regions with high GDP may experience more severe environmental pollution, especially in areas with developed heavy industry and transportation systems, further amplifying the synergistic impact of GDP and hospital resources on the distributional disparities of lung cancer patients.

4. Discussion

In this study, GIS spatial analysis models were applied to explore the spatial distribution characteristics of lung cancer patients in Jiangsu Province, identifying areas of patient aggregation and the distribution of cold and hot spots [37,38]. Furthermore, the geographical detector model was utilized to investigate the complex relationships between the distribution of lung cancer patients in Jiangsu Province and air pollution, medical resources, and other socioeconomic factors, which hold certain reference values for public health management [39].

First, the hotspot areas for lung cancer patients were concentrated in Xuzhou City and Pizhou, indicating that these regions may face higher air pollution and industrial emissions, which could contribute to higher lung cancer incidence rates. Air pollutants, such as $PM_{2.5}$, SO_2 , and PM_{10} , were the primary ecological factors, with $PM_{2.5}$ having the most significant impact. This was followed by cities in the southern part of Jiangsu, such as Nanjing and Suzhou, suggesting that these areas may be influenced by more environmental or lifestyle-related health risk factors. For instance, the rapid urbanization process in the southern part of Jiangsu, along with lifestyle habits like smoking rates and air quality, may also be associated with the rise in incidence rates, further confirming the association between air pollution and lung cancer incidence [40,41]. In the context of sustainable urban development, reducing air pollutant emissions not only helps to reduce the incidence of lung cancer but also improves the overall quality of life and health of residents. Effective pollution control and health management strategies should be an important part of the coordinated development of ecological environment and social health.

Additionally, there is a complex relationship between the level of economic development and health outcomes, such as higher diagnosis rates due to better medical records and screening systems, reflecting the significant impact of socioeconomic conditions on disease diagnosis, management, and treatment [42–45].

On the other hand, the cold spot areas for lung cancer patients were concentrated in the Suzhou–Wuxi–Changzhou metropolitan circle (Suzhou, Wuxi, Changzhou), indicating that the lung cancer incidence rate in these areas was significantly lower than in other regions. This may be related to these cities' relatively better air quality, comprehensive medical resources, and higher health awareness. Their effective environmental management and public health policies may have played a positive role in prevention. The results of the analysis showed that the southern part of Jiangsu has a relatively dense distribution of medical resources, while the northern part has fewer hospitals. This disparity reflects the uneven economic development levels between regions within Jiangsu Province. The southern part of Jiangsu is more economically developed and can support the construction of higher quality and quantity of medical facilities, while the northern part is relatively economically lagging, with insufficient medical resource allocation. This imbalance in resources may increase the difficulty for patients in the northern part to access timely and high-quality medical services, leading to delayed treatment or cross-regional treatment phenomena. These phenomena reflect the uneven distribution of medical resources in China, highlighting the necessity to strengthen medical infrastructure construction and improve early screening and diagnostic capabilities in relatively resource-deficient areas. The balanced allocation of urban and rural medical resources is a key part of sustainable urban development. By strengthening the construction of medical infrastructure in resource-poor areas, the gap between urban and rural areas can be narrowed, and the right to health of residents in each region can be guaranteed, thus providing basic support for the overall healthy development of society. This pursuit of health equity is also consistent with the health goals of sustainable development.

In order to achieve the sustainable development goals of cities, the combination of environmental protection and public health strategies should be prioritized in areas with a high incidence of lung cancer. By continuously reducing industrial emissions and strengthening health risk management, we can reduce the health burden while promoting economic development and sustainable development and the construction of healthy cities. The spatial aggregation trends of patient density and medical resources reveal public health challenges in the prevention and treatment of lung cancer in Jiangsu Province. High-incidence areas, especially industrially developed cities like Xuzhou, need to further strengthen lung cancer prevention and control measures, such as early screening, health education, and pollution control. Moreover, in the northern part of Jiangsu, where medical resources are scarce, there should be an increase in the construction of hospitals and specialized medical institutions to enhance the health security level of residents. At the same time, the issue of scarce medical resources in the northern part of Jiangsu requires attention, and national and provincial governments should increase medical investment in these areas, improve the diagnostic and treatment capabilities and equipment levels of local hospitals, and narrow the urban–rural medical gap. Environmental protection departments should also work closely with health departments in disease prevention and control measures, forming a comprehensive response plan through inter-departmental cooperation. It should be made to promote inter-departmental cooperation, starting from pollution control, optimal allocation of resources, and health education, which can not only improve the prevention and control effect of lung cancer but also provide important support for the sustainable development of the whole city. This cross-disciplinary collaboration is an important means to achieve a win–win situation for health and the environment.

This study utilized multifactorial spatial analysis to elucidate the intricate relationships among air pollution, medical resources, and lung cancer incidence rates, offering substantial scientific evidence for the optimization of regional lung cancer prevention and control strategies. Future research endeavors could leverage GIS technology to visual-

ize the spatial distribution of lung cancer patients and hospitals, thereby providing an intuitive representation of patient density and medical resource allocation across various regions [46,47]. This approach is invaluable to policymakers and public health administrators. Spatial analysis not only aids in identifying high-risk areas and major risk factors but also promotes the synergistic development of regional health management and environmental protection, aligning with the principles of sustainable urban development. By optimizing the allocation of medical resources and improving the efficiency of environmental health risk management, cities can better harmonize ecological and environmental conservation with public health initiatives, ultimately advancing longer-term social development goals. Spatial analysis of this nature can facilitate the identification of high-risk areas, surveillance of significant risk factors, and the enhancement of medical resource allocation, leading to improved coverage and efficiency of healthcare services. Furthermore, it can elucidate the influence of additional societal factors such as lifestyle choices, smoking habits, and industrialization processes on lung cancer incidence trends. It is essential to consider the cumulative effects of air pollutants and the long-term exposure impacts on diverse population groups, as well as to compare lung cancer distribution patterns across different regions within the country. This comprehensive analysis will furnish a more exhaustive scientific foundation for the development of nationwide public health policies. At the same time, these policies should aim to promote balanced development between urban and rural areas and between regions, especially in terms of reducing the burden of disease, improving the quality of life and environmental quality, and ensuring a sustainable development path that attaches equal importance to health and the environment.

5. Conclusions

Lung cancer has emerged as one of the most significant threats to human health and life. In response to this critical issue, this study analyzed the spatial distribution characteristics of lung cancer in Jiangsu Province in 2020, revealing significant regional disparities. Notable spatial clustering characteristics were observed, particularly in Xuzhou City in the northern part of Jiangsu and Nanjing and Suzhou in the southern region. The differentiated spatial distribution pattern of lung cancer is the result of a combination of various factors, including economic, social, environmental, and policy elements, with environmental factors playing a dominant role. Accordingly, correlation analysis was conducted on selected influencing factors from various categories. The results of the analysis indicated that the concentrations of various air pollutants were the primary factors affecting lung cancer incidence. Meanwhile, medical condition constraints impacted the prevalence of carcinogenic factors, while urban economic development indirectly reflected both air pollution levels and medical conditions. This further showed that reducing the concentration of air pollutants and improving air quality is not only one of the key strategies for lung cancer prevention and control but also the only way to promote sustainable urban development and improve the health and quality of life of residents. Through the interaction analysis of dual factors, we found that the factors affecting lung cancer in Jiangsu Province, in order of impact from greatest to least, were PM_{2.5} concentration, SO₂ concentration, PM₁₀ concentration, the number of hospital distributions, NO₂ concentration, GDP value, and O₃ concentration.

This study employed GIS modeling techniques to investigate the spatial distribution patterns within the field of epidemiology, offering valuable insights for public health management. However, long-term public health management needs to be not only based on current epidemiological data but also closely integrated with urban planning and environmental governance to achieve the dual goals of ecological health and sustainable urban development. But, due to the limitations in data acquisition, there was an absence of long-term baseline data on patient distribution, which precluded the examination of temporal trends. Furthermore, the factors contributing to lung cancer incidence are multifaceted, including not only air quality and socioeconomic development but also personal lifestyle habits and familial genetic predispositions, which were not considered in this study.

Future research will further explore the long-term effects of socioeconomic and natural environmental factors on disease incidence and integrate sustainable urban development strategies with interdisciplinary collaboration to provide a scientific basis for more effective public health and environmental policies. It will explore how to enhance the accuracy and reliability of studies by improving data collection and analysis methods, including the use of new data sources and analytical tools. At the same time, recognizing the importance of long-term monitoring and evaluation and establishing an effective monitoring system to track the long-term changes in the impact of environmental and socioeconomic factors on lung cancer is considered crucial.

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