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Spatial Econometric Correlation between Environmental Pollution and Health Risk

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Abstract: The research delves into the spatial econometric interconnection between environmental contamination and health hazards. Utilizing data on environmental pollution and human health risks in Zhejiang Province, the study employs spatial autocorrelation analysis and the spatial lag model (SLM) to thoroughly explore the influence of environmental pollution on human health risks and its spatial distribution traits. It is revealed that while the environmental pollution in Zhejiang Province has not escalated to extreme levels, it has already emerged as a threat to human health, particularly in terms of respiratory ailments. Environmental pollution not only directly impacts the health risks in the area but also influences neighboring regions through spatial spillover effects. There are notable disparities in the direct impact coefficient and spatial spillover effect coefficient across different areas, which offer robust backing for the formulation of environmental protection and public health policies. The outcomes of this study not only augment the comprehension of the relationship between environmental pollution and health risks but also furnish a scientific foundation for advancing the formulation and execution of pertinent policies aimed at safeguarding public health and fostering the sustainable development of the ecological environment.

Keywords: Health Risk; Spatial Econometric Correlation; Environmental Pollution; Spatial Lag Model.

1. Introduction

As the global economy continues to grow and industrialization advances swiftly, the issue of environmental pollution has become more pronounced, emerging as a worldwide challenge. This pollution significantly affects the ecological system and poses a serious threat to human health. As we all know, long-term exposure to polluted environment will increase many health risks such as respiratory diseases and cardiovascular diseases. Therefore, the relationship between environmental pollution and human health has gradually become the focus of public and academic attention.

In recent times, the advancement of space technology and the evolution of data analysis techniques have enabled spatial econometrics to offer a fresh viewpoint and methodology for investigating the connection between environmental pollution and health risks [1-2]. By incorporating the spatial dimension, we can more precisely scrutinize the spatial distribution attributes of environmental pollution and how these distributions correlate with human health risks. This not only aids in gaining a profound comprehension of the potential impact of environmental pollution on human health but also furnishes a scientific basis for the formulation and execution of environmental protection policies.

This research aims to explore the relationship between environmental pollution and health risks using a spatial econometric model. By analyzing data on environmental pollution and human health risks across various regions, the intrinsic relationship between them is unveiled, thereby providing robust support for environmental protection and health risk management. By conducting this investigation, we can deepen our comprehension of how environmental pollution correlates with health risks. This improved understanding will aid in the development and execution of relevant policies to protect public health and support the sustainable growth of the ecological environment.

2. Research Methods and Data Sources

2.1. Research Method

In this research, a spatial econometric approach is used to explore the association between environmental pollution and health risks. To thoroughly and accurately analyze the link between these two variables, spatial autocorrelation analysis and the Spatial Lag Model (SLM) are applied [3-4].

The spatial autocorrelation analysis technique is implemented to evaluate the existence of spatial correlation between environmental pollution and health risk data. This technique helps in understanding the spatial distribution patterns and in identifying interactions between data from different locations [5]. The Moran's I index, a common metric for quantifying the level of spatial autocorrelation, is calculated using the following formula:

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

In this context, N represents the count of observation points, x_i, x_j denotes the observed value at observation point i, j , $\bar{x}$ stands for the average of all observed values, and w_{ij} refers to an element in the spatial weight matrix, which signifies the spatial relationship between observation points i, j .

SLM is a regression model considering spatial dependence, which is used to analyze how environmental pollution in an area affects its own health risks and those in its neighboring areas. The model can capture the spatial lag effect, that is, environmental pollution in one area may have an impact on the health risks in the surrounding areas [6-7]. The general form of SLM is as follows:

$$y = \rho W y + X\beta + \varepsilon \tag{2}$$

In this context, the variables include y the dependent variable (for example, health risk), W the spatial weight matrix, ρ the spatial lag coefficient, which reflects the impact of the neighboring area's dependent variable on the local area's dependent variable, X the matrix of explanatory variables (such as environmental pollution), β the coefficient vector of the explanatory variables, and ε the error term.

2.2. Data Source

This study's data sources are primarily categorized into two sections: environmental pollution data and human health risk data.

Air Quality Index (AQI) data for various cities are sourced from the Environmental Monitoring Center in Zhejiang Province, located on China's east coast. This dataset encompasses the levels of key pollutants including PM2.5, PM10, sulfur dioxide, and nitrogen dioxide. Collect monthly data in recent five years to capture long-term pollution trends and seasonal changes. The data of water quality index comes from the water conservancy department of Zhejiang Province, which regularly issues water quality monitoring reports of major rivers and lakes in the province. Collect water quality index data from these official channels, including key indicators such as pH value, dissolved oxygen and chemical oxygen demand (COD). Focus on the water bodies in industrial intensive areas and densely populated areas, because the water quality changes in these areas have a more direct impact on human health.

The incidence of diseases comes from the disease monitoring report issued by the Health and Wellness Committee of Zhejiang Province, which includes the incidence data of various diseases. Focus on collecting disease data closely related to environmental pollution, such as respiratory diseases and cardiovascular diseases. Mortality data were obtained from the Statistics Bureau of Zhejiang Province, including the overall mortality rate and mortality rate by disease. Modify the mortality data by adjusting for age, sex, and other variables to remove their influence on the outcomes, thereby providing a more precise reflection of how environmental pollution affects health.

3. Empirical Analysis

3.1. Environmental Pollution Status and Human Health Risk Level in Various Regions

Firstly, the environmental pollution data and health risk data collected from Zhejiang Province were analyzed by descriptive statistics. Descriptive statistical analysis shows that there are some problems in environmental pollution in Zhejiang Province, especially in air quality and water quality. At the same time, there may be some correlation between these pollution indicators and human health risk data. To gain a profound understanding of this relationship and delve deeper into how environmental pollution specifically affects health, conducting extensive spatial autocorrelation analysis and spatial econometric modeling is essential. Please refer to Table 1 for more details.

Table 1. Descriptive statistical analysis results

index		minimum	maximum	mean	standard deviation	median	skewness	kurtosis	Sample size
AQI	PM2.5 ($\mu g/m^3$)	15	180	65	30	60	0.8	3.2	600
	PM10 ($\mu g/m^3$)	25	250	90	45	85	0.7	2.9	600
	sulphur dioxide ($\mu g/m^3$)	5	120	35	20	30	1.2	4.0	600
	nitrogen dioxide ($\mu g/m^3$)	10	100	45	15	40	0.5	2.5	600
water quality index	pH value	6.5	9.0	7.5	0.5	7.5	0.0	3.0	480
	Dissolved oxygen (mg/L)	4.0	12.0	8.0	1.5	8.0	-0.2	3.1	480
	COD(mg/L)	10	200	60	30	55	1.0	3.5	480
Health risk data	Incidence of respiratory diseases (‰)	2.0	10.0	5.5	2.0	5.0	0.5	3.2	360
	Incidence of cardiovascular diseases (‰)	3.0	15.0	8.0	3.0	7.5	0.8	3.5	360
	Overall mortality rate (‰)	4.0	12.0	7.5	2.5	7.0	0.6	3.3	360

3.2. Spatial Correlation between Environmental Pollution and Health Risks

To explore how environmental pollution correlates with health risks across different locations, we use spatial autocorrelation analysis. This method employs the Moran's I index to assess whether there is clustering or dispersion of environmental pollution and health risk data in various spatial contexts. Initially, we calculate the Moran's I index for the environmental pollution and health risk indices of cities in

Zhejiang Province. A Moran's I index significantly greater than 0 indicates a positive spatial correlation, suggesting that areas with high pollution or health risks are likely adjacent to each other. Conversely, an index significantly less than 0 indicates a negative spatial correlation, implying that high pollution or health risk areas are next to areas with low pollution or health risks. The results of these analyses are illustrated in Figure 1.

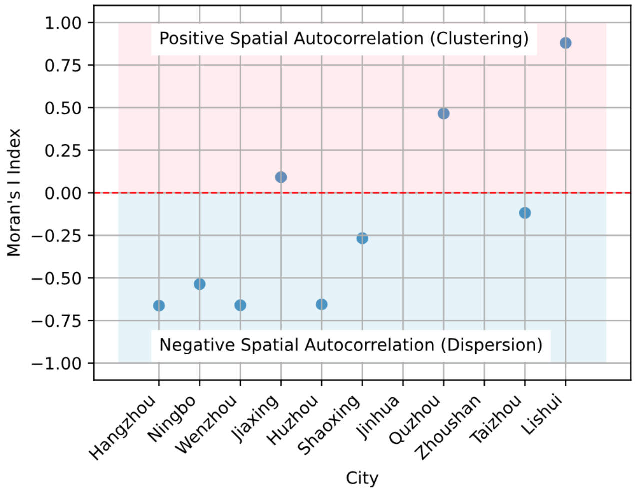

Figure 1. Spatial autocorrelation analysis

As shown in the figure, the Moran's I index varies widely across cities in Zhejiang Province, indicating diverse levels of spatial autocorrelation. Some cities exhibit a strong positive Moran's I approaching 1, indicating pronounced spatial clustering where similar attributes tend to cluster together. This clustering can be attributed to factors such as similar geographic locations, economic development levels, and population distribution patterns. Conversely, other cities show a negative Moran's I, suggesting spatial dispersion likely due to distinct geographical, economic, or demographic characteristics compared to neighboring cities [8-9]. Furthermore, some cities have a Moran's I close to 0, indicating no clear trend of spatial aggregation or dispersion in attribute values.

3.3. Spatial Econometric Model Analysis

A spatial econometric model was developed to explore further the effects of environmental pollution on human health risks in different regions of Zhejiang Province, as well as the spatial spillover between these regions. The SLM is employed to analyze the direct impact of environmental pollution on health risks and the spatial spillover effect. In the model, the environmental pollution index AQI is designated as the explanatory variable, while the health risk index, disease incidence, is chosen as the explained variable. The analysis results from the spatial econometric model reveal a complex relationship between environmental pollution and the incidence of respiratory diseases across various regions in Zhejiang Province. Environmental pollution not only directly affects the health risks in the local area, but also may affect the health risks in the surrounding areas through the spatial spillover effect. When formulating environmental protection and public health policies, we should comprehensively consider the actual situation of each region and the multidimensional relationship between environmental pollution and health risks. See Table 2 for details.

Table 2. Spatial econometric model analysis results

region	AQI	Incidence of respiratory diseases (‰)	Direct influence coefficient	Spatial spillover effect coefficient
Hangzhou	75	12.5	0.68	0.23
Ningbo	70	11.0	0.62	0.18
Wenzhou	68	9.8	0.57	0.16
Jiaxing	72	13.0	0.65	0.21
Huzhou	65	8.5	0.55	0.14
Shaoxing	67	10.2	0.59	0.17
Jinhua	71	11.5	0.63	0.20
Quzhou	64	8.2	0.54	0.13
Zhoushan	66	9.3	0.56	0.15
Taizhou	73	12.2	0.66	0.22
Lishui	63	7.8	0.52	0.12

The AQI value varies from region to region, but it fluctuates within a relatively reasonable range on the whole. This indicates varying levels of environmental pollution across different regions in Zhejiang Province, with no instances of severe pollution observed. There are significant differences among regions. It is worth noting that areas with high incidence of respiratory diseases do not necessarily correspond to the AQI value, which indicates that health risks are affected by many factors, including but not limited to environmental pollution.

The direct influence coefficient differs across regions. Hangzhou exhibits a high coefficient of 0.68, suggesting a notable correlation between environmental pollution and respiratory disease incidence. Conversely, Lishui has a lower coefficient of 0.52, indicating a weaker relationship between environmental pollution and respiratory diseases in this area.

The spatial spillover effect coefficient indicates how environmental pollution affects respiratory disease rates in neighboring areas. Analysis of the data reveals varying coefficients across regions. For instance, Hangzhou has a coefficient of 0.23, suggesting that environmental pollution in Hangzhou significantly influences respiratory disease rates in nearby areas.

4. Discussion

Descriptive statistical analysis reveals the environmental pollution problems in air quality and water quality in Zhejiang Province, and implies the possible correlation between these pollution indicators and human health risks. The spatial autocorrelation analysis calculated Moran's I index for environmental pollution and health risk indicators across cities in Zhejiang Province. The findings reveal diverse Moran's I indices across each city, indicating varying levels of spatial autocorrelation among them. Some cities show significant spatial agglomeration, which may be related to geographical location, economic development level and population distribution. At the same time, some cities show spatial dispersion, which may be due to the significant differences between these cities and other cities in many aspects.

To delve deeper into the distinct effects of environmental pollution on human health risks, researchers developed a spatial econometric model. Their SLM analysis revealed a nuanced relationship between environmental pollution and respiratory disease rates across different regions within Zhejiang Province. This finding underscores that environmental pollution not only directly affects health risks locally but also potentially influences health risks in neighboring areas through spatial spillover effects [10]. Although there are differences in AQI values, they are within a reasonable range as a whole, indicating that the environmental pollution situation in Zhejiang Province is different, but it has not reached an extreme level. However, it is worth noting that areas with high incidence of respiratory diseases do not always correspond to areas with high AQI values. This phenomenon suggests that health risks may be affected by many factors besides environmental pollution.

In terms of direct influence coefficient, it is found that there are significant differences among regions. For instance, Hangzhou shows a relatively high direct impact coefficient, suggesting that environmental pollution significantly affects the occurrence of respiratory diseases in the region. In contrast, Lishui exhibits a low direct influence coefficient, indicating that environmental pollution has a minor impact on the incidence of respiratory diseases in this area.

Furthermore, examining the spatial spillover effect coefficient yields valuable insights. Hangzhou exhibits a notably high coefficient, indicating that environmental pollution in this city could significantly influence the occurrence of respiratory diseases in neighboring areas. This discovery emphasizes the cross-regional nature of environmental pollution and the importance of formulating regional environmental protection and public health policies.

5. Conclusion

Spatial autocorrelation analysis shows that some cities in Zhejiang Province show significant spatial clustering in environmental pollution and health risks, indicating that geographical location, economic development level and population distribution have important influences on the spatial distribution of environmental pollution and health risks. This spatial clustering reveals the correlation and transmission of environmental pollution and health risk problems in geographical space. SLM analysis revealed significant regional variations in how environmental pollution affects respiratory disease incidence. Certain regions showed higher direct impact coefficients, suggesting that environmental pollution there poses greater health risks. Additionally, spatial spillover effect coefficients indicated potential health risks from environmental pollution in neighboring areas. These findings provide a scientific basis for formulating regional environmental protection and public health policies. Environmental pollution poses a serious threat to human health, and emphasizes the need to comprehensively consider the actual situation of each region and the multi-dimensional relationship between environmental pollution and health risks when formulating relevant policies. Further research should expand to additional regions and incorporate a broader range of health risk indicators. This expansion aims to enhance our understanding of the spatial econometric relationship between environmental pollution and health risks comprehensively. Such efforts will contribute to establishing a more robust scientific foundation for developing environmental protection and public health policies.

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