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Associations between Land-Use Patterns and Cardiovascular Disease Mortality in the Beijing—Tianjin–Hebei Megacity Region

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Abstract: Megacity regions where human activities are intensive are key areas for CVD prevention and control in China. Optimizing land-use patterns has been widely recognized as an important public health intervention. Ecological space, agricultural space, and construction space are three basic management objects in China's new land-use management system. Given that most existing studies focused on a single type of land use, this study treats them as a whole and not only explores the impact of each type, but also systematically investigates the effects of the interactions between any two types of land use and the whole land-use pattern. Specifically, this study first constructs a hierarchical index system, then uses spatial error models (SEM) to explore the global associations between each index and age-standardized CVD mortality rates (ASMRs) and uses the multiple geographical weighted regression model (MGWR) to explore the spatial heterogeneity of factor effects. The possible association between land-use patterns and CVD mortality is then explored, and recommendations for policy formulation are provided. The analysis results show that the overall pattern of moderately decentralized and organically combined land use can control CVD mortality to a certain extent, but the specific influence mechanisms show significant differences according to different land-use types, relationships, and location conditions. First, in terms of single-type land-use distribution, the concentration of ecological space has positive health benefits, while a too high concentration of agricultural space has negative effects. Second, the combination of different types of land use has a significant association with CVD, in which the mixed layout of ecological and agricultural space helps to suppress CVD, while ecological and construction space need to be appropriately regularized and should not be too interspersed. Third, the same index may have different effects in different regions, suggesting that policy makers need to tailor their policies to local conditions.

Keywords: megacity regions; cardiovascular disease; land-use patterns; geostatistical modeling; spatiotemporal big data

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1. Introduction

Cardiovascular disease (CVD) is the primary cause of mortality in rural and urban areas of China, threatening the health of citizens and leading to substantial economic and social damage. According to the statistics presented in the 2021 China Cardiovascular Health and Disease Report [1], the number of CVD patients in China has surged to 330 million. In 2019, CVD was responsible for 46.74% and 44.26% of mortality rates in rural and urban areas, respectively. This evidence indicates that prevention and treatment of CVD in China pose a significant challenge. Densely populated megacity regions are pivotal in preventing and controlling CVD due to the high intensity of urban construction and industrial development, coupled with a relatively poor ecological environment. Such areas also subject residents to high work and life pressure and an abundance of environmental factors that induce CVD [2].

Environmental Health Theory emphasizes the integral relationship between environmental factors and human health. It posits that physical, chemical, biological, and socio-economic elements in our surroundings significantly impact health outcomes [3]. This theory encompasses the direct and indirect effects of environmental conditions on health, ranging from air and water quality to socio-economic status and lifestyle choices [4,5]. It underscores the necessity of addressing environmental determinants to improve public health and well-being [6]. Taking inspiration from environmental health theory, land-use patterns, including most of the environmental factors, are crucial in mitigating CVD risks in megacity regions [7]. There is a new land-use management system in China, which emphasizes the basic management objects in three types of spaces: ecological space, agricultural space, and construction space [8]. Among them, ecological space, whose main function is to provide ecological products or services, includes woodlands, water surfaces, wetland deserts, etc.; agricultural space, whose main function is to provide agricultural products, mainly refers to agricultural land such as woodlands and croplands; and urban space is the main space for human habitation and activities. Drawing control lines based on the distribution of the three types of space, protecting key natural resources, and controlling all types of construction and production activities is the fundamental principle of planning and optimizing land use in China's new land-use management system. Accordingly, the primary objective of enhancing public health is to properly arrange the layout of the three types of land use.

A significant amount of research has examined the association between three types of space and CVD. (1) When it comes to ecological space, numerous studies have extensively documented its health-enhancing effects. Ecological spaces have been dubbed "therapeutic landscapes" by several researchers [9] due to their abundant health benefits, which have been thoroughly assessed. The primary means by which eco-parks contribute to public health is through the reduction in CVD risk by encouraging physical activity among locals [10–12]. Moreover, studies have shown the impact of environmental factors, such as air pollution and temperature, on cardiovascular health. Extended exposure to fine particulate matter air pollution [13,14] or low and high temperatures can significantly increase morbidity and mortality rates for CVD [15]. (2) In terms of construction space, urban sprawl and urbanization have also been found to slightly raise the risk of CVD. Specifically, compact urban land-use patterns considerably contribute to the incidence of heart disease and hypertension, whereas access to healthcare facilities and more efficient land use act as inhibitors [16]. A lower rate of hypertension development among residents is associated with higher walkability in the local region [14]. Moreover, the cardiovascular health of residents is affected by both the residential environment [9] and industrial structure [13]. (3) In terms of agricultural space, Votsi et al. [17] explored the link between patterns of agricultural spaces and CVD risks by analyzing the correlation between 39 natural land cover types and five representative indicators of human health in Italy. The findings demonstrate that the expansion of agricultural land has led to a decline in the quality of local health. A significant body of research has examined the adverse impacts of chemicals utilized in the agricultural production processes [18–20]. As documented in a systematic literature review, many pesticides create pollution in the environment, which may be linked to various cardiovascular diseases [18].

From a landscape ecology perspective, there are intricate connections among the three space types that impact the health of the population as a functional whole [21]. Several studies have investigated the health effects of various factor combinations. Forman [22] systematically described changes in land-use patterns resulting from agricultural development, urbanization, deforestation, population movement, introduction of novel disease pathogens, water and air pollution, loss of biodiversity, and other environmental problems. He then explored the impacts of degraded environments on public health. Schmidt and Ostfeld [23] noted that land-use changes resulting from forest fragmentation and urbanization may result in a loss of biodiversity and alterations in species distribution, thereby increasing the potential for zoonotic diseases, including Lyme disease. Nonetheless, existing works still exhibit weaknesses. Firstly, there is a limited number of relevant studies, and the primary focus remains on the public health consequences of ecological degradation from urbanization. In addition, the interplay between the three types of space has not been exhaustively examined. Secondly, there exists a scarcity of China-specific studies. Due to the recent establishment and revolutionization of the land-use management system, China's megacity regions are facing a distinctive and demanding situation in governing, and public health concerns within these areas are increasingly prominent, necessitating targeted research.

To address the identified research gaps, this study focuses on the Beijing–Tianjin–Hebei megacity region (BTH), utilizing multi-dimensional spatiotemporal big data and spatial statistic modeling techniques to investigate the potential associations between the distribution patterns of the three land-use categories on public health. The study's innovations can be summarized in three aspects. First, this study created a hierarchical land-use pattern characterization index system to accurately identify and capture the land-use pattern. This system includes a single-type distribution index, a dual-factor interaction index, and an all-factor pattern index, which describe the distribution and combination of the three land-use categories throughout the entire study area. Second, this study utilized the spatial error model (SEM) and multiscale geographically weighted regression (MGWR) to quantitatively measure the association between each pattern index and public health from both global and local perspectives. Third, based on the results of model calculations and existing research results, this study analyzes the global influence mechanisms on public health, explores the regional variability of these mechanisms and their causes, and discusses the strategies and ideas for optimizing the land use and promoting public health through policy and technological solutions.

The paper is structured as follows. Part two introduces in detail the main land-use pattern measures used in this paper, geostatistical methods, and the screening process of the data and variables used in the study. Part three systematically presents the computational results of the models, including the global and local regression model outcomes. In Section 4, the study's findings from the two model types are analyzed based on the authors' experience and existing research. The discussion focuses on the potential pathways of land-use patterns that affect CVD mortality. Finally, Section 5 provides policy recommendations for future land-use optimization in the Beijing–Tianjin–Hebei megacity region by summarizing the key findings of this study.

2. Methods and Data

2.1. Methods

2.1.1. Spatial Autocorrelation

We used spatial autocorrelation analysis in this study to illustrate the similarities in mechanisms influencing CVD mortality within adjacent units [24]. Spatial autocorrelation can be classified into global and local spatial autocorrelation based on the analysis scale. The former concentrates on the overall spatial distribution features of geographical attributes, while the latter indicates the degree to which the variable is linked to the surrounding area. In this investigation, Moran's I and Local Moran's I are employed to represent the aforementioned two characteristics, respectively [25].

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

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

where n is the total sample size, and x_i and x_j represent the ASMR values of study units i and j, respectively. $\bar{x}$ is the mean ASMR value of all units, and W_{ij} is the spatial weight matrix. $m = \left(\sum_{j=1, j \neq i}^{n} x_j^2 \right) / (n-1) - \bar{x}^2$.

Both indicators vary from −1 to 1. Positive values indicate a significant spatial clustering of high or low ASMR values, referred to as H–H and L–L types, respectively. Negative values indicate significant heterogeneity in the spatial distribution of assessed ASMR values, referred to as H–L and L–H types.

2.1.2. Land-Use Patterns and Spatial Pattern Indices

The land-use patterns are quantified by calculating spatial pattern indices across 3 categories: single-type distribution index, bi-type interaction index, and all-type index. The spatial pattern indices have distinct purposes: the single-type distribution index measures characteristics of each type of land-use, the bi-type interaction index shows the relationship between two types of land use, and all-type index reflects the overall land-use pattern features of the entire country (Table 1).

Table 1. Overview of spatial patterns indices [26–28].

Categories	Variables	Code	Calculation
Single-type distribution index	Mean of patch area	AREA_MN	$AREA_{MN} = mean\left(AREA\left[patch_{ij}\right]\right)$, where AREA[$patch_{ij}$] is the area of each patch in hectares.
	Patch density	PD	$PD = \frac{N}{A} \times 10000 \times 100$, where N is the number of patches and A is the total landscape area in square meters.
	Largest patch index	LPI	$LPI = \frac{max_{j=1}^{n}(a_{ij})}{A} \times 100$, where max($a_{ij}$) is the area of the patch in square meters and A is the total landscape area in square meters.
	Mean shape index	SHAPE_MN	$SHAPE_{MN} = mean(SHAPE[patch_{ij}])$, where SHAPE[$patch_{ij}$] is the shape index of each patch.
	Aggregation index	AI	$AI = \left[\frac{g_{ii}}{max - g_{ii}}\right](100)$, where g_{ii} is the number of like adjacencies based on the single-count method and $max - g_{ii}$ is the class-wise maximum number of like adjacencies of class i.
Bi-type interaction index	Contagion	CONTAG	$CONTAG = 1 + \frac{\sum_{q=1}^{n_a} p_q ln\left(p_q\right)}{2ln\ (t)}$, where p_q the adjacency table for all classes divided by the sum of that table and t the number of classes in the landscape.
	Landscape shape index	LSI	$LSI = \frac{E}{E_{min}}$, where E is the total edge length in cell surfaces and E_{min} is the minimum total edge length in cell surfaces.
	Edge Density	ED	$ED = \frac{E}{A} \times 10000$, where E is the total landscape edge in meters and A is the total landscape area in square meters.
All-type index	Landscape shape index	LSI	$LSI = \frac{E}{E_{min}}$, where E is the total edge length in cell surfaces and E_{min} is the minimum total edge length in cell surfaces.

Table 1. *Cont.*

Categories	Variables	Code	Calculation
All-type index	Patch density	PD	$\mathrm{PD} = \frac{\mathrm{N}}{\mathrm{A}} \times 10000 \times 100$, where N is the number of patches and A is the total landscape area in square meters.
	Landscape division index	DIVISION	$\mathrm{DIVISION} = 1 - \sum_{i=1}^{m} \sum_{j=1}^{n} \left(\frac{a_{ij}}{A} \right)^2$, where a_{ij} is the area in square meters and A is the total landscape area in square meters.
	Splitting index	SPLIT	$\mathrm{SPLIT} = \frac{A^2}{\sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij}^2}$, where a_{ij} is the patch area in square meters and A is the total landscape area.
	Effective mesh size	MESH	$\mathrm{MESH} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij}^2}{A} \times \frac{1}{10000}$, where a_{ij} is the patch area in square meters and A is the total landscape area in square meters.
	Largest patch index	LPI	$\mathrm{LPI} = \frac{\max(a_{ij})}{A} \times 100$, where $\max(a_{ij})$ is the area of the patch in square meters and A is the total landscape area in square meters.
	Edge density	ED	$\mathrm{ED} = \frac{E}{A} \times 10000$, where E is the total landscape edge in meters and A is the total landscape area in square meters.

2.1.3. Estimating the Global Impact of Factors

Incorporating spatial dependence into the model can enhance the model's accuracy. This study used the SEM [29] model to accomplish this objective. The SEM model assumes that the residuals of regression outcomes exhibit spatial autocorrelation, and consequently, mistakes from one spatial feature are portrayed as a weighted average of the errors of its neighbors.

$$y = X\beta + \mu \tag{3}$$

$$\mu = \lambda_{Err} W_{\mu} + \varepsilon, \tag{4}$$

where y represents the dependent variable, X refers to the independent variable, β represents the model coefficient, and μ refers to the random disturbance term with spatial autocorrelation. Further decomposition of μ reveals that W_{μ} is the spatial neighbor weight matrix of the error term, λ_{Err} refers to the regression coefficient of the spatial residual term, and ε is the independent and identically distributed error term.

2.1.4. Estimating the Localized Effects of Factors

The expansive geography of the BTH region, along with discernible disparities in economic and social development as well as variations in the developmental levels of each area, suggests potential spatial heterogeneity in the impact mechanism of land-use patterns on CVD mortality. Therefore, this study utilizes the MGWR model [30].

The MGWR model employs a multi-bandwidth method, enabling the adjustment of bandwidths for different variables to achieve distinct spatial smoothing levels. This approach characterizes the spatial process of each variable, enhancing model credibility and realism [30]. The MGWR model is defined as follows.

$$y = \sum_{k=1}^{K} \beta_{bk}(u_i, v_i) x_{ik} + \varepsilon, \tag{5}$$

where $\beta_{bk}(u_i, v_i)(k = 1, 2, \ldots, K)$ denotes the regression coefficients of local variables, while *bki* stands for the bandwidth corresponding to the regression coefficients of variable *k*. Additionally, (u_i, v_i) represents the spatial coordinates of the geographic center point of cell *i*.

2.2. Study Area

This study takes Beijing, Tianjin, and Hebei in China as examples, encompassing 152 counties, with a total area of approximately 149,000 square kilometers, while excluding counties with incomplete data. The counties form the fundamental unit of this study. Specifically, the geographically adjacent counties in the main urban area of the same city are combined into a single unit, while the remaining counties are considered independent units. This is owing to the contiguity of land-use patterns and consistency of economic and social characteristics shown in main urban areas in the same city, which are not as evident among peripheral counties. As a result, the robustness can be ensured and 108 study units are obtained (Figure 1).

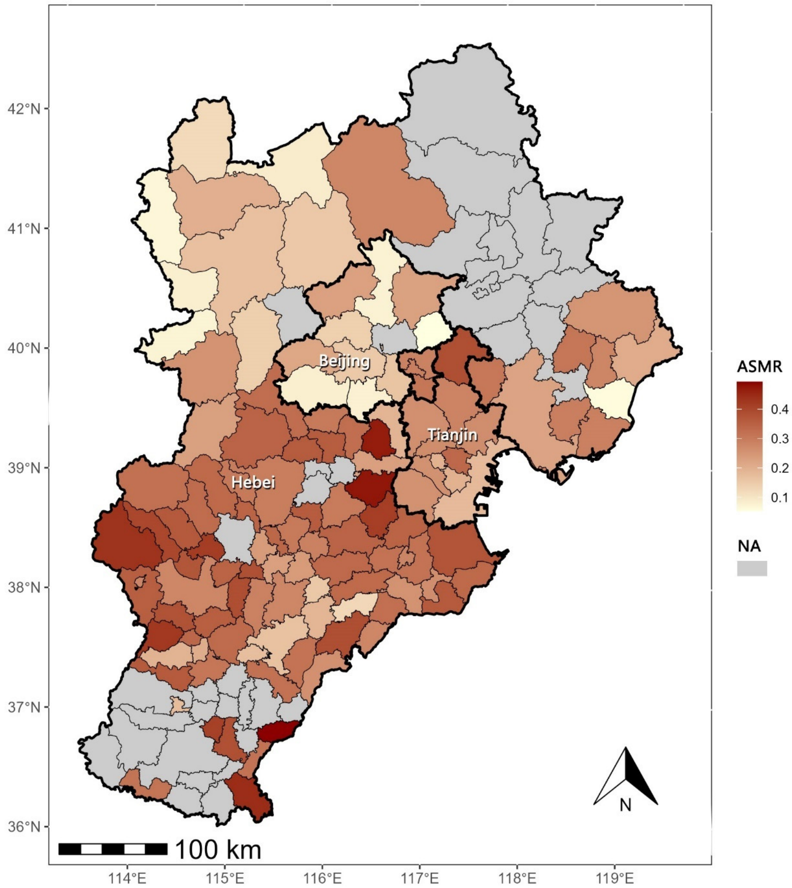


Figure 1. Spatial distribution of ASMR in BTH.

2.3. Variables

2.3.1. Research Data

(1) Dependent variable

The dependent variable employed in this study comprises cardiovascular disease mortality statistics sourced from the National Center for Disease Control and Prevention (CDC). The CDC aggregated the data at the county level, recording CVD mortality rates for all age groups across all counties in the BTH region in 2018. Subsequently, this study calculated the ASMR [31] to eliminate age structure effects. The value of the $ASMR_A$ for study unit A was computed as follows.

$$ASMR_A = \frac{\sum_x \left(m_x^A P_x^A\right)}{\sum_x P_x}, \quad (6)$$

where m_x^A represents the mortality rate of age group x in study unit A. P_x^A is the total number of individuals in the age group x who are exposed to cardiovascular disease risk factors in study unit A. Based on Figure 1, the spatial distribution of ASMR indicates that the risk of CVD was higher in the southern area of the entire BTH megacity region than in its northern counterpart.

(2) Independent variables

The spatial pattern indices of different space types were calculated using the open-source CCI-LC land cover database in this study. The spatial distribution of 18 land-use types in the BTH region was recorded through the interpretation of the Sentinel 3 satellite remote sensing data in 2018 with a maximum spatial resolution of 300 m. This study categorized the land uses into three groups: agricultural space covering approximately 104,700 km^2, construction space covering about 18,900 km^2, and ecological space that covers approximately 105,300 km^2. According to China's land-use classification standards, parks and green spaces that fall within urban space are classified as construction space. On the other hand, the ecological space in this study mainly refers to ecological land situated outside of urban spaces.

To account for other confounding factors, this study incorporated 6 control variables in the analysis. These variables comprised four economic and social variables, as well as two variables representing the level of health care services.

2.3.2. Independent Variables Selection

To enhance the robustness of the model estimation outcomes, this study conducts further filtering of independent variables. Firstly, we calculated univariate correlations between each factor and the dependent variable, and excluded factors with p-values exceeding 0.2. Secondly, linear regression models were built between each factor and other factors, and the variance inflation factor (VIF) was calculated. The factor with the largest VIF value was then excluded, repeating the same process until all factors' VIF values were below 5.0. In this way, we obtained the independent variables filtered in this study (Table 2).

Table 2. Variables description.

Types	Variables	Code	Mean	Std.	Min.	Max.
Dependent variable	ASMR	CVD	−0.045	1.012	−2.302	2.038
Independent variables	Aggregation index for ecological space	AI_E	−0.018	1.005	−3.051	1.393
	Aggregation index for construction space	AI_T	0.037	1.022	−1.735	3.647
	Patch density for agricultural space	PD_A	0.054	1.019	−0.847	3.625
	Contagion for agricultural and ecological space	$CONTAG_{AE}$	−0.018	1.001	−1.783	1.199
	Landscape shape index for agricultural and ecological space	LSI_{AE}	0.063	1.004	−1.443	3.976
	Edge density for agricultural and construction space	ED_{AT}	0.020	1.015	−2.100	2.657
	Edge density for ecological and construction space	ED_{ET}	0.044	1.021	−0.621	4.829

Table 2. *Cont.*

Types	Variables	Code	Mean	Std.	Min.	Max.
Independent variables	Effective mesh size for 3 types of land use	MESH	0.023	1.047	−0.875	7.051
	Splitting index for 3 types of land use	SPLIT	0.038	1.013	−0.804	6.006
Control variables	Gross domestic product per capita	GDP	0.028	1.051	−0.319	9.894
	Percentage of output from polluting industries	POLLUTE	−0.011	1.050	−1.568	6.780
	Percentage of low-educated population (below high school)	LOW_EDU	−0.052	1.018	−3.383	1.012
	Percentage of low-income population (below 2500 yuan/month)	LOW_INCOME	−0.061	1.026	−2.410	0.983
	Hospital beds per capita	BED	−0.017	1.028	−1.943	4.540
	Accessibility for healthcare services	ACCESS	0.020	1.046	−0.650	6.678

Note: The codes for single-factor land-use pattern and two-factor interactive land-use pattern have subscripts. Subscript E represents ecological space, A represents agricultural space, and T represents construction space. If the subscript contains only one letter, it indicates a single-factor spatial pattern indicator. If the subscript contains two letters, it indicates a two-factor interaction spatial pattern indicator. For instance, the agglomeration index AI_E exclusively measures the ecological space category, whereas LSI_{AE} compares the relative links between agricultural and ecological spaces.

3. Results

3.1. Spatial Autocorrelation for ASMR

The global Moran's I for ASMR measured 0.379, indicating spatial autocorrelation of the dependent variables (Figure 2). The northwestern, central, and western parts of the BTH region yield multiple high–high and low–low clusters. The H–H clusters have been mostly identified in districts and counties of western and central Hebei Province, coupled with a few districts in the south, where neighboring districts with higher ASMR were usually at a higher mortality. The clusters with L–L levels were predominantly concentrated in most of Beijing and the northwestern region of Hebei Province. Typically, the adjacent districts in these clusters that exhibited lower ASMR had a reduced mortality of CVD.

3.2. Global Effects of Land-Use Pattern Characteristics

The results of the OLS model (Table 3) indicate a significant value for the Moran's I, suggesting the presence of spatial autocorrelation in the error term. As the Lagrange multiplier values for the spatial error form are more significant than those for the spatial lag form, the subsequent analysis in this study was conducted using SEM. The SEM model results (Table 3) demonstrate a variety of connections between land-use patterns and ASMR. These associations can have a significant impact on public health, whether they involve the single-type land-use distribution, the bi-type interaction land-use pattern, or the all-type land-use pattern.

Table 3. Results of regression models.

Types	Categories	Variables	OLS Model		SEM Model	
			Coefficient	*p*-Value	Coefficient	*p*-Value
Landscape pattern variables	Univariate land-use pattern	AI_E	−0.105	0.397	−0.179 †	0.088
		AI_U	0.059	0.705	−0.118	0.428
		PD_A	−0.433 **	0.008	−0.261 †	0.076
	Bivariate interactive land-use pattern	$CONTAG_{AE}$	−0.253	0.180	−0.151	0.371
		LSI_{AE}	−0.269 †	0.072	−0.256 †	0.072
		ED_{AT}	0.163	0.243	0.085	0.529
		ED_{ET}	0.111	0.414	0.248 †	0.069

Table 3. *Cont.*

Types	Categories	Variables	OLS Model		SEM Model	
			Coefficient	*p*-Value	Coefficient	*p*-Value
Landscape pattern variables	Multivariate land-use pattern	MESH	0.180	0.172	0.296 *	0.025
		SPLIT	0.249	0.152	0.123	0.387
Control variables	Economic and social factors	GDP	0.154	0.153	0.129	0.148
		POLLUTE	0.146	0.187	0.107	0.299
		LOW_EDU	0.684 **	0.001	0.578 **	0.004
		LOW_INCOME	−0.133	0.342	−0.170	0.286
	Healthcare services	BED	−0.067	0.572	−0.040	0.705
		ACCESS	0.110	0.291	0.217 *	0.012
	Statistical diagnosis		R-squared: 0.400 Adjusted R-squared: 0.302 Log likelihood: −126.472 AIC: 284.944 Moran's I (error): 2.139 *** Lagrange Multiplier (error): 4.7389 ** Robust LM (error): 5.703 **		R-squared: 0.457 Log likelihood: −124.182 AIC: 280.364	

†: $0.05 \leq p < 0.1$, *: $0.01 \leq p < 0.05$, **: $0.001 \leq p < 0.01$, ***: $p < 0.001$.

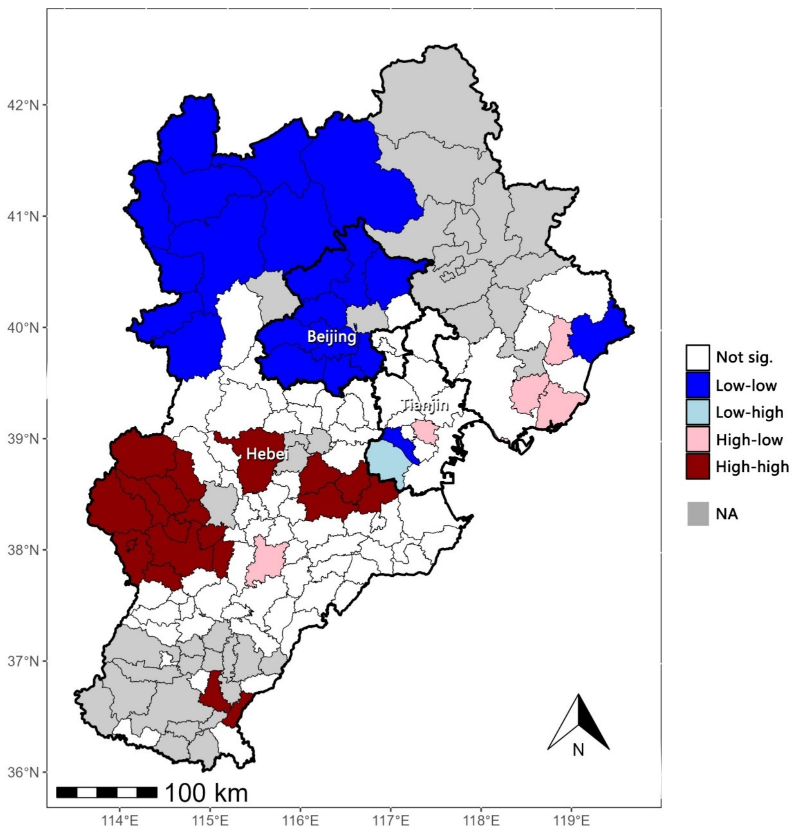


Figure 2. Local spatial autocorrelation for ASMR.

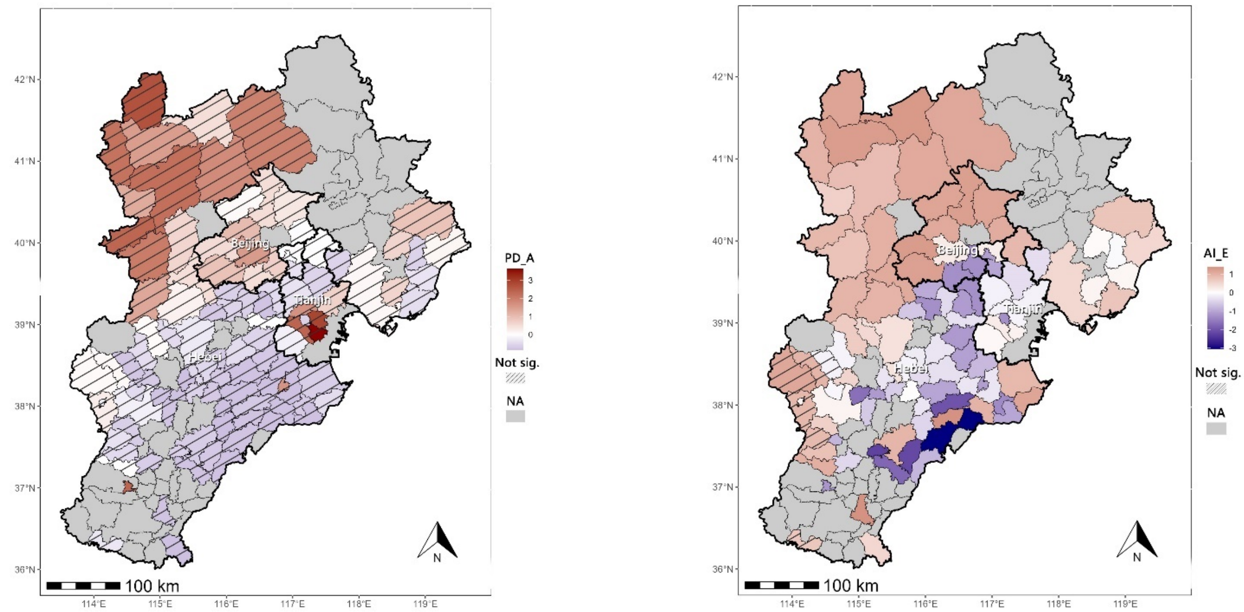
1. Among the single-type distribution indices, AI_E is significant at the p = 0.1 level with negative coefficients, indicating a negative correlation between ecological space clustering and ASMR, i.e., the more concentrated the ecological space, the stronger the CVD mortality inhibition. PD_A also showed a significant negative correlation with ASMR, which suggests that fragmented patches of agricultural space are positive for public health.

2. Among the bi-type interaction indices, LSI_{AE} is significantly negative at the level of $p = 0.1$. This suggests that a more complex interaction between agricultural and ecological spaces is more effective at reducing CVD mortality. Conversely, a more regular pattern of these two types of land use in the combination zone will have a negative effect. The correlation between ED_{ET} and ASMR is more substantial, suggesting that a fragmented and staggered distribution between ecological and construction spaces will better control CVD mortality. Conversely, when these two types of land use are relatively close and compact, they provide greater health benefits.
3. Among the all-type land-use patterns, MESH has a significant positive association with ASMR, indicating that higher MESH values correspond to higher ASMR. MESH is defined as the fragmentation of various patch types within a given study unit. Greater fragmentation and decentralization lead to a more positive effect and containment of CVD mortality, whereas concentrating the three types of land use may increase CVD mortality.

Additionally, the economic and social situations, along with the level of healthcare service development, are significant contributors to CVD mortality. Among these variables, the LOW_EDU factor exhibits the strongest positive correlation with the dependent variable, suggesting that improving public education levels is of utmost importance. Furthermore, healthcare service accessibility had a more substantial and profound effect compared to the number of hospital beds per capita.

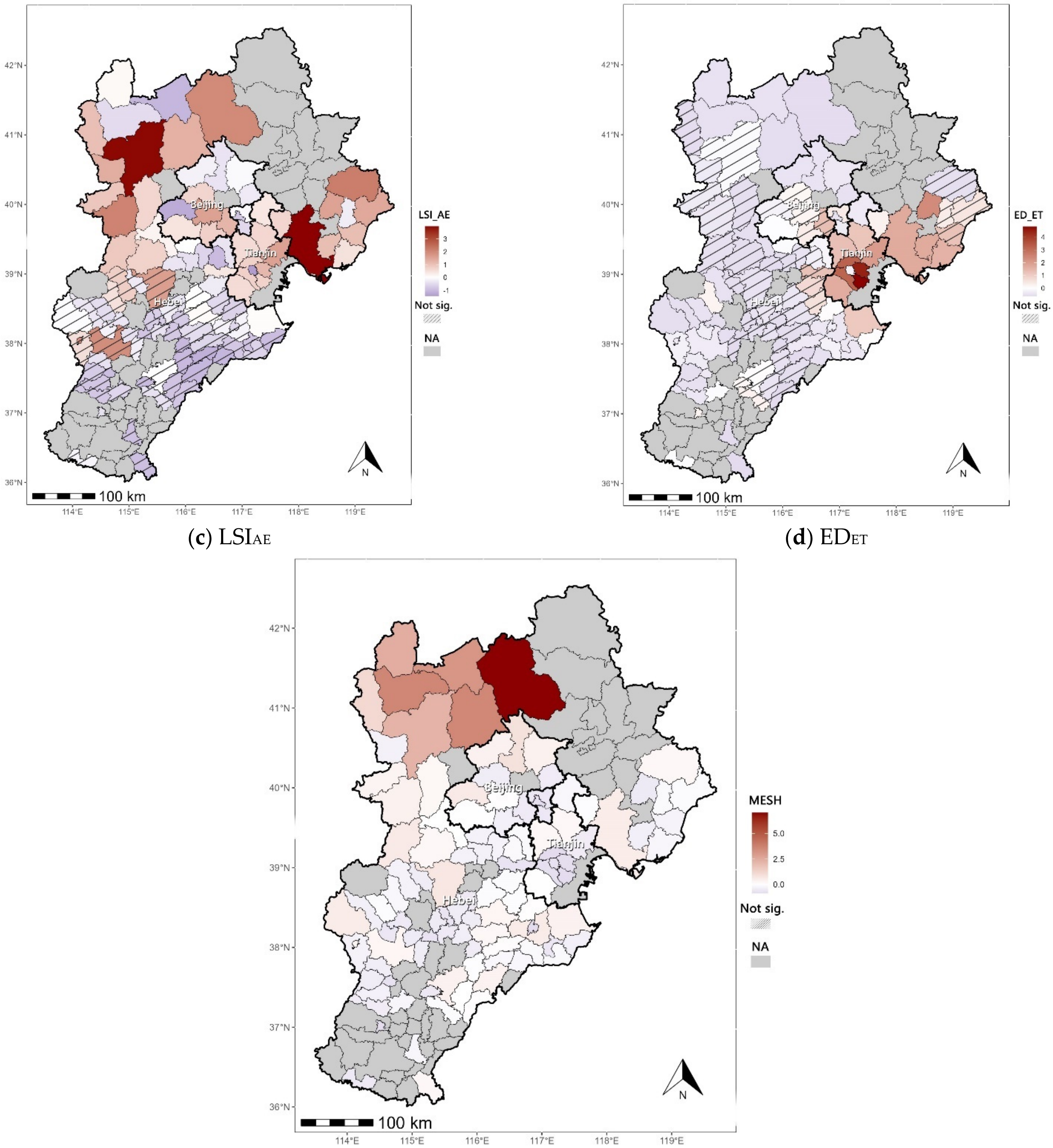
3.3. Local Effects of Land-Use Pattern Characteristics

The MGWR model's calculation results (Figure 3) demonstrate that national land-use patterns have clear spatial heterogeneity impacts on public health. The spatial pattern indices' effects have varying intensities across different regions, and the same land-use pattern feature may either suppress CVD in some areas or increase its prevalence in others.



(**a**) PD_A (**b**) AI_E

Figure 3. *Cont.*



(**c**) LSI_{AE} (**d**) ED_{ET}

(**e**) MESH

Figure 3. Distribution of significant landscape pattern variables.

Specifically, (1) AI_E has a negative correlation with ASMR in the central and southeastern BTH region. The strongest correlation was found in the southeastern region, indicating that decentralized ecological space can aid in suppressing CVD in these regions. In the western, northern, and eastern regions, AI_E exhibited a positive correlation with ASMR, indicating that public health is more adversely affected in more decentralized ecological space. (2) The spatial clustering of LSI_{AE} was relatively insignificant but showed significance in the central and northern regions of the study area. The indicator displayed a negative correlation with ASMR in the central portion of the study area. LSI_{AE}'s definition of integrating agricultural and ecological spaces aids in decreasing ASMR. Conversely, a positive correlation was seen in the northwestern and northeastern regions of the study area, indicating that the mixing of the two types of land use will have a negative impact. (3) The correlation between ED_{ET} and ASMR was negative in nearly all regions, indicating that ecological space and construction space are more fragmented than construction space alone. This fragmentation has a detrimental effect on public health and suggests that combining ecological and built-up space is not conducive to reducing CVD mortality. (4) A positive correlation between MESH and ASMR is evident in nearly all areas, signifying the detrimental effects of concentrating the three types of land use. (5) Moreover, the global model acknowledges the impact of PD_A, yet significance is lacking for most regions at the local level.

4. Discussion

According to the results shown above, we can discuss the association between land-use patterns and CVD from four perspectives.

(1) The moderate dispersion and organic combination of different types of land use enhances public health.

The results of the SEM model reveal an evident negative correlation between the global MESH score and ASMR. This suggests that an excessive concentration in the patch distribution of BTH is unfavorable to CVD control. Conversely, a moderate scattering of the different types of patches will be related to better health outcomes.

According to the principles of landscape ecology, the metropolitan environment is a complex system that relies not only on the isolated impact of each patch, but also on the interactions between patches, regardless of whether they belong to the same or different types of land use. An effective mosaic arrangement of different patch types can enhance the contact area between them, facilitate integration between the three land-use categories, and promote a higher intensity and likelihood of interaction, which provide benefits in two distinct manners: (1) the improvement of ecosystem service quality. The expansion of contact between patches leads to enhanced material and energy flow among diverse elements of the landscape, resulting in the "edge effect" in ecology [32]. This effect supports heterogeneity in landscape ecological patterns and species diversity, consequently improving ecosystem service quality in megacity regions [33]. Furthermore, it betters the urban habitat quality and reduces the likelihood of CVD. Finally, it encourages outdoor activities among residents. Moderate fragmentation of patches results in lower travel costs to ecological space for most people. This, in turn, promotes outdoor activities, generating positive incentives for individuals to engage in these activities [34].

(2) The impact of patch density characteristics depends on the unique properties of land use.

According to the model results, ecological and agricultural spaces exhibit contrasting behaviors regarding the patch distribution density indicator, mainly because the trend of the ecosystem service value and the contribution to public health of the two types of land use differs when the degree of agglomeration increases.

A concentrated patch distribution contributes to a low level of CVD mortality. Several ecological studies have demonstrated that the area of a patch not only affects species distribution and productivity levels, but also impacts energy and nutrient allocation. Generally, patch area is proportional to the total amount of energy and mineral nutrients in the area, and species diversity and productivity levels increase with patch size [35,36]. Therefore, it is evident that ecological patches of larger size typically have greater ecological and recreational worth, while also making a greater contribution to public health.

For the same size of patch, an increase in the segmentation leads to greater public health benefits. When agricultural production is carried out on a large scale, there is usually a high intensity of pesticide and chemical fertilizer usage which exposes populations to a greater risk of CVD [20]. Meanwhile, the concentrated distribution of agricultural land patches typically results in a uniform and closed management mode that obstructs public access, and the landscape features become relatively monotonous, thereby weakening the attraction of outdoor recreation for residents. On the flip side, when agricultural space is more dispersed and the area of a single patch is small, it is often integrated with other types of land use in the surrounding area, forming "agritourism" [37,38], "rural tourism" [39], and other similar combinations. While this integration may weaken the agricultural production function, it can promote leisure and recreation activities. Scattered agricultural lands can offer flexible opportunities for profit or non-profit to the residents, thus enhancing their motivation to engage in outdoor activities and contributing to public health. These spaces have a unique and powerful attraction for residents of megacity regions [40].

(3) The spatial combination of patches has an impact on the role of each type of land use.

Along with the individual patch distribution density, the combination of different land uses may have either positive or negative effects on ecological and recreational values. This paper mainly discloses the influence of two pairs of spatial relationships.

The interconnectedness of agricultural space and ecological space plays a crucial role in mitigating CVD mortality. The primary reason for agricultural space having a low ecological value is their concentrated distribution, which causes single landscape characteristics, low species diversity, and mostly artificially distributed natural vegetation. Although agricultural production functions are relatively strong in these areas, they fail to meet the requirements of a perfect biological habitat, resulting in a so-called "green desert" [41]. However, the integration of both agricultural and ecological patches can establish farmland ecological networks and significantly augment the ecological and recreational tourism value of farmland [42].

On the contrary, it is advisable not to combine ecological and construction spaces in an excessively fragmented manner. This is due to the large contact area that results from such a layout, which intensifies the intervention in natural ecological processes and may lead to the risk of ecosystem degradation in metropolitan areas with high levels of human activity [43,44]. On the other hand, a more regular boundary shape between the two types of land use is a more reasonable layout since it does not significantly increase the travel cost for residents to access open spaces, and it better preserves the ecosystem's function.

(4) Varying levels of natural, social, and economic development lead to the spatial heterogeneity of impacts.

The concentration of AI_E in the northwest of BTH has a positive impact, while in the southeast, it brings health benefits. This is because the northwestern section serves as the ecological reserve for the entire BTH and is predominantly forested land. However, the clustering of patches does not result in significant environmental quality enhancement. Instead, due to the excessively large area of ecological space and the scattered distribution of settlements, two problems were created: insufficient socialization from low population density, and difficulty supporting municipal facilities like heating. These issues are exacerbated by the region's high average elevation and low temperature [15,45,46]. In contrast, densely populated towns and cities in the southeast could benefit from the provision of ecological patches clustered at scale, as they offer scarce ecological and recreational values that are pivotal to the region. Their positive benefits are evident.

LSI_{AE} exhibits a negative correlation with CVD mortality in central BTH and a positive correlation in the peripheral region. The primary reason for this is the higher level of urbanization in the central area, where scenic and tranquil landscapes hold great allure and assume an essential role in the outdoor pursuits of the inhabitants. In peripheral areas where agricultural and ecological spaces are prevalent, most residents opt for artificial urban parks and public squares due to resource scarcity. However, the integration of these land uses has resulted in reduced agricultural production efficiency and poorer income and quality of life for rural populations, leading to negative impacts on their health.

Positive associations are found between ED_{ET} and CVD mortality in nearly all areas of BTH. However, the eastern coastal areas demonstrate the most pronounced effect, while the impact in northwestern areas is comparatively weaker. This discrepancy may be attributed to various ecological and industrial factors characteristic of this megacity region. The eastern area is marked by greater land salinization, comparatively fragile ecology [47], and concentrated coastal ports and petrochemical industries [48]. These factors lead to ecosystems that are particularly vulnerable to human activities, which are more likely to deplete the value of services when ecological and construction spaces are intertwined.

MESH values demonstrated an overall favorable correlation with CVD mortality, with the greatest correlation observed in the northwestern part, which is largely mountainous and offers limited construction space, resulting in densely constructed urban areas with sparse parks and green spaces. When certain types of land use are concentrated, residents lack access to outdoor recreational areas, which can negatively impact the prevention and treatment of CVD.

5. Conclusions

Public health problems in China's megacity regions have become increasingly prominent and have been found to be closely related to land-use patterns. In the context of China's new land-use management system, three types of land use, namely ecological space, agricultural space, and construction space, have become the basic targets of management, but existing studies have not yet fully revealed the intrinsic association between the layout characteristics of these three types of land use and the risk of CVD. In this regard, this study conducts a systematic exploration based on multi-dimensional spatiotemporal big data and geostatistical methods. First, the spatial autocorrelation of the response variables is analyzed to identify the existence of spatial effects. Second, SEM models are used to reveal the effects of the distribution characteristics of each type of land use and the spatial relationships among them on CVD mortality within the study area. Finally, the MGWR model is used to examine the variability of the effects of each significant factor across regions.

The study's findings suggest a significant association between the land-use patterns and CVD mortality in BTH, emphasizing the vital role of prudent and rational land-use optimizing as a fundamental tool for enhancing public health. There are three main conclusions. First, moderately decentralized land-use patches which combine different types of land organically can increase access to high-quality ecological spaces and enhance outdoor activities for residents. However, this does not imply that each type of space should follow identical arrangement principles. Promoting the dispersion of agricultural space will have significant positive benefits. Therefore, ecological spaces require a degree of concentration to realize scale effects. Second, various types have intricate interactions, which subsequently affect the ecological and recreational value of the area as well as the ASMR. Therefore, it is imperative to optimize land use not in isolation of a particular type, but from a holistic perspective that fully considers the different types as part of a complicated system. Third, association between the same spatial pattern indicator and CVD varies significantly across different areas of BTH, even though the influence of economic and social conditions has been controlled. Therefore, decision makers must tailor management policies to the local context.

The findings of this study also have policy implications. In general, optimizing the land-use pattern of BTH should adhere to a strategy that combines agglomeration and dispersion and is based on different land-use types and site characteristics. Specifically, four principles may need to be considered when policies related to land-use pattern are made. First, it is essential to achieve an organic integration of the entire spatial area, facilitating the exchange of material and energy across different patch types, as well as to promote outdoor activity. Second, a certain scale must be maintained for ecological and construction spaces to take advantage of the scale effect, with a focus on strengthening internal biodiversity and improving landscape value in ecological spaces. The built area should enhance the establishment of parks and green spaces, improve the accessibility of ecological land while preserving its functional integrity, and leverage its potential for promoting public health. Third, the dispersion of agricultural space and its integration with other types of space should be strengthened. Spatial integration can create modes like "urban agriculture" and "agritourism". Given that BTH does not bear the burden of agricultural production, it is advisable for land-use planning and optimizing to achieve arable land growth. Instead, the value of agricultural space in promoting public health, leisure, and recreation should be fully utilized. Forth, land-use optimizing policies are drafted flexibly in tandem with the economic and social development of various regions. For instance, in the mountainous northwestern areas of BTH, towns and cities should be guided to organize their land use in clusters, alongside the introduction of ecological open spaces within built areas. Conversely, in the eastern coastal areas, the primary focus is on controlling town construction and industrial development stringently, while safeguarding the delicate seaside ecosystems [49].

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