Quantifying spatial non-stationary response of influencing factors on ecosystem health: An example in the Inner Mongolia, China during 1995 to 2020

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Abstract

The identification of ecosystem health and its influencing factors is crucial to sustainable management of ecosystem and ecosystem restoration. In spite of numerous studies on ecosystem health have been carried out in different perspectives, few studies have investigated the spatiotemporal heterogeneity between ecosystem health and its influencing factors systematically.

Considering this gap, the spatial relationships between ecosystem health and its factors concerning climate, socioeconomic and natural resource endowment at the county level were estimated based on a geographically weighted regression (GWR) model. The spatio-temporal distribution pattern and driving mechanism of ecosystem health were systematically analyzed. Results showed that:(1)The ecosystem health level in Inner Mongolia spatially increases from northwest to southeast, displaying notable global spatial autocorrelation and local spatial aggregation.(2)The factors influencing ecosystem health exhibit significant spatial heterogeneity. Annual average precipitation (AMP),biodiversity(BI) was positively correlated with ecosystem health, annual average temperature(AMT) and land use intensity(LUI)are estimated to be negative.(3) Annual average precipitation (AMP) significantly improves ecosystem health, whereas annual average temperature (AMT) significantly worsens eco-health in the eastern and northern regions. LUI negatively impacts ecosystem health in western counties (such as Alxa, Ordos, and Baynnur).This study contributes to extending our understanding of ecosystem health depend on spatial scale, and could inform decision-makers about how to control various influencing factors to improve the local ecology under local conditions. Finally, this study also proposed some relevant policy suggestions and provide effective ecosystem preservation and management support in Inner Mongolia.

1. Introduction

Urbanization in China has made remarkable progress during the past 40 years, the urbanization rate has more than doubled 57.35 percent in 2017 compared to 17.92 percent in 1978, the average urbanization rate in China from 1978 to 2017 was about 2.45 times greater than that of the world during the same period (Ren et al. 2018). Since the beginning of 21st century, Inner Mongolia urbanization rate had risen to 60.3% by 2015.High-speed urbanization has led to significant landscape pattern alterations, which has altered ecosystem structure and function (Huilei et al. 2017).As the world’s second-largest economy, China has made remarkable achievements in its economic development. Following the exploitation of the west region, Inner Mongolia become one of China’s fastest developing provinces and the second largest coal-producing province (Xiao et al. 2020).The economic prosperity result in severe ecosystem destruction due to overexploitation of resources (Wang et al. 2019).These environmental problems in turn also pose a threat to the sustainable development of urbanization and the economics. Due to this, how to balance socioeconomic development with the environment has become a critical issue (Zeng et al. 2016).It is therefore vital to evaluate ecosystem health to support sustainable development and ecosystem management policies. The health of ecosystems has been studied at many different scales and in different habitats, including provinces (Meng et al. 2018), large cities (Su and Fath 2012), urban agglomerations (Kang et al. 2018), rivers (Cheng et al. 2018), wetlands (Chi et al. 2018) and forests

(Styers et al. 2010). Currently, there are few studies that examine the association between ecosystem health and its influencing forces, which cannot reflect the degree of interaction and influence between humans and the environment.

A regional ecosystem's health is the ability to both maintain its structure and function as well as to provide ecosystem services sustainably influenced by human intervention, which was regarded as the most effective method for evaluating the quality of an ecosystem (Constanza 1992; Kang et al. 2018). Three types of analysis frameworks have been proposed so far for regional ecosystem health assessments: evaluating the subsystem as well as PSR model (P is pressure, S is state, R is response) (Sun et al. 2016) and VORS model (V represents vigor, O represents organization, R represents resilience, and S represents ecosystem service) (Spiegel et al. 2001).Early efforts picked index from the compound subsystem of resource-environment-society-economy (Meng et al. 2018). During the ecosystem health evaluation, we focused on the causal relationship between human activities and ecosystem quality, which resulted in the development of various indicators including the PSR system and the DPSIR system. While both groups are capable of monitoring ecosystem status and external disturbances, neither group is capable of measuring ecosystem service provision. It is however possible to overcome this obstacle by utilizing the VORS functions. VORS try to define ecosystem health in terms of the quality of both naturalistic ecosystems and ecological services for human beings, which is based on the VOR model. VORS is described using four main components: V is vigor, O is organization, R is resilience and S is ecosystem services. Vigor is an indication of the metabolism, primary productivity and activity of a regional ecosystem, and organization is an indication of the number of interactions between the different sub-ecosystems, respectively, while a resilience component describes how well an ecosystem can adapt to external disturbances and a ecosystem services function component highlights the provision of ecological services influenced by spatial adjacency relationships among different ecosystems (Constanza 1992; Rapport et al. 1998).In this paper, the VORS framework was used to evaluate the ecosystem health of Inner Mongolia in light of the comprehensive measurement of natural ecological states.

There is very limited research into how environmental factors impact ecosystem health. As a way of addressing this issue, Feng et al. (2016) identified Environmental factors and ESs from a global perspective in an attempt to show that both of them were related to each other. Turner and Qiu (2013) found that ESs are correlated both on the local (cell) scale and at the landscape scale, and a series of significant explanatory variables were identified. Studying global regression without taking into account geographical variations in regression parameters, as a result, their findings represent an average for all of the study areas. Due to the fact that two closely related factors, precipitation and temperature, were found to have a highly irregular spatial distribution (Turner et al. 2013), the correlations between ecosystem health and these factors show spatial heterogeneity as well (Zhang et al. 2020).Global regressions, for instance ordinary least squares regression(OLS),When calculations are performed based only on the "average" or "global" percentages of parameters, they hide information about the local characteristics of the relationship between the variables, thereby hiding the real phenomenon (Fotheringham and Brunsdon 2010).Since an increasing number of studies have proven that the geographically weighted regression

model can address the aforementioned problem (Han et al. 2019; Zhang et al. 2020),local regression has gradually taken the place of global regression, becoming tool of Spatial relationships analysis in the ecological processes. Previous studies concerning ecosystem health and its driving forces in Inner Mongolia is insufficient. We adopted the VORS model, using a 2×2 minimum spatial grid to evaluate the ecosystem health in Inner Mongolia. In addition, we applied GWR model to quantifying spatial non-stationary response of influencing factors on ecosystem health. This novel exploration can fill the research gap in the study area.

As part of this article, we examined regional differences in ecosystem health using VORS model at the 2×2 minimum spatial grid scale from 1995 to 2020 and analyzed the spatial correlations between ecosystem health and its influencing forces related to meteorology, socio-economics, and resource endowment, using a GWR model On the basis of the county level, which is a basis for the decision making relating to ecological management in Inner Mongolia.The aim of this study was to determine: (1) the spatial heterogeneity of ecosystem health in Inner Mongolia; and (2) the non-stationary spatial relationships correlation within ecosystem health and influencing forces investigated. The results of our study will be helpful in forming a conservation policy to conserve the environment in study site.

2. Materials And Methods

2.1 Study area

Inner Mongolia is a typical arid and semi-arid region situated in northern China(116°42'E, 43°38'N) characterized by the mid-temperate continental climate and it has a surface area of roughly 1,180.000 square kilometers(Fig. 1).The temperature in the northeastern part of Inner Mongolia fluctuate from −25.1°C to 20°C,while in western Inner Mongolia, temperatures range from 10–20°C.Rainfall varies from 106.1 millimeters to 373.4 millimeters in an annual cycle, eighty-two percent of the country’s water resources are located in the east, while water resources in the middle and west are not sufficient. Therefore, four distinct regions can be identified within the Inner Mongolia in accordance with their climates and land use patterns. The northern part is made up of Hulunbuir and Xing'an, the eastern part is from Tongliao city to Xilin Gol city, middle part is comprised of Ulaan Chab to Baynnur, and the western part is Alxa. After the western region exploitation, Inner Mongolia has experienced rapid economic and urban growth in the past few decades and the growth of coal mining has been largely responsible for this development, leading to a severe degradation of ecosystems. Therefore, it is urgently necessary with the goal of formulating targeted policies aimed at protecting the environment, and the assessment of ecosystem health is essential for making a distinction between the formulation of ecological protection policies and the development of ecological civilization in Inner Mongolia.

2.2 Data sources

Generally, there are two categories of data that can be grouped into the following: spatial datasets and statistical datasets. In terms of spatial datasets, they have been provided by Resources and Environmental Science Data Centre and National Academy of Sciences of China((available at:

http://www.resdc.cn),including LUCC data (with a resolution in space of 1km),climate data with a spatial resolution of 1km×1km including average annual precipitation and average annual temperature, normalized difference vegetation indicator(NDVI),county boundaries of the administrative area in Inner Mongolia and the digital elevation model (DEM) has a resolution in space of one kilometer.

The statistical datasets, concerning GDP density, density of population and urbanization ratio, were gathered from Inner Mongolia Statistical Yearbook(1995–2020).The data were preprocessed using ArcGIS10.5 and Fragstats4.2 software. Using Fragstats4.2 software, we calculated the landscape indices of ecosystems.

2.3 Methods

2.3.1 Assessment of ecosystem health

Ecosystem health can be directly measured and fully assessed by its four main aspects: vigor, organization, resilience, services. By applying the VORS framework developed by Peng et al. (2015), we evaluated ecosystem health at the regional matrix. It should be noted that it is important to normalize each element to a value ranging from 0 to 1.The formula of calculating the ecosystem health index is conducted in the following way:

$$EHI = \sqrt[4]{EV \times EO \times ER \times ES}$$

1

In this case, the ecosystem health indicator (EHI) ranks 0-1depending on how healthy each ecosystem is. The ecosystem health index is divided into five categories using the equal-interval method: Highest Health(value from 0.8 to1),Suboptimal Health(value from 0.6 to 0.8),Average Health(value from 0.4 to 0.6),Unhealthy(value from 0.2 to 0.4),Degraded(value from 0 to 0.2).Ecosystem vigor represents net primary production as well as metabolism of ecosystem. This paper quantifies the ecosystem vigor by utilizing the NDVI (normalized difference vegetation index) which has been extensively utilized in ecosystem health assessments thanks to its ability to assess the character of eco-environments (Peng et al. 2017; Liao et al. 2018).

1) Ecosystem organization describes the ecosystem complexity as well as the structural stability. In this paper, The landscape pattern indicators was used to evaluate ecosystem organization, which include factors such as connectivity and heterogeneity of the landscape (He et al. 2019).Specifically, Our reflection of landscape heterogeneity was represented by mean patch fractal dimension (MPFD) and Shannon’s diversity index (SHDI).The landscape connectivity index includes two main components: the first was the connectivity of an overall landscape determined by the landscape contagion as well as fragmentation index, the second was the connectivity of important ecological patches (forests, streams, grasslands) determined by the cohesion and fragmentation index. Additionally, as far as previously documented studies and the advice of experts, the weight of overall landscape connectivity is 0.35,

connectivity of ecological patches weight is 0.30 and landscape heterogeneity weight is 0.35 (Pan et al. 2020).

Specifically, the following is the calculation method:

$$EO = 0.35LH + 0.35LC + 0.30IC = (0.25SHDI + 0.10MPFD) + (0.25FN_1 + 0.10CONT) + (0.07FN_2 + 0.03COHE_1 + 0.07FN_3 + 0.03COHE_2 + 0.07FN_4 + 0.03COHE_3)$$

2

Where *EO* means ecosystem organization. *FN1*,*FN2*,*FN3*,*FN4* represent landscape fragmentation indicator, forestland fragmentation index, grassland fragmentation index, and water fragmentation index, respectively; *CONT* ,*COHE1*, *COHE2*, *COHE3* stands for landscape contagion index, forest cohesion index, grassland cohesion index and water cohesion index.

2) Ecosystem resilience refers to an ecosystem's ability to remain structurally stable regardless of the interference of human beings or any external factors (Rapport et al. 1998).The area-weighted ecosystem resilience coefficients(ERC) is a measure of ecosystem resilience for all kind of land use. Specifically, based on specialist knowledge and relevant researches (Peng et al. 2017; Pan et al. 2020),Ecological resilience coefficient is determined. Below is the exact calculation formula:

$$ER = \sum_{i=1}^{n} A_i \times ERC_i$$

3

Where resilience of the ecosystem was abbreviated as *ER*, *n* stands for the number of different types of land use, A_i reflects the area proportion of land use type *i.*

3) Ecosystem services describe the capacity of ecosystem to generate products and benefits to mankind. An ecosystem service can be analyzed and measured by two different ways: The first is by evaluating the coefficients of ecosystem service provided by different land uses (Xie et al. 2017), which is obtained by comparing the ecosystem service value of a given land use type with that of all land uses. Secondly, Spatial neighboring coefficients differ among land uses, which was depending on Inner Mongolia's actual situation and related literature. The specific calculation formula is as follows:

$$ES = \sum_{j=1}^{n} ESC_j \times \left(1 + \frac{SNE_j}{100}\right) / n$$

4

Where *ES* refer to ecosystem services, The ESC_j coefficients are the coefficients describing the ecosystem services provided by the pixel *j*, SNE_j can be defined as the total of correlation coefficients between two spatial neighbors of the pixel *j*. *n* indicates the amount of pixel.

2.3.2.Spatial correlation test

The spatial autocorrelation analysis was applied to investigate the spatial dependencies of ecosystem health and its agglomeration pattern in Inner Mongolian. Spatial autocorrelation consist of both global autocorrelation as well as local autocorrelation, and can therefore indicate the degree to which the attribute of one area is dependent on the attribute of another. In order to identify the spatial agglomeration of the entire research area, Moran's I index was utilized, as shown in Eq. (5) (Moran 1950).LISA (Anselin 1995) (indicator of spatial association at a local level) is widely used to measure the spatial association between the value of one attribute and the value of the adjacent attribute (Eq. (6)).

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \quad (5)$$

$$Local\ Moran's\ I = \frac{n(x_i-\bar{x})\sum_{j=1}^{m} w_{ij}(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \quad (6)$$

Where *n* represents the overall number of grids in Inner Mongolia; *m* represents the amount of grids located geographically next to grid $j;\ i\neq j;\ s=1/n\sum_{i=1}^{n}(xi-\bar{x})^2;x_i\ ,\ x_j$ indicate the ecosystem health value of grid *i* and *j* ; and *x* stands for the mean value of ecosystem health. Parameter *I* value varies from − 1 to 1 and the absolute magnitude of *I* index is in accordance with the degree of spatial autocorrelation. When *I* > 0, correlation between spatial variables is positive, when *I* < 0, correlation between spatial variables is negative, and when *I* = 0, No spatial relation exists. There are four kinds of local autocorrelations that are considered in this study: including high-high (HH), high-low (HL), low-high (LH), low-low (LL), and units with a high level of ecosystem health are encircled by units with low ecosystem health level, which indicate the aggregate of units that exhibit a high level of ecosystem health, the aggregate of units that exhibit a low ecosystem health level, and units with a low level ecosystem health are surrounded by units with a high level ecosystem health, accordingly.

2.3.3.Modeling the determinants of ecosystem health

2.3.3.1 Variable selection

In this paper, the following factors have been selected as candidate variables for examining influential factors of ecosystem health. Based on previous research, seven factors in the field of meteorology, socio-economics, and natural resource endowments were considered (Bebianno et al. 2015; Cheng et al. 2018). Specifically, the average annual temperature(AMT), average annual precipitation (AMP) was used to define the meteorological condition. The socioeconomic development was measured by per area Gross Domestic Product (GDP), population density (PD), urbanization rate (UR), and land use intensity (LUI).Biodiversity index (BI) was used to reflect resource endowment.

As there is a high correlation between socioeconomic determinants, unsuitable choice of variables could lead to collinearity. Therefore, this study used ArcGIS exploratory regression to analyze ecosystem health figures and independent variables from in the year from 1995 to 2020 in all their possible combinations. Based on each regression model, the corresponding bias-adjusted Akaike information criterion (AICc) ,adjusted R^2 and maximum variance inflation factor (Max-VIF) were respectively obtained. In fact, the three elements are actually tests for selecting the most appropriate regression model based on statistical principles. First step in selecting an suitable model involved pre-screening and identifying regression models whose maximum variance inflation factor (Max-VIF) was below 7.5.In second stage, the Adjusted R^2 was ranked in descending order; the results are displayed in Table 1.According to Table 1 below, Variable combination models AMT + AMP + LUI + BI ranked first in 2000,2005,2010,2015 and second in the fittest degree in 2020, accordingly. Furthermore, its counterpart Max-VIF was comparatively smaller. Thus, AMT + AMP + LUI + BI were chosen as the independent variables in this study.

Table 1
Selection of independent variables.

	Variable Combination	Adjusted R^2	AICc	Max-VIF
1995	AMT + LUI + BI	0.831	-267.190	2.375
	LUI + BI	0.816	-259.638	1.035
2000	AMT + AMP + LUI + BI	0.851	-281.053	1.975
	AMP + LUI + BI	0.842	-276.541	2.742
2005	AMT + AMP + LUI + BI	0.865	-273.130	1.430
	AMP + LUI + BI	0.852	-264.941	2.702
2010	AMT + AMP + LUI + BI	0.838	-262.537	1.588
	AMP + LUI + BI	0.820	-253.373	2.769
2015	AMT + AMP + LUI + BI	0.866	-271.667	2.057
	PD + AMP + AMT + LUI + BI	0.835	-267.095	2.214
	GDP + AMP + AMT + LUI + BI	0.813	-245.598	2.501
2020	AMP + UR + LUI + BI	0.893	-296.267	2.579
	AMT + AMP + LUI + BI	0.886	-289.108	1.706

2.3.3.2 Geographically weighted regression model

Firstly, the factors of the health ecosystem were examined using Ordinary Least Square (OLS).In OLS regression model, dependent and independent variables are assumed to behave the same in all locations within the given geographical area. Hence, it is unable to measure the non-stationarity of spatial distributions of ecosystem health. In this regard, the estimation of parameters via OLS model tends to be biased and inefficient. After that, we used model with variable parameters(GWR) (Fotheringham et al. 2003), which tests whether variables are spatially interconnected across locations.

The OLS regression model is described by the Eq. (7):

$$y_i = \beta_0 + \sum \beta_j x_i + e_i$$

7

Where y_i represent the ecosystem health value for the ith county, and x_i is its determinants .Similarly,β_0 represents the constant and β_j represents the coefficient that should be estimated for the dependent variable, while e_i represents the stochastic error term. As shown in Eq. (8), The GWR model can be described as a modification of Eq. (7):

$$y_i\left(u_i, v_i\right)=\beta_0\left(u_i, v_i\right)+\sum \beta_j\left(u_i, v_i\right) x_i+e_i\left(u_i, v_i\right)$$

8

Where (u_i,v_i) indicates the geographic location or the geographical site coordinate (i.e.,counties). In this study, u_i and v_i here are the longitudes and latitudes of the ith county's center point, respectively. The GWR is a model that fits datasets of observations nearby a specific county, resulting in a set of parameters that can be estimated separately for each county. GWR not only estimates parameters for each observation individually, but also gives greater observed data(i.e.,counties) near the center as opposed to those at a greater distance.

Using the GWR model, the estimated coefficients can be written as follows, Eq. (9):

$$\hat{\beta}\left(u_i, v_i\right)=\left(X' w\left(u_i, v_i\right) X\right)^{-1} X' w\left(u_i, v_i\right) Y$$

9

Where w(u_i,v_i) is a diagonal spatial weight matrix per observation (i.e., county).A weight matrix for spatial patterns represent the central idea of the model; The parameter value is determined by the bandwidth and geographic location which is used to describe the non-stationarity characteristics for a location (Poudyal et al. 2012; Yang and Wong 2013).In our case, we utilized ArcGIS 10.5 to assess GWR and OLS models. In GWR models, Gaussian functions were used to assign Weight in space matrices, and across verification processes, the appropriate bandwidth was determined to reduce the Akaike Information Criteria (AICc).

3. Results

3.1 Spatial distribution of EHI

As can be seen in Fig. 2, ecosystem health in Inner Mongolia increases from the west to the north from 1995 to 2020.The high levels including highest Health and the suboptimal health was mostly distributed in the north part (Hulunbuir and Xing'an), and in the east part of the region (from Tongliao to Xilin Gol), which was an area with high vegetation coverage and ecological integrity. In contrast, the low level areas including unhealthy and degraded were located in the west (Alxa) of the region, where there is no vegetation. However, most of the average level was concentrated in the middle part (from Ulaan Chab to Baynnur) of the region.

Ecosystem health value changed at different rates in different regions. Specifically, there was a downward trend in west ecosystem health, from 0.26 in 1995 to 0.21 in 2020, and the state of ecosystem health was at degraded levels. The urbanization and economic development in this area has caused extensive expansion of urban construction. As a result of this urban expansion, the regional landscape has been profoundly transformed by excessive population growth, limited land resources, local natural ecosystem alteration and pollution without effective pollution prevention (Myagmartseren et al.

2017).There are many cities with low incomes where the government is not able to fulfill all of its responsibilities, leading to a shortage of services and facilities (Hardoy et al. 2013). Moreover, in urban areas, vegetation is being replaced by concrete, asphalt, and other hard surfaces that have a much lower potential heat storage, resulting in an increase in land surface temperature (Guan et al. 2016).2)The ecosystem health mean value in the east and the middle has declined from 0.53 in 1995 to 0.52 in 2020, essentially stabilizing at the average level. The mean value of ecosystem health in the east and middle indicated a declining trend, dropping from 0.53 in 1995 to 0.52 in 2020, which was fundamentally kept at the average health level. Liu et al. (2010) confirmed the grassland in the middle of Inner Mongolia is degrading, and something has to be done about that. Climate conditions play a major function in plant growth, especially in arid and semi-arid regions like Inner Mongolia (Li et al. 2006).According to the China Meteorological Administration, in Inner Mongolia most grass withered in 2014 due to the lack of precipitation at a crucial time for grass to begin growing. It has been reported by Chuai et al. that during the period from 2000 to 2007 the temperature increases and precipitation reductions had caused damage on shrubs, pastures, and steppes (Chuai et al. 2013).3) In 1995, mean score of ecosystem health in the north was 0.77; by 2020, this value increased to 0.79,primarily remained at the high level. Over the past few years, in concern with the application of the primary function zone project and the Grain for Green Project, there has been a gradual decrease in the amount of interference imposed by humans on the natural ecosystem of these areas (Yang et al. 2020).Therefore, these areas have improved their ecological carrying capacity and the restoration of vegetation.

3.2 Spatial autocorrelation of EHI

The global Moran's indicator values were 0.6638,0.6615,0.6607,0.6573, 0.6568, and 0.6432 in Inner Mongolia from 1995to2020,respectively,which was significantly at 1% level. It is evident that ecosystem health exhibits significant spatial autocorrelation in Inner Mongolia. Grids with equivalent ecosystem health showed significant spatial agglomeration effects, and the agglomeration degree steadily declined from 1995 to 2020.

This map illustrate that two parts of the region showed positive spatial autocorrelation (High–High or Low–Low) at 5% significance level. Negative spatial autocerrelation (Low-High or High-Low)was not observed in the research region from 1995 to 2020.The high-high type was mainly situated in the northeastern region, while the low-low type was distributed in the western region, coal mining area. During the research period, the LISA clustering pattern of mean ecosystem health was barely changed (Fig. 3).

3.3 Factors influencing the EHI

3.3.1Model diagnosis

The results of comparing GWR and OLS regarding their predictive capabilities and problem-solving abilities related to spatial autocorrelation are presented in Table 2.In much of the literature, AICcs and adjusted R^2s depicts predictive power of models (Su et al. 2014). As is shown in Table 2, we can see that

GWR had a higher adjusted R^2value than OLS and GWR had a lower AICc value than OLS. According to these findings, GWR proves to have a more powerful explanatory power than OLS. Thus, in our research, GWR model proved to be reliable as well as stable, and it also performed better than global regression in terms of clarifying the relationship between ecosystem health and the driving forces.

Table 2
Statistical test comparison of OLS and GWR from 1995 to 2020.

	AICc		**Ajusted R^2**	
	AICo	AIC_G	R^2_O	R^2_G
1995	-267.342	-290.769	0.833	0.869
2000	-281.053	-316.044	0.851	0.895
2005	-273.130	-302.850	0.865	0.900
2010	-262.537	-290.834	0.838	0.878
2015	-271.667	-306.255	0.866	0.906
2020	-282.364	-319.204	0.892	0.912

Notes: AIC_O and AIC_G are the Akaike Information Criterion for OLS and GWR; R^2_O and R^2_G are the coefficient of determination value for OLS and GWR.

3.3.2 Estimates produced by the GWR model

Based on the GWR model outcomes, we can conclude that the regression coefficient values varied between different regions. Corresponding local coefficients for Temp, PRE, LUI, and BI varied between counties on the EHI, illustrating the obvious spatial heterogeneity between the EHI and the influencing factors. Based on the regression coefficients of each factor, the non-stationary spatial distributions of ecosystem health to the influencing factors were plotted (Fig. 3–6).Positive regression coefficients indicate that increased influencing factors will result in an increased likelihood of ecosystem health, while negative regression coefficients indicate that rise in the influencing factors are likely to lead to a decline in ecosystem health.

Figures 3-4 illustrate the spatial relationship between EHI and meteorology, including annual mean temperatures and annual mean precipitation. According to the corresponding regression coefficient maps, ecosystem health is adversely affected by temperature. Counties with significant negative impacts are mostly situated in the north part of the region, including many counties in Hulunbuier, Xing'an, and Tong Liao. Despite the significantly negative impact of the region being relatively unchanged, there are differences in component counties between different time periods. Among the northeastern counties with low temperature condition, the EHI showed the most sensitivity to temperature. Middle or western parts of

the region with higher temperatures and less rainfall have a lower significance degree of negative impact. The most prominent and positive responses to precipitation were observed in the northeastern states of Inner Mongolia, whereas the lowest responses were observed in the western counties with higher temperatures and lower precipitation. In general, model results concluded that climate in Inner Mongolia was the most significant determinants affecting ecosystem health. Our findings are in agreement with the conclusions of previous research in China (He et al. 2019).The Meadow Steppe ecosystems in northeastern regions are extremely susceptible to climate fluctuations.

Figure 5 presented the spatial relationship between LUI and EHI. In Inner Mongolia, the regression coefficient maps indicate that LUI has negatively affected ecosystem health from 1995 to 2020.There are no positive correlations between LUI and ecosystem health in the study region. In general, the cities with the biggest negative impacts are located in the west part of the region, including Alxa and parts of the Baynnur and Ordos. The degree of negative impact decreases from the west to the north of Inner Mongolia. Alxa Plateau refer to area of ancient highlands severely eroded. There are three deserts in this region: Badain Jaran, Tengger, and Ulanbuh. The main landscapes are deserted mountains, sand-covered deserts and gobis, which occupied over 70% of the whole area. A primary cause of desertification in Inner Mongolia is land reclamation, because of Plant composition and additionally wind-exposed soil, these two aspects have resulted in soil nutrient depletion and deterioration of soil structures due to wet weather and water erosion. Hence, fertile soil has become barren since fertile land has been transformed into barren land. Ordos, With the development of urbanization, has become one of the most rapidly growing cities. Economic development was characterized by natural resource extraction and infrastructure construction, resulted in deforestation and ecosystem health disruption. Their results implied that land use intensity does aggravate the degradation of ecosystem health in the western part of the region.

Figure 6 illustrates the spatial relationship between BI and EHI. During the study period, the spatial distributions of the regression coefficients of biodiversity index were basically the same, but the coefficients increased to varying degrees, which indicated that the positive impact of BI on EHI showed an increasing trend especially after the Grain for green policy in 2000.This implies that government policy is beneficial to increase vegetation coverage and greatly improve the ecological health of the overall region. Specifically, the regression coefficient graphs demonstrate that the counties with a greater positive effect are primarily centralized in the northeastern region, involving the provinces Hulunbuir, Xing’an, and Tong liao. The significance degree of positive impact increases gradually from the west to the north of Inner Mongolia. It has been found in previous studies that total annual precipitation, which is the primary influence on NDVI in Inner Mongolia, has a positive correlation with the NDVI. Precipitation is highest in Hulunbuir and the Xing’an League in northeastern Inner Mongolia, these areas had the highest vegetation cover in Inner Mongolia, where forests and typical steppe are present. Desert is the dominant landscape pattern in the west part of the region, while grassland is mainly found in the middle part of the region. Implementing the "Grain to Green" project at the start of the 21st century has led to the conversion of sporadic farmland into grassland or forests. It is also beneficial for the regional ecosystem health.

4. Discussion

4.1 Comparison with previous studies

We evaluated the spatial distribution of ESH from 1995 to 2020.The results showed that the areas with relatively weak ESH were mainly located in western Inner Monglia, which mainly comprise desert area and fast growing socioeconomic area indicating that policy makers should take some strategies to combat with desertification and implement the industrial transformation and upgrading energy-intensive industry. Areas with strong ESH were located in northern areas, there are many mountains and much forest land distributed in this region such as Daxinganling virgin forest which also plays a certain role in ESH protection. The areas with average ESH were distributed in the eastern and middle part of the region suggesting that the classic ecology concepts or theories and the applicable ecological principles of grassland conservation or management should be taken into account in grassland dominated area.

In terms of driving force, the findings of our study present that ecosystem health level is strongly influenced by both meteorological and socioeconomic factors. This is in accordance with prior studies that showed regional ecological sensitivity is heavily determined by climatic factors (Meng et al. 2016; Zhang et al. 2017),and Wetland, grassland, and woodland ecosystem changes were affected by the complicated combination of climate and human force (Wan et al. 2018; Li et al. 2019).However, the non-stationary spatial interaction between ecosystem health and the influencing forces have not been enough. Until recently, studies of the factors that influence ecosystem health have neglected the point of view that ecosystem constituents affected by energy transfer and related to information exchange, which displays a notable spatial diffusion impact. Furthermore, urbanization transmits factors of production including capital, labor as well as industry between areas. That is to say the urbanization of adjacent region adversely affect local ecosystem (Xie et al. 2021).At present, researchers have started to be aware of this fact and have begun exploring the spatial variation relationship using OLS model .For example, Li et al. (2021) explored the urbanization’s impact on ecosystem health applying GWR model. Effects of land use change on ecosystem services have been examined by researcher Chen et al. (2019) utilizing GWR model. GWR model can provide location guidance for decision making in contrast with global regression model. The spatial link between the individual locations can be reflected by the local regression equation. Furthermore, previous studies only pay attention to one specific element concerning urbanization, disregarding other meteorological and socioeconomic elements, which do not permit objectively evaluating the influencing factors on ecosystem health.

4.2 Implications of spatial non-stationary responses

Our study found that ecosystem health in Inner Mongolia was strongly related to climate factors (PRE, TEM), resource endowment factors (BI), and socioeconomic factors (LUI), and that the Characteristics and intensity of those correlations demonstrated obvious spatially heterogeneity, Hence, decision-makers may intend to design interventions which can improve synergistic effects, but have the contrary result in other location. Our results can help decision-makers to identify the spatial distributions of each response, which can be controlled so as to promote ecosystem health. For example, in this study, we found that strong correlation exists between temperature and ecosystem health, and it showed a negative correlation

in study area, suggesting that managers and policy makers should attempt to decrease the temperature in order to improve ecosystem health. In a previous study, clustered vegetation was found to be an effective means of regulating the surface temperature (Estoque et al. 2017).Designers should strive for higher density of forest canopy to minimize evaporation and solar radiation, as precipitation has a positive correlation with ecosystem health in the overall study area. The implementation of precautions, such as monitoring of meteorological disasters, should also be conducted in order to minimize the impact of climate extremes on the ecosystem.

The results of our study indicate that the effect of BI factor on EHI is positive in the study area, recommending that decision makers should strive to improve the ecosystem health through ecological conservation policies. Projects such as Grain for Green and National parks and Nature reserves contribute to protecting the environment and managing natural resources. For instance, Xilin Gol Biosphere Reserve, West Ordos Nature reserve, Da Qing Shan National Nature Reserve in Northern Hohhot, National Nature Reserve in Heilihe in the boundary area of the country of Chi Feng and Cheng De Natural Barrier to Protect China's northern region have positive influence on natural ecosystem since grasslands were maintained as well as forests were cultivated in a positive way in the mentioned area. Additionally, Shelter Belt Construction Project in the Three-North area also assisted the protection of the environment and the conservation of nature (Rajagopalan et al. 2014).In terms of LUI, the spatial associations between ecosystem health and LUI showed that the proportions of land use categories were definitely associated with ecosystem health deficits and surpluses. The EHI was generally stronger in counties with greater percentage of pastures and forests. Additionally, urbanization areas and agricultural reclamation displaced the green space, which then resulted in a decline in the EHI or even deficit. It is therefore vital to optimize land use structure and avoid excessive reclamation and construction.

4.3 Limitations

It is important to note that our study has some limitations. In the first place, despite the fact that using a local regression model will enable us to estimate the spatial interaction between ecosystem health and influencing force, the GWR model also has an important limitation, which presumes that the interaction between independent variables and dependent variables differs at the same spatial level. Therefore, it is necessary to investigate interactions on multiple scales among response and explanatory variables. Second, we determined non-stationary relationships between ecosystem health and motivating forces at the administrative units. In spite of its convenience for the establishment and application of environmental conservation policies, the relationship between responses may vary at different scales (Su et al. 2020).Thus, we have not analyzed these relationships at other scales.Statistical data was not available at scale of grid cells, which was the main reason for this. If the statistical data were transformed from the level of the administrative division to the level of grid cell, it would be possible to study the scale effect correlation between the variable and its response.

5. Conclusion

In this paper,we evaluate the ecosystem health conditions from 1995 to 2020 and explore the factors contributing to spatial ecosystem health differences. Traditional econometric and spatial models only

account for the significance of a specific determinant from a global viewpoint, while ignoring the geographic heterogeneity of those Indications. In this study, using exploratory spatial data analysis, we examined the characteristics of agglomerations in the Inner Mongolia ecosystem health from 1995 to 2020, and utilized GWR model to assess the different effects of influencing determinant on ecosystem health in the study area.

We can obtain the following conclusions from the results. Inner Mongolia's ecosystem health level improved from northwest to southeast, and there was an upward trend, followed by a downward trend from 1995 to 2020.Grids with similar ecosystem health exhibit effects of spatial agglomeration, and spatial agglomeration degree decreased gradually from 1995 to 2020.Using the geographic variation analysis, it was revealed that influencing factors affecting ecosystem health exhibited intensive spatial heterogeneity. Particularly, the meteorological factors concerning average annual temperature and average annual precipitation contributed significantly to determining the ecosystem health in each region. Moreover, annual average temperature(AMT) and land use intensity(LUI)are negatively correlated with ecosystem health, whereas the coefficients of annual average precipitation(AMP), biodiversity(BI) are estimated to be positive indicating the positive impact on ecosystem health. The counties where ecosystem health can be significantly improved by annual average precipitation (AMP) are predominantly located in the eastern and northern regions, whereas the counties where ecosystem health can be significantly alleviated by annual average temperature (AMT) are predominantly located in the same region. Moreover, LUI exerts a negative influence on ecosystem health in western regions of counties (such as Alxa, Ordos, and Baynnur). The distribution of counties strongly influenced by Biodiversity index gradually increases from the southwest to northeast of the Inner Mongolia. By evaluating relationship between ecosystem health and its influencing force in Inner Mongolia, we can offer guidelines for functional implementation and the management of ecosystems as well as their restoration in different regions.

Declarations

Author Contributions: Conceptualization, L.G.; methodology, L.N. and Y.S.; formal analysis, L.N.; investigation, L.N.; data curation, L.N. and Y.S.; writing—original draft preparation, L.N.; writing—review and editing, L.G. and L.N.; visualization, L.N.; supervision, L.G. All authors have read and agreed to the published version of the manuscript.

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Ethics approval: The work presented is original and has not been published elsewhere in any form or language. No data, text, or theories by others are presented as if they were the author's own.

The work doesn't include figures that have already been published elsewhere. The research did not involve humans or animals for which informed consent is required to participate.

Consent to participate: Not applicable.

Consent for publication: All authors agree with the content of the manuscript and give explicit consent to submit.

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Figures

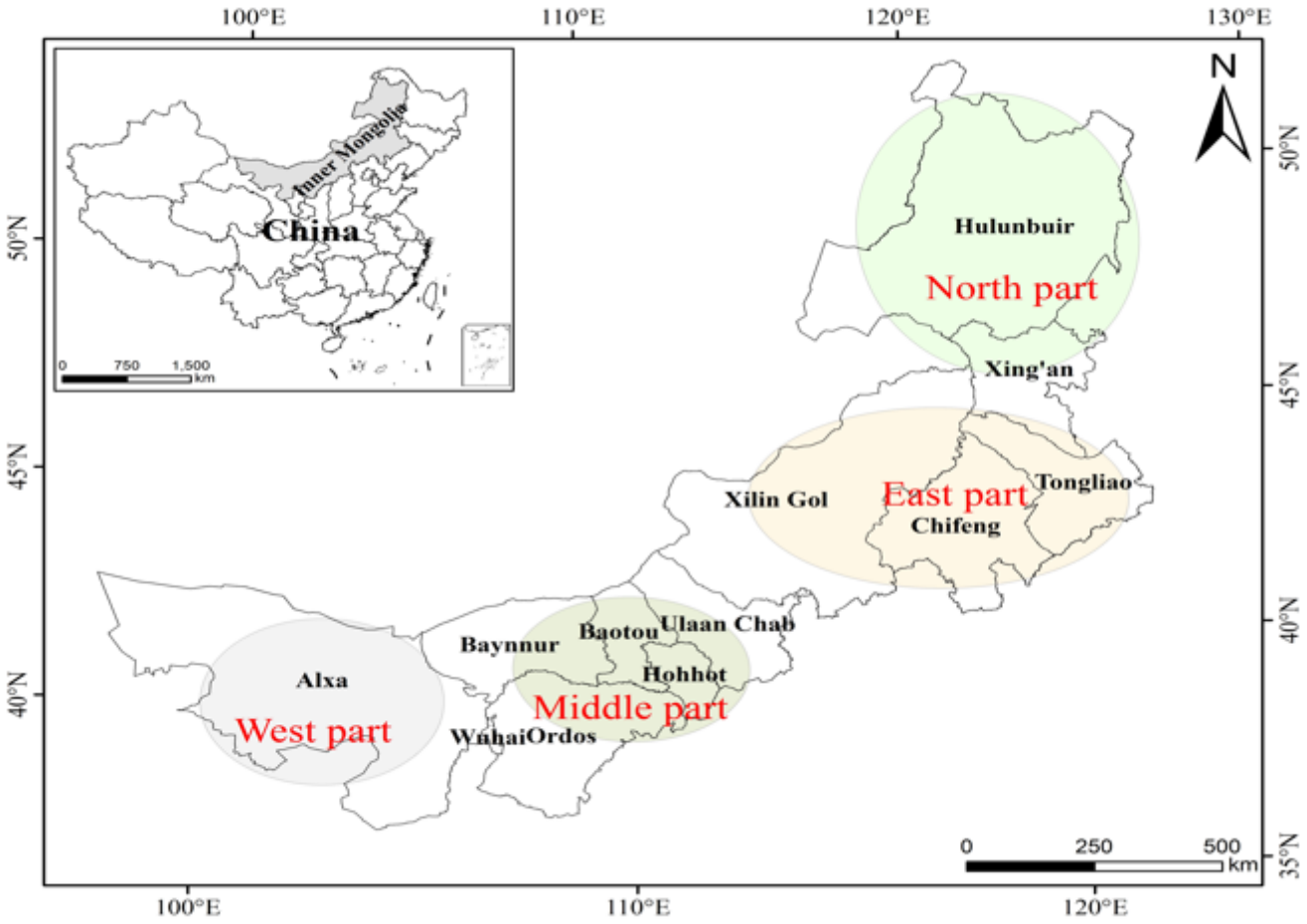

Figure 1

Geographic location and Spatial extent of the study area.

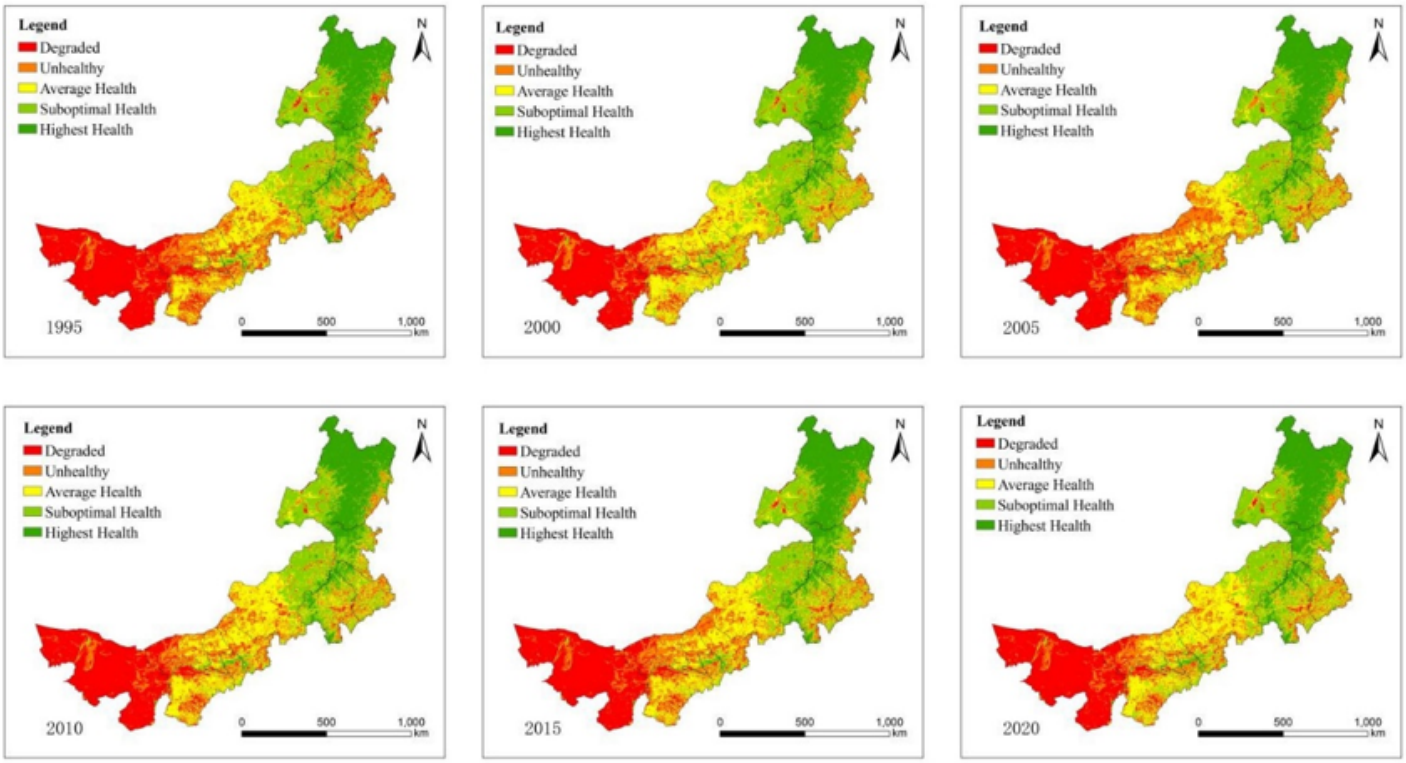

Figure 2

Spatial distribution of ecosystem health in Inner Mongolia from 1995 to 2020.

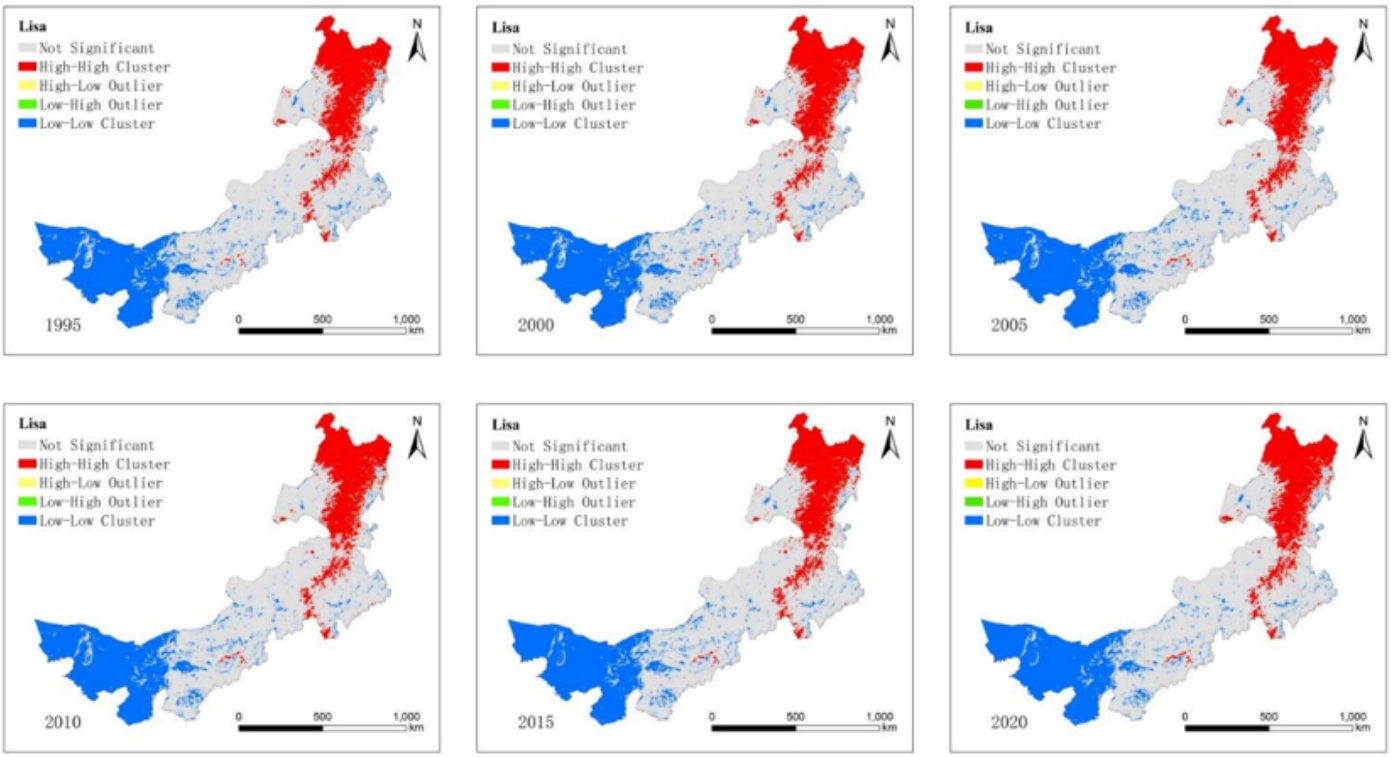

Figure 3

The cluster map of spatial association for EHI in Inner Mongolia from 1995 to 2020.

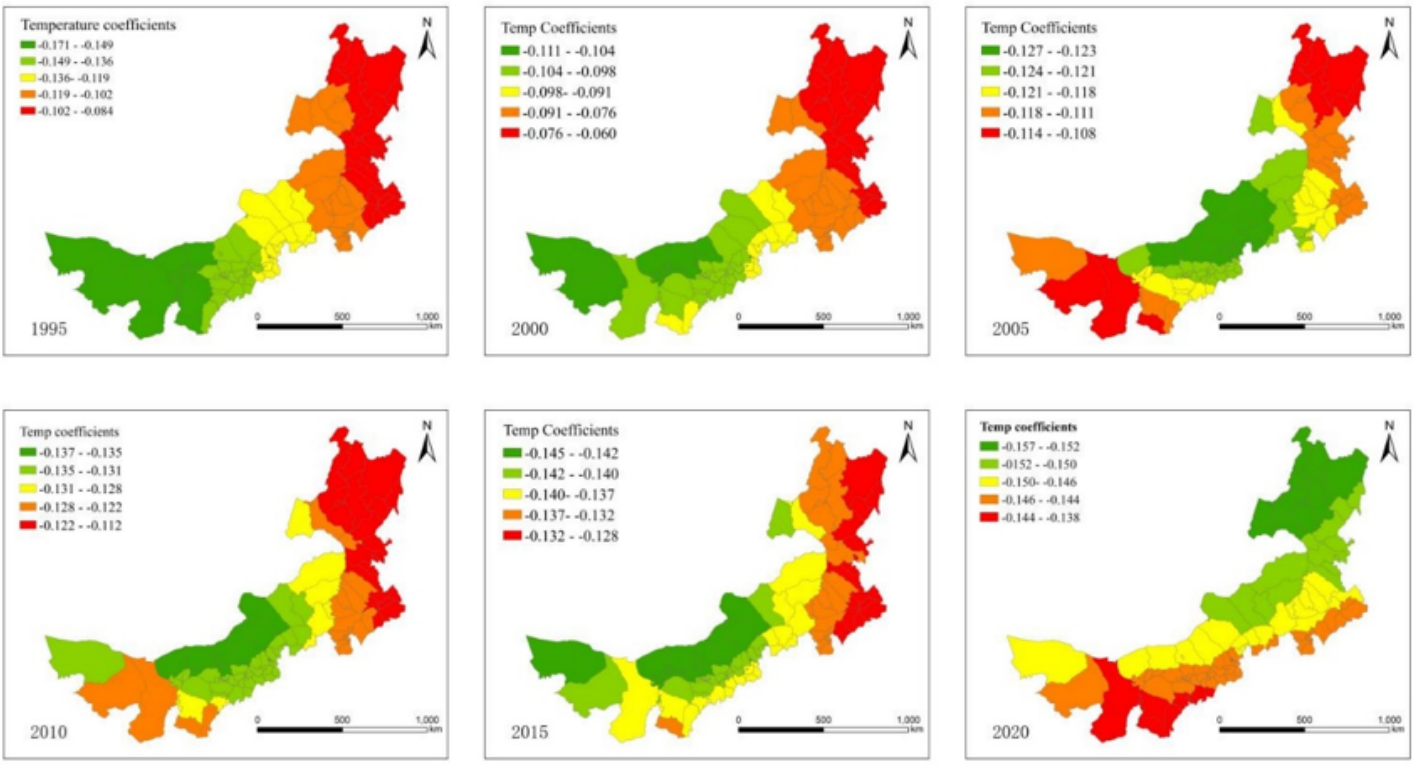

Figure 4

Spatial variability of the geographically regression coefficients of the Temp from 1995 to 2020.

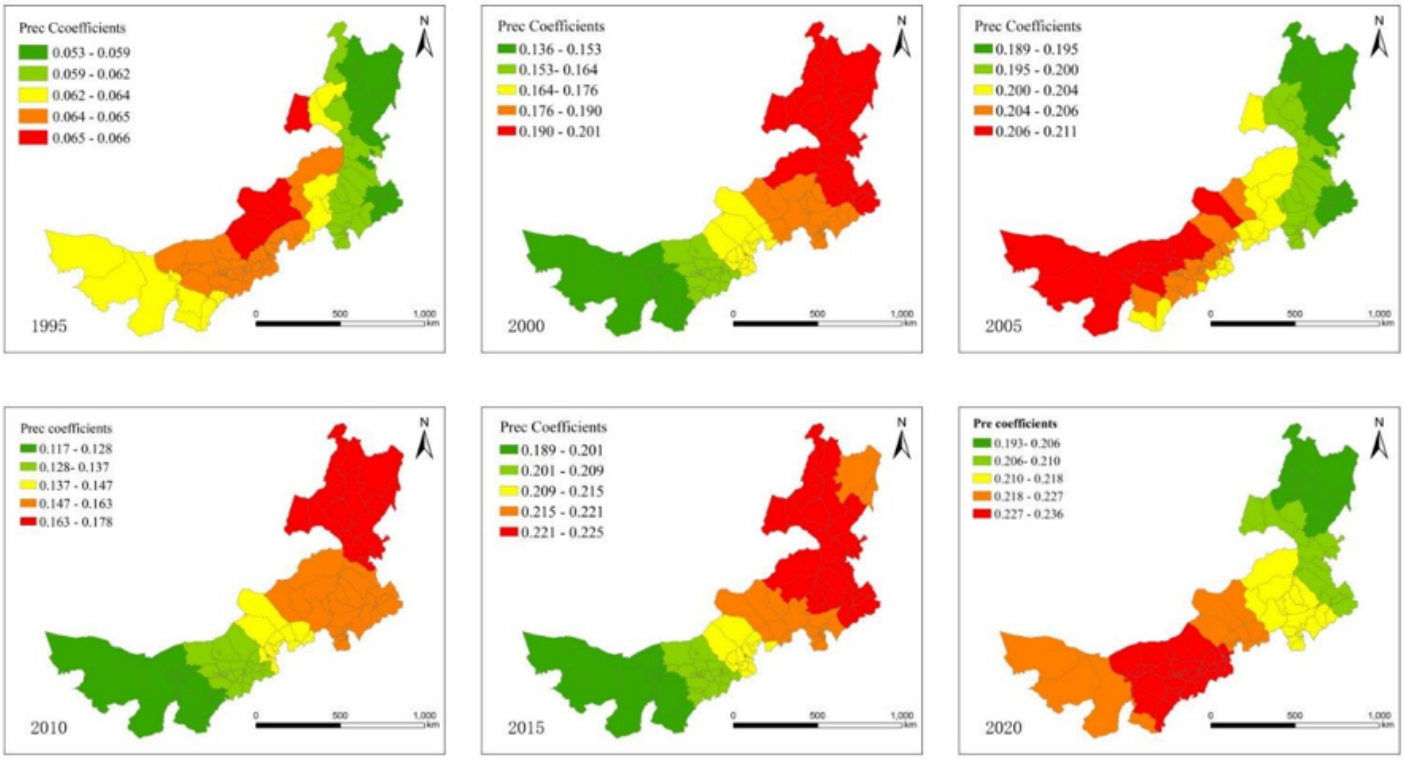

Figure 5

Spatial variability of the geographically regression coefficients of the PREC from 1995 to 2020.

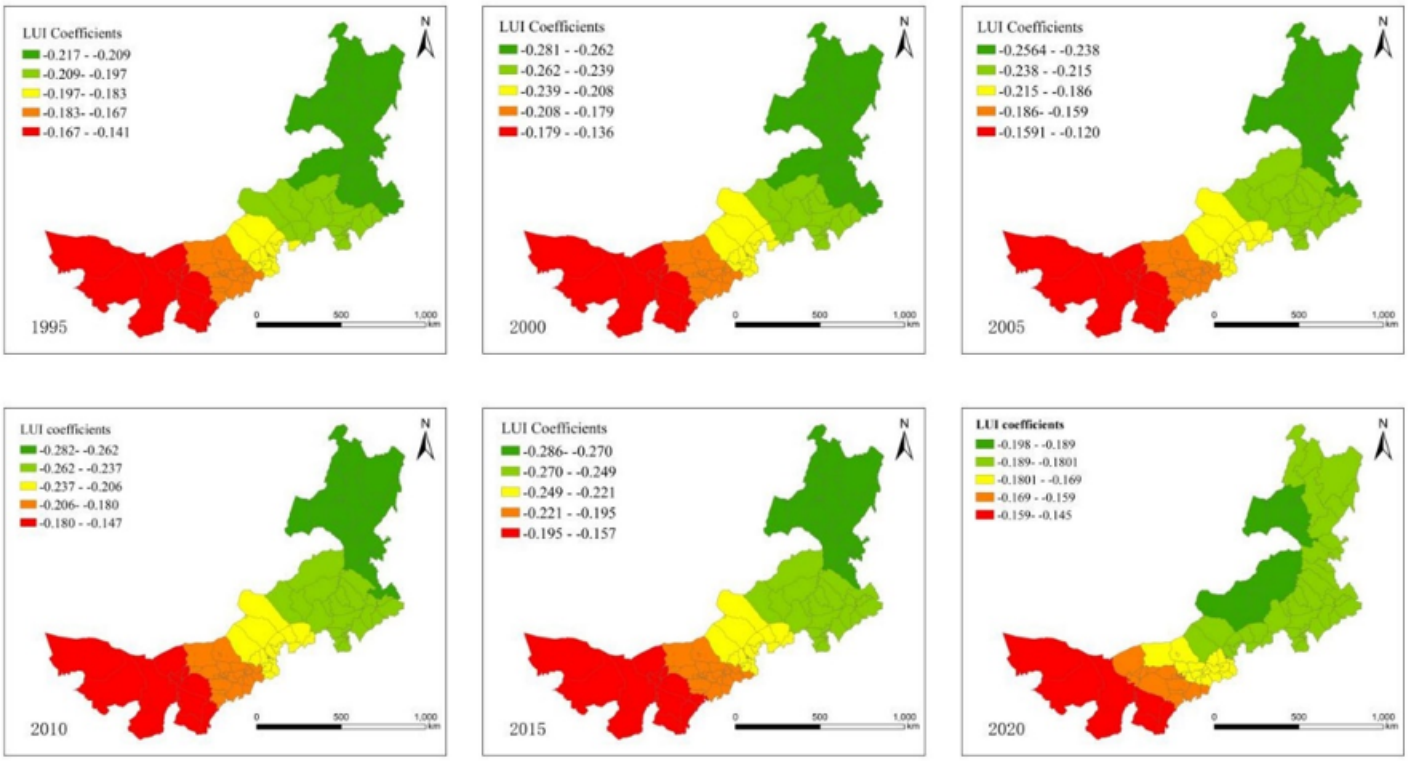

Figure 6

Spatial variability of the geographically regression coefficients of the LUI from 1995 to 2020.

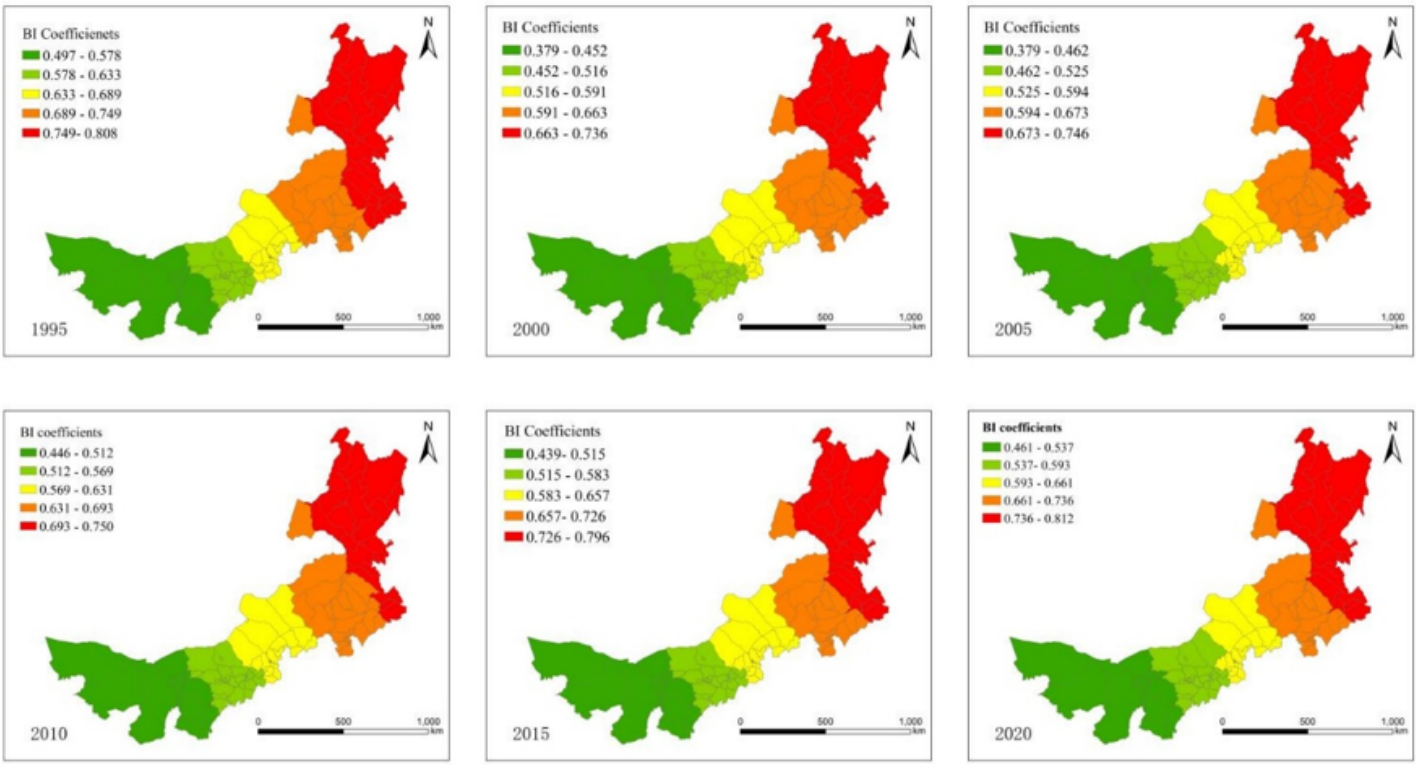

Figure 7

Spatial variability of the geographically regression coefficients of the BI from 1995 to 2020.