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The Impact of Urban Land Misallocation on Inclusive Green Growth Efficiency

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Abstract: Inclusive green growth (IGG）, as a new way to attain sustainable development, aims to achieve comprehensive and coordinated economic, social, and environmental development. How to define IGG and explore its driving factors is key to realizing IGG. This study takes China as an example, using panel data from 30 provinces in mainland China from 2009 to 2018 for research. The epsilon-based measure (EBM) model and Global Malmquist–Luerberger (GML) index are used to evaluate China's inclusive green growth efficiency (IGGE), and a spatial panel regression model of the impact of urban land resource misallocation on IGGE is established. The research found that (1) China's IGGE level from 2009 to 2018 displayed an upward trend, and combined with exploratory spatial data analysis (ESDA), it was found that IGGE has an obvious spatial correlation; (2) the regression model shows that the misallocation of land resources hinders the improvement of IGGE in China; and (3) the decomposition of spatial spillover effects demonstrates that the misallocation of land resources has negative externalities, which will also have adverse effects on neighboring areas.

Keywords: inclusive green growth efficiency; urban land resource; resource misallocation; spatial spillover effect

1. Introduction

With the continuous improvement of global industrialization and urbanization, the contradiction between economic development, social equity, and environmental protection has become increasingly prominent, bringing huge challenges to the sustainable development of the world. Over the past 20 years, economic growth has lifted 660 million people out of poverty and raised the income levels of millions of people, but growth has often come at the expense of the environment. In particular, developing countries are facing greater economic and environmental pressures. For a long time, several emerging economies have grown faster than developed countries, but the growth process requires a lot of resources, which may cause serious environmental damage. At the same time, the problem of inequality is constantly increasing, which will bring great social risks. Although developing countries should focus on meeting basic needs and expanding growth opportunities, they do not need to achieve this goal at the cost of unsustainable environmental degradation.

The theme of the 2012 United Nations Conference on Sustainable Development (Rio+20) was "Green Economy in the Context of Sustainable Development and Poverty Eradication" and proposed inclusive green growth with the purpose of finding new sustainable development paths(Ali, 2007). In the same year, the Word Bank released

Inclusive Green Growth: The Pathway to Sustainable Development, proposing that the essence of inclusive green growth is to achieve economic, social, and environmental sustainability(Horwood, 2005). Inclusive green growth (IGG) has become a new path of sustainable development and has attracted the attention of all countries. In 2012, the United Nations Environmental Programme (UNEP) developed the Green Economy Progress (GEP) framework to assess the level of inclusive green growth in various countries. In 2016, the United Nations New Sustainable Development Goals (SDGs) proposed a comprehensive approach to thoroughly address the three dimensions of social, economic, and environmental development. The concept of IGG, with the goal of eradicating poverty and protecting the environment, has attracted widespread attention from countries around the world.

In recent years, the research results on IGG have been enriched, but there is currently no unified method for measuring IGG(Whajah et al., 2019). Existing research believes that IGGE should include two aspects: Inclusive growth and green growth. The United Nations Development Program (UNDP) believes that IGG includes fairness and inclusiveness in economic, social, and environmental aspects(Spratt & Griffith-Jones, 2013). Albgoury believes that IGG emphasizes that, while economic growth can improve the welfare of present and future generations, IGG is more of a social welfare concept(Albagoury, 2016). Bouma and Berkhout believe that IGG needs to take into account the greenness, inclusiveness, and welfare of economic growth(Berkhout et al., 2018). Therefore, when measuring IGG, more scholars have followed the methods of inclusive growth and green growth. Some scholars use methods such as the GDP per capita and income inequality, and other scholars use the generalized concentration curve and indifference curve(Aoyagi & Ganelli, 2015; Oyinlola et al., 2020). Aoyagi and Ganelli use Gini coefficients and Bonferroni indices to measure the level of inclusive green growth(Aoyagi & Ganelli, 2015). More scholars use the method of comprehensive indicators to conduct comprehensive evaluations based on SDGs. With the integration of the concepts of green growth and inclusive growth, some scholars have approached studies from the perspective of total factor productivity, taking income disparity and environmental pollution as undesirable products to build an index system for inclusive growth(Hu & Wang, 2019). Sun et al. proposed a comprehensive directional distance function to evaluate the inclusive green growth(Sun et al., 2020).

Since the reform and opening up in 1978, China's economy has grown rapidly, becoming the second largest economy in the world. However, behind China's economic growth are huge energy consumption and pollution emissions, which have had a serious negative impact on China's environment(Song et al., 2018; Song et al., 2020). How to achieve sustainable development in China and coordinate the relationship between environmental pollution, energy consumption, and economic growth has always been the focus of academic research. The Chinese government is now aware that it is unsustainable to sacrifice the environment to obtain economic benefits, and has actively worked to reduce pollutant emissions and protect the ecological environment(Hao et al., 2018; Shuai & Fan, 2020; Wang et al., 2019). The report of the 19th National Congress clearly stated that it is necessary to focus on the people; accelerate the construction of ecological civilization; promote green development; and highlight the sustainable development of society, the economy, and the environment. It can be said that transforming the economic development mode and realizing inclusive green growth have become the main goals of all sectors of Chinese society.

However, there is no general consensus on how to implement such a transformation in order to achieve green and inclusive growth. Existing research is more focused on

exploring the driving factors of IGG based on technological progress, poverty reduction, and environmental regulation. However, there are a few studies that have been conducted from the perspective of resource allocation, especially research from the perspective of urban land resource allocation. In the process of China's economic growth, China's unique land system has made great contributions to economic growth and industrial structure adjustment(Y. Liu et al., 2018). Land transfer is an important part of the urban land system. The price and scale of land transfer are used to allocate different land resources to urban divisions and industrial sectors, so as to realize adjustments and upgrades of the industrial structure, and ultimately have an impact on China's overall economy(Yang et al., 2019). China's urban land is owned by the state and has long relied on the government to allocate land(T. Liu et al., 2016). In 2001, China started the reform of land marketization and sold state-owned land through bidding, auctions, and listings. However, in the process of land market reform, local governments rely on increasing the price of residential and commercial land to obtain fiscal revenue, and lower the price of industrial land to attract investment, resulting in a low land use efficiency and thus a misallocation of land resources(Lian et al., 2019; Xuemei et al., 2014). The misallocation of land resources has led to an imbalance of the industrial structure, especially the pollution caused by the industrial structure dominated by heavy industry. Due to the decentralization system and promotion mechanism, the competition among regional governments for attracting investment has led to the spatial spillover effect of negative externalities in environmental pollution. Local governments attracting high-polluting enterprises for economic development will cause regional environmental pollution to become more serious. It is surprising that these crucial issues have not yet attracted widespread attention and investigations.

The main contributions of this research are as follows: (1) Using the undesired EBM model and the Malmquist–Luenberger (ML) index to incorporate economic growth, social equity, and ecological environment into the evaluation of China's inclusive green growth efficiency, providing new ideas for IGGE measurement, and (2) analyzing the driving factors of IGGE from the perspective of resource misallocation, providing a sustainable development idea for optimizing resource allocation for developing countries that lack element input.

2. Methodology

2.1 Study area

The research objects of this article are 30 provincial administrative units (provinces, autonomous regions, and municipalities) in mainland China from 2009 to 2018. Hong Kong, Macau, Taiwan, and Tibet are not included due to a lack of data. According to the level of economic development and geographical distribution, mainland China can be divided into three regions: The east, the middle, and the west. The economic development of the three regions presents a stepped characteristic. Among them, the economic development level of the eastern coastal areas is relatively high; the economic level of the central region lags behind that of the central region, and the characteristics of labor-intensive industries are obvious. The ecological environment in the western region is relatively fragile, and the overall industrial level is lower than that in the eastern and central regions. All of the data were obtained from the China Statistical Yearbook and the Statistical Communique on National Economy and Social Development(China, 2018, 2000~2017).

Fig. 1. The distribution of the eastern, central, and western regions of China.

2.2 methods

2.2.1 Method for inclusive green growth efficiency (IGGE)

Data envelopment analysis is currently one of the most important methods for efficiency estimation, especially the combination of the Malmquist index and data envelopment analysis, which can be employed to estimate the total factor productivity (TFP）(Hidayati et al., 2017; Malmquist, 1953). However, under the condition of a constant input, the total factor productivity obtained by combining the Malmquist index and the output-oriented directional distance function has a large deviation, and it is impossible to consider the bad output in economic operations, such as environmental pollution(Chambers et al., 1996; Mandal, 2010). In order to overcome the problems of slack variables caused by the use of radial and directional Data Envelopment Analysis (DEA) to calculate the directional distance function, Chambers et al. proposed the Malmquist–Luenberger (ML) index, taking into account the input and output changes(Chambers et al., 1996). Oh further proposed the Global Malmquist–Luenberger (GML) index to solve the problem of undesired output changes(Oh, 2010). This method avoids the unsolvable problems of the traditional ML index and circulating accumulation simultaneously.

When calculating the directional distance function of GML, this study adopted the EBM model. The EBM model was originally proposed by Tone and Tsutsui, combines the advantages of the traditional DEA model and the SBM model, and is compatible with radial and nonradial mixed distance functions(Tone & Tsutsui, 2010). We defined the Super-EBM model and included the undesired outputs. The measurement formula is as follows:

$$r^* = min\frac{\theta - \varepsilon\sum_{i=1}^{m}\frac{w_i^- s_i^-}{x_{i0}}}{\phi + \varepsilon^+\left(\sum_{r=1}^{s}\frac{w_r^+ s_r^+}{y_{i0}} + \sum_{p=1}^{q}\frac{w_p^{z-} s_p^{z-}}{z_{p0}}\right)}$$

$$s.t.\begin{cases}\sum_j^n x_{ij}\lambda_j + s_i^- = \theta x_{i0}, i = 1,2,\cdots,m \\ \sum_j^n y_{rj}\lambda_j - s_r^+ = \theta y_{i0}, r = 1,2,\cdots,s \\ \sum_j^n z_{ij}\lambda_j + s_p^- = \theta z_{i0}, i = 1,2,\cdots,q \\ \lambda_j \geq 0, s_i^-, s_r^-, s_p^- \geq 0\end{cases}. \quad (1)$$

In Formula (1) r^* represents the efficiency value of the EBM model, and n is the number of decision-making units (DMUs). x, y, and z represent the inputs, desirable outputs, and undesirable outputs, respectively. m, s, and q represent the numbers of inputs, desirable outputs, and undesirable outputs, respectively. s_r^+ and s_p^- indicate the slack variable of desirable outputs and undesirable outputs, respectively. w is the weight of the DMUs. λ, θ, and ε represent the parameters.

The EBM model measures the efficiency values based on comparable cross-sections, and the efficiency values at different times are not comparable. In order to solve this problem, the Global Malmquist–Luenberger index is used for dynamic measurement based on the EBM model, and the dynamic changes in efficiency are further decomposed into changes in technological efficiency and changes in production technology to reflect changes in the production frontier.

$$GML_t^{t+1} = \left[\frac{1+\vec{D}_0^t(x^t,y^t,z^t;y^t,-z^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},z^{t+1};y^{t+1},-z^{t+1})} \times \frac{1+\vec{D}_0^{t+1}(x^t,y^t,z^t;y^t,-z^t)}{1+\vec{D}_0^t(x^{t+1},y^{t+1},z^{t+1};y^{t+1},-z^{t+1})}\right]^{\frac{1}{2}} \quad (2)$$

The ML index can further be decomposed into products of two components, which are the efficiency change (GECH) and technology change (GTCH):

$$GML_t^{t+1} = GECH_t^{t+1} \times GTCH_t^{t+1}, \quad (4)$$

$$GECH_t^{t,t+1} = \frac{1+\vec{D}_0^G(x^t,y^t,z^t;y^t,-z^t)}{1+\vec{D}_0^G(x^{t+1},y^{t+1},z^{t+1};y^{t+1},-z^{t+1})}, \quad (5)$$

$$GTCH_t^{t+1} = \left[\frac{1+\vec{D}_0^{t+1}(x^t,y^t,z^t;y^t,-z^t)}{1+\vec{D}_0^t(x^t,y^t,z^t;y^t,-z^t)} \times \frac{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},z^{t+1};y^{t+1},-z^{t+1})}{1+\vec{D}_0^{t+1}(x^{t+1},y^{t+1},z^{t+1};y^{t+1},-z^{t+1})}\right]^{\frac{1}{2}}. \quad (6)$$

The $GECH_t^{t,t+1}$ measures the change in relative efficiency between t and t + 1, and the $GTCH_t^{t+1}$ measures the shift in the frontier with the geometric mean of the technical change between t and t + 1 using input vectors from the two periods. These indexes indicate productivity improvements if their values are greater than one.

This study incorporated economic, social, and environmental factors into the IGGE measurement framework, fully considering environmental pollution and social imbalances(Elhorst et al., 2013). IGGE includes environmental protection and social equity in the process of economic growth. Inclusive growth should weigh efficiency and equity, and green growth should take into account both productivity improvement and environmental protection. Therefore, our input indicators mainly include factor inputs, including labor, capital, land, and energy. Desired output indicators include the economic growth, the growth of the industrial sector, and the increase in household consumption. The unemployment rate and environmental pollution discharge are regarded as undesired outputs(Ahmed, 2012; Fowowe & Folarin, 2019).

Table 1 Input and output indicators for the inclusive green growth efficiency (IGGE).

Indicator type	Indicator	Indicator description
Input	Labor input	Employment in secondary and tertiary industries
	Capital input	Investment in fixed assets
	Land resource input	Measured by built-up area of each province
	Energy input	Measured by the total energy consumption of each province
Desirable output	Economic output	Gross regional product （GRP）
	Social output	Urban and rural residents' consumption ratio
	Industry output	The value of the output of secondary and tertiary industries

Undesirable output	Social output	Unemployment rate
	Environment output	Industrial wastewater discharge, industrial waste gas emissions, and industrial solid waste production

Note: Since the EBM model measures the relative efficiency, capital depreciation does not have much of an impact on the relative ranking, and the results obtained by different depreciation rates are different, so this article does not depreciate capital. The calculation of the IGGE of each province is based on the MAXDEA Pro software.

2.2.2 Exploratory spatial data analysis

This study used ESDA to analyze the spatial heterogeneity and spatial dependency of IGGE. Spatial dependency analysis can be mainly divided into global spatial autocorrelation and local spatial autocorrelation analysis(Anselin & Cho, 2002). Global spatial autocorrelation can be represented by Global Moran's I:

$$Moran's\ \ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2 \sum_{i=1}^{n}\sum_{j=i}^{n} w_{ij}}. \tag{7}$$

Here, $Y_i$is the observation value of the i-th province, and $\bar{Y}$ is the sample mean. The spatial weight matrix w_{ij} is constructed by a reciprocal of the geographical distance:

$$w_{ij} = \begin{cases} \frac{1}{d_{ij}}, i \neq j, i, j = 1,2,\cdots,n \\ 0, i = j \end{cases}. \tag{8}$$

The d_{ij} is the geographical distance between the i-th and j-th province. This study used the latitude and longitude of the capital city to calculate the distance between provinces.

$$Z_I = \frac{I - E[I]}{\sqrt{V[I]}} \tag{9}$$

Among them,

$$E[I] = -\frac{1}{n-1}, \tag{10}$$

$$V[I] = E[I^2] - E[I]^2. \tag{11}$$

Local spatial autocorrelation analysis measures and statistically tests the indicators of local indications of spatial association (LISA). The local Moran's I can be calculated using the following formula:

$$I_i = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}. \tag{12}$$

2.2.3 Regression model

According to the existing literature, this study hypothesized that the misallocation of land resources, as a kind of element misallocation, can have an impact on the economic structure and pollution emissions, thereby affecting the level of IGGE. Therefore, a basic regression model of land resource misallocation (LandMisAll) affecting IGGE was established.

$$IGGE_{it} = \alpha + \beta_0 LandMisAll_{it} + \beta_j Contral_{it} + \varepsilon_{it}, \tag{13}$$

where i and t are time and individual effects, respectively, which refer to 30 provinces in China from 2009 to 2018. α is the intercept term and $\beta$is the estimated coefficient of the model. $Contral_{it}$represents the control variables, indicating other variables that can affect IGGE, and ε_{it} represents the random error terms.

Model (13) has static panel data, but existing research points out that the individual behavior of economic variables is affected by past behavior; that is, IGGE is a process of

dynamic development and accumulation. Therefore, we inserted the lag term of the explained variable IGGE into the model to obtain the model (14)

$$IGGE_{it} = \alpha + \eta IGGE_{i,t-1} + \beta_0 LandMisAll_{it} + \beta_j Contral_{it} + \varepsilon_{it}. \quad (14)$$

The dynamic panel model has an endogenous problem caused by the reciprocal causation of variables and missing variables. In order to solve this problem, we used the System Generalized method of moments (SYS-GMM) with the lagged variables in the model as instrumental variables. Furthermore, combined with ESDA, this study hypothesized that the misallocation of land resources affects IGGE and has a spatial correlation, so the model (14) was added to the spatial weight matrix and extended to the spatial dynamic panel model(Elhorst et al., 2013; Lee & Yu, 2010).

$$IGGE_{it} = \alpha + \eta IGGE_{i,t-1} + \eta w_{ij} IGGE_{i,t} + \eta w_{ij} IGGE_{i,t-1} + \beta_0 LandMisAll_{it} + \beta_j Contral_{it} + \varepsilon_{it} \quad (15)$$

Land misallocation (LandMisAll) refers to the difference in the marginal output of land with different uses, but China lacks micro-data corresponding to land at this stage. Considering that China's land use is sold according to the land use determined by the land plan, the land market for different uses is segmented. The most important one is the difference between residential land and industrial land. Therefore, this study used the ratio of residential land transfer price to industrial land transfer price to indicate the degree of land misallocation. In order to obtain a more robust estimation result, it employed both residential land and industrial land newly transferred areas, and the agreement transfer land area was compared with the total transfer area as a robustness index to test the misallocation of land resources.

The control variables selected in this study mainly include the technology level (RD), expressed as the proportion of regional research and development expenditure in GDP; the education level of residents (Edu), which is expressed in terms of per capita years of education; the direct use of foreign direct investment (FDI), which is expressed by the proportion of FDI in GDP; the degree of openness (Open), which is expressed by the proportion of total import and export trade in GDP; the urbanization level (Urban), which is expressed as the proportion of urban population; the level of local economic development, which is expressed by GDP per capita (Gdpc); and the environmental regulation level (ER), which was selected to control the impact of environmental governance on IGGR, expressed by the comprehensive utilization rate of industrial solid waste. The descriptive statistics of variables are shown in Table 2.

Table 2 Descriptive statistics of regression variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
IGGE	300	1.2178	0.249	0.7100	2.2225
LandMisAll	300	0.6019	0.5924	0.0200	6.4149
RD	300	0.0145	0.0105	0.0021	0.0601
Edu	300	8.7961	0.946	6.7639	12.3891
FDI	300	0.0231	0.0203	0.0000	0.1563
Open	300	0.3173	0.3914	0.0284	1.8910
Urban	300	0.5354	0.1356	0.2825	0.8961
Gdpc	300	2.7759	1.5455	0.5812	8.5954
ER	300	0.0096	0.0021	0.0042	0.0182

3. Results

3.1 The temporal-spatial characteristics of IGGE

Fig. 1 shows the basic situation of IGGE in China from 2009 to 2018. It can be seen that, in 2009, the IGGE level in most regions of China was between 0.7 and 1.5, and the IGGE in the central and western regions exhibited spatial clustering. Except for Ningbo, Shandong, and Guangdong in 2012, the IGGE level of most regions in China exceeded 1, and the overall level was between 1 and 1.5. In 2015, the IGGE level in the Jiangxi area rose, but that in Xinjiang fell to the 0.7-1 range. In 2018, the number of regions with IGGE exceeding 1.5 reached 13 provinces, and all regions except Guangdong had IGGE values exceeding 1. This shows that China's IGGE level basically displayed an upward trend from 2009 to 2018, and regions with the same IGGE level exhibited obvious spatial agglomeration characteristics.

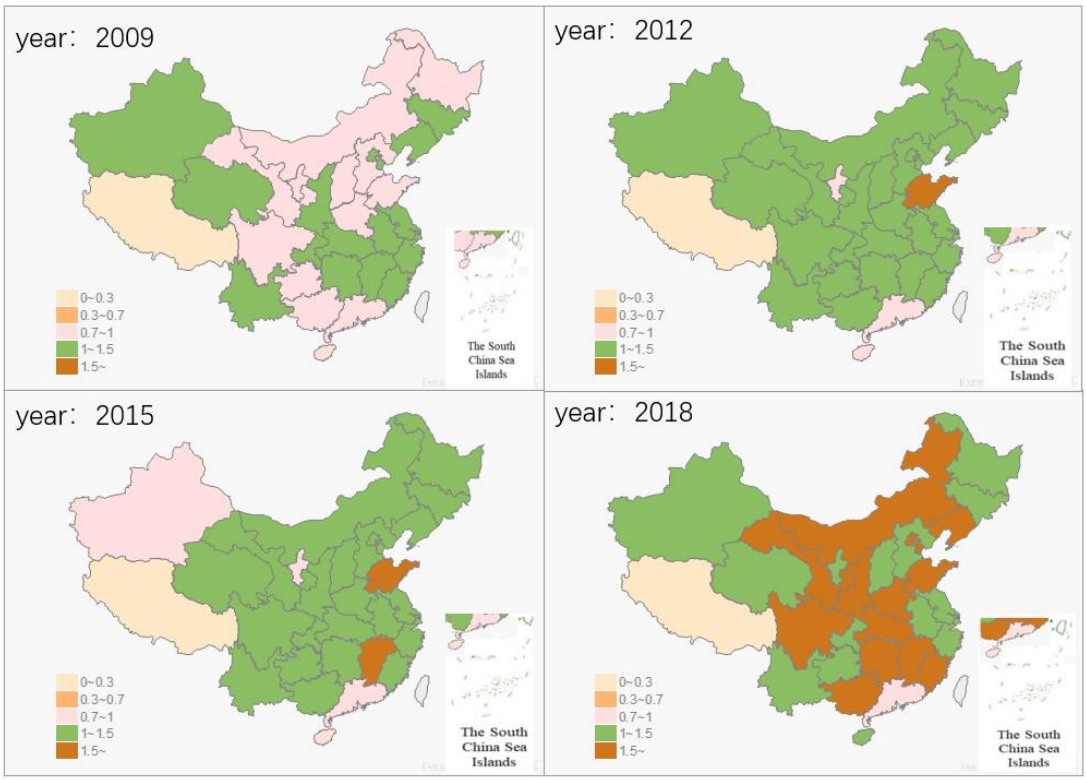

Fig. 2 The trend of IGGE from 2009 to 2018.

According to Fig. 2, it can be seen that China's IGGE level shows an obvious spatial correlation. Therefore, this study introduced Moran's I to test the spatial correlation of IGGE from 2009 to 2018, as shown in Fig. 3. According to Fig. 3, in 2009-2018, the IGGE between Chinese provinces showed a positive spatial correlation, with Moran's I ranging from 0.119 to 0.135. China's IGGE has obvious phase characteristics. The spatial correlation degree of IGGE in the three phases of 2010-2012, 2013-2015, and 2016-2017 exhibited a clear upward trend. However, from 2015 to 2018, the IGGE level of each province began to fluctuate, which was mainly caused by competition for investment and political promotion among Chinese local governments.

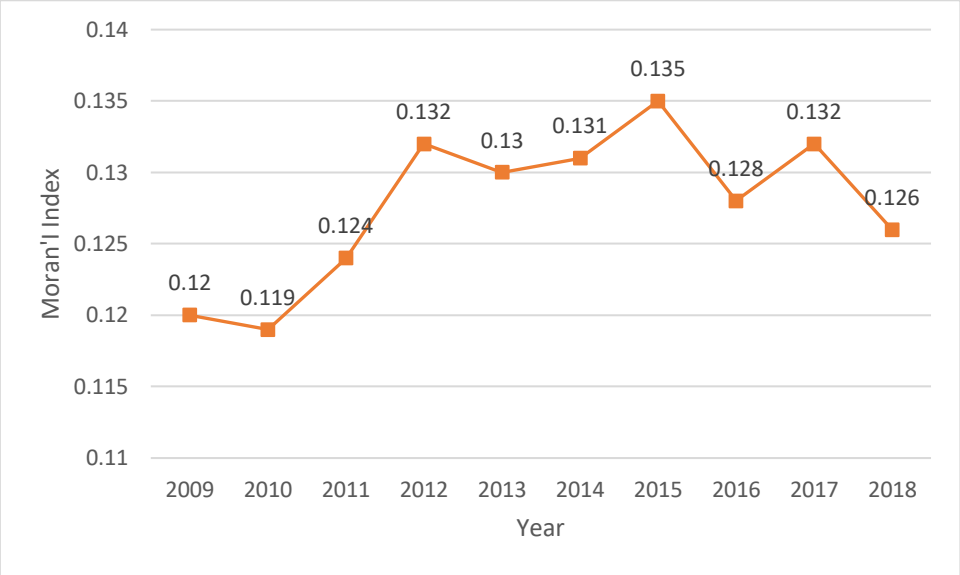

Fig. 3 The value of global Moran's I.

Fig. 4 shows the local Moran value distribution of China's IGGE level in some years. The first quadrant HH represents the spatial connection form in which the area unit with a high observation value is surrounded by the area with a high value. The second quadrant LH represents the spatial connection form in which the area unit with a low observation value is surrounded by the area with a high value. The third quadrant LL represents the spatial connection form in which the area unit with a low observation value is surrounded by the area with a low value. The fourth quadrant HL represents the spatial connection form in which the area unit with a high observation value is surrounded by the area with a low value. The important advantage of the Moran scatter plot is that it is able to specifically distinguish between the high value and high value, low value and low value, high value and low value, and low value and high value between the regional unit and its neighbors. When comparing Fig. 2 and Fig. 3, it is not difficult to find that, in 2009, the distribution of IGGE in China was relatively concentrated, and the IGGE difference between neighboring regions was small. In 2012 and 2015, most regions were concentrated in the HH and LL regions, indicating that the IGGE levels in neighboring regions during this period displayed obvious agglomeration characteristics. The distribution of the four quadrants in 2018 is relatively balanced, and the differences between regions have further expanded.

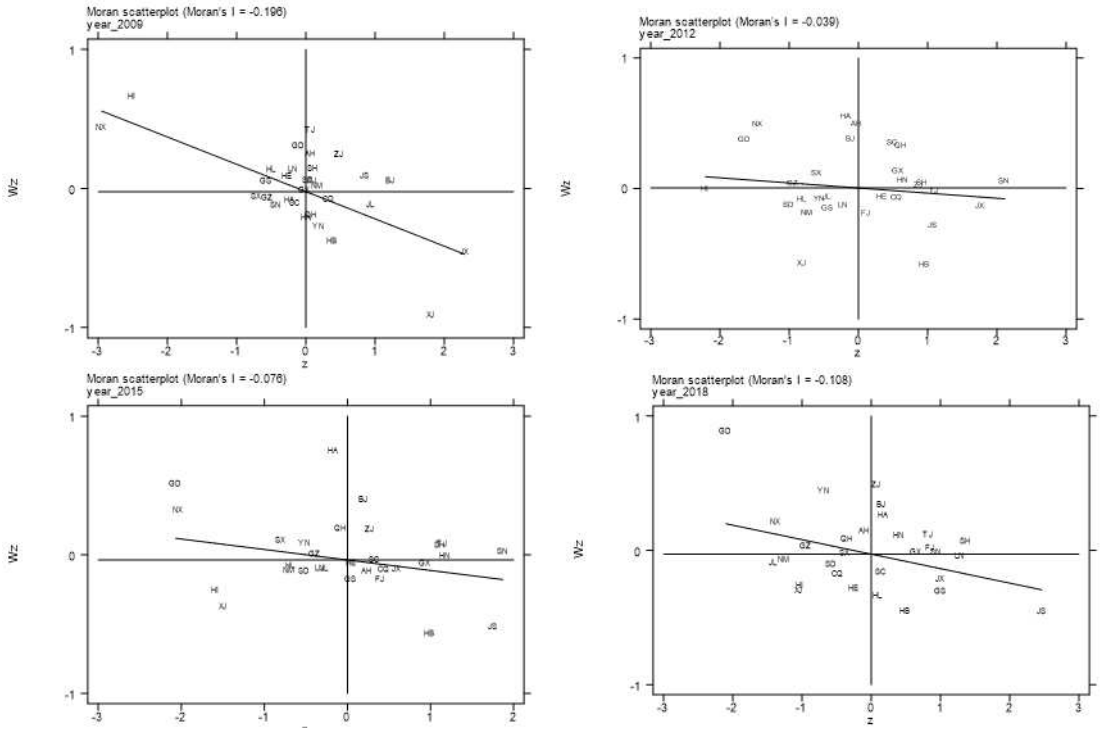

Fig. 4 Local Moran's I value.

3.2 regression model results

The estimation results of land resource misallocation affecting IGGE are shown in Table 3. The first two columns are the GMM estimation results of non-spatial panels, and the third and fourth columns are SDM results estimated by GMM, respectively. The estimation results of AR (1) and AR (2) show that the random disturbance term has first-order serial autocorrelation, but not second-order serial autocorrelation. The Sargen test cannot reject the null hypothesis that "there is no over-identification (all instrumental variables are valid)". It shows that the dynamic GMM estimation result is robust.

Table 3 regression model results.

Variable	GMM	GMM	SDM	SDM
L.Igge	1.0093***	0.6637***	0.9701***	0.9566***
	(10.36)	(18.76)	(21.65)	（20.69）
Land_misallocation	-0.0026***	-0.0394***	-0.0028**	-0.0020*
	(3.91)	(-3.35)	(-2.02)	(1.85)
Rd		19.2390***		6.2188**
		(6.20)		（2.49）
Edu		0.0782***		0.0378
		(7.70)		(1.49)
FDI		3.1769***		3.1180***
		(3.09)		(3.00)
Open		-0.3962***		-0.1260*
		(-3.99)		(-1.73)
Urban		-2.2121		0.1262***
		(-0.28)		(2.99)
Gdpc		0.0932**		-0.0234

		(2.35)		（-1.00）
Er		-24.0303***		0.6599
		(-4.71)		（0.18）
Constant	0.0389***	1.0007***	0.0065***	0.0059***
	(3.54)	(3.15)	（12.86）	（12.90）
AR (1)	-1.85*	-1.98**	-1.72*	-1.82*
	[0.065]	[0.048]	[0.085]	[0.069]
AR (2)	-0.60	-0.69	-0.77	-0.95
	[0.552]	[0.491]	[0.441]	[0.341]
Sargen test	28.76	25.81	23.03	29.81
	[0.799]	[0.214]	[0.775]	[0.757]
Spatial Rho			0.4771***	0.2361**
			(5.65)	(2.16)
W* L1. Igge			-0.3848***	-0.8054***
			(-3.68)	(-5.20)
W*Land			-0.1406**	-0.0079**
			(-2.50)	(2.10)
W*Rd				13.3774
				(0.68)
W*Edu				-0.0459*
				(-1.87)
W*FDI				0.9593
				(0.14)
W*Open				-0.4598**
				(-1.98)
W*Urban				0.2147
				(0.14)
W*Gdpc				0.2059***
				(2.99)
W*Er				-23.8548
				(-1.43)

Note: ***, **, and * are significant at the levels of 1%, 5%, and 10%, respectively; () is the T value; and [] is the P value.

It can be seen from Table 3 that the row coefficient where the lag coefficient of IGGE is located is positive and significant at the 1% statistical level; that is, the development of IGGE in the previous period has a significant positive impact on its value in the current period. This shows that IGGE's promotion is a long-term accumulation and development process. Areas with higher IGGE levels in the early stage may achieve higher levels at this stage. The Spatial Rho coefficient is positive and the significance test is significant, which is consistent with the ESDA test, proving that the impact of land resource misallocation with IGGE is spatially correlated.

The coefficient of LandMisAll is significantly negative, indicating that the misallocation of urban land resources in China hinders the improvement of IGGE. As China's local governments are more inclined to use lower industrial land prices to attract industrial investment, and to increase commercial and housing prices to obtain fiscal revenue, this will lead to misallocations in land prices and land areas for different uses, increase production costs, and backlog R&D investment. Although the misallocation of land resources increases local fiscal revenue in the short term, it reduces the marginal output of land and is ultimately detrimental to economic growth. In particular, in order to achieve economic growth, some regions ignore environmental protection and reduce

industrial land prices to attract investment. This has led to the agglomeration of high-polluting enterprises and further hindered the improvement of IGGE.

3.3 Spatial spillover effect

Table 4 reports the estimated results of direct effects, indirect effects (spatial spillover effects), and total effects of the spatial model. The short-term effects of the misallocation of land resources have all passed the significance test. Due to the feedback effect of the spatial effect, the coefficient of the short-term direct effect of land resource misallocation is different from the coefficient in the fourth column of Table 3 of the model. The short-term spatial spillover effect of the misallocation of land resources is significantly negative, indicating that the misallocation of land resources is not only detrimental to the improvement of IGGE in the region, but also adversely affects the IGGE in neighboring areas. From the perspective of long-term effects, the misallocation of land resources has a more significant negative impact on IGGE in the region, and the coefficient of long-term spatial spillover effects is not significant.

From the perspective of the spatial spillover effect and total effect of the control variables, RD has a short-term positive spillover effect on IGGE in neighboring areas, and its short-term and long-term total effects are both positive, indicating that RD is an important factor in the improvement of the IGGE level. Strengthened RD investment can effectively promote the improvement of IGGE. The short-term effects of residents' education level (Edu) are all significantly positive, indicating that the improvement of residents' education level will promote the growth of IGGE in this region and neighboring areas, and the flow of talent will enhance the overall IGGE of the region. The spillover effect of the direct use of foreign direct investment is negative, passing the 10% significant test, which shows that the use of FDI in China has led to the agglomeration of polluting companies, forming "pollution refuges", which will adversely affect IGGE in neighboring areas. The level of urbanization (Urabn) has a positive impact on IGGE. However, the level of opening to the outside world (Open) is not conducive to the improvement of the IGGE level in the short term, which has adverse effects on the region and neighboring areas, and the total effect in the short and long term is negative. The regional economic development level (Gdpc) short-term spillover effect and short-term total effect are positive, indicating that regions with higher economic development levels have a positive effect on the improvement of IGGE in neighboring areas.

Table 4 Direct and indirect marginal effects.

	Short-term Effects			Long-term Effects		
Variable	Direct	Indirect	Total	Direct	Indirect	Total
Land_misallocation	-0.0006**	-0.0068**	-0.0074**	-0.2113**	0.2036	-0.0078
	(-2.05)	(-2.06)	(-2.06)	(-2.10)	(0.10)	(-0.06)
Rd	6.4476*	16.9711*	23.4188*	31.2318	-1.8738	29.3580*
	(1.90)	(1.72)	(-1.88)	(1.02)	(-1.00)	(1.87)
Edu	0.0389**	0.0729**	0.1118**	0.5627	-0.4223	0.1404*
	(2.32)	(2.22)	(1.96)	（1.04）	(-1.03)	(1.92)
FDI	3.0612***	-0.9206**	-2.1406	-16.2501	13.4975	-2.7526
	(2.86)	(-2.09)	(0.21)	（-1.02）	(0.98)	(-1.21)
Open	-0.1323*	-0.6195**	-0.7519***	-0.9691	0.0282	-0.9409***
	(-1.73)	(-2.40)	(2.70)	(-1.03)	(1.00)	(-2.68)

Urban	0.1173**	0.4051**	0.5224**	4.3418	-3.7190	0.6229
	(2.26)	(2.20)	（2.26）	(1.05)	(1.04)	(1.24)
Gdpc	-0.0183	0.2567***	0.2383***	0.2077	0.0927	0.3004**
	(-0.81)	(2.81)	（2.70）	(1.02)	(1.01)	(2.55)
Er	0.3331	-33.1448	-32.8112	-25.0183	-16.1969	-41.2152
	(0.09)	(-1.55)	（-1.47）	(-1.03)	(-1.02)	(-1.42)

Note: ***, **, and * are significant at the levels of 1%, 5%, and 10%, respectively; () is the T value; and [] is the P value.

4. Conclusion and Policy Implications

4.1 Conclusion

Over the years, China has taken GDP as an important goal of economic growth, which has led to income gaps and environmental pollution, exerting great pressure on China's sustainable development. With the continuous improvement of the level of economic development, China has begun to transform its economic growth mode to achieve inclusive green growth as an important goal of sustainable development. Based on this topic, this study used a combination of the EBM model and ML index to measure China's IGGE at the provincial level from 2009 to 2019, and incorporated economic growth, environmental protection, and social equity into the unified framework of IGGE. It analyzed the impact on IGGE from the perspective of the misallocation of land resources, and considered the spatial interaction caused by regional competition.

Studies have shown that China’s IGGE level has continued to increase in recent years. In 2009, more than half of China’s provinces had IGGE levels below 1, and no province exceeded 1.5. However, by 2018, the IGGE level of most provinces in China exceeded 1, and even one-third of the provinces reached a high level of 1.5. At the same time, the distribution of IGGE is characterized by obvious spatial agglomeration, and the agglomeration level of IGGE in neighboring provinces is continuously improving. From the regression results, we can conclude that the misallocation of land resources does hinder the improvement of China's IGGE level. China has achieved rapid economic growth by relying on land finance, but the long-term unbalanced land planning has also hindered China's sustainable development. The estimation of the spatial regression model shows that the misallocation of land resources has spatial spillover effects. Driven by factors such as local competition and the flow of factors, the misallocation of land resources not only adversely affects the IGGE in the region, but may also damage the improvement of IGGE in neighboring regions.

4.2 Policy Implications

At present, IGGE is an important path for achieving sustainable development. In particular, developing countries are faced with three pressures from economic growth, social equity, and environmental protection, and need to play to their comparative advantages and find effective ways to improve IGGE. For developing countries, government departments play a leading role in economic operations. The government's control of industrial and commercial land can easily lead to the misallocation of land resources and reduce the marginal output of land resources. This will adversely affect the long-term economic growth and environmental protection of the region. Relying on the development path of lowering industrial land prices to attract investment will lead to the agglomeration of high-polluting enterprises and cause the economy to be locked in an unsustainable growth path. Compared with ways to increase IGGE, such as increasing

investment and technological innovation, it is easier to adjust the structure of factor allocation to exploit the comparative advantages of developing countries. At the same time, this study verifies that the misallocation of land resources will hinder the improvement of IGGE. Therefore, it is necessary to promote the reform of land marketization, optimize the structure of the land supply, break the monopoly of local governments over land resources, and further exert the basic role of the market in resource allocation. In particular, IGGE exhibits obvious spatial agglomeration and spatial spillover effects. Regional cooperation should be carried out to allow regions with higher IGGE levels to have a leading role in low-efficiency regions.

4.3 Limitations and Outlook

Although this study used China's provincial data from 2009 to 2018 to obtain sufficient conclusions, the provincial data ignore internal differences and there are large errors in both the estimation of IGGE and the measurement of the mismatch level of land resources. In particular, due to the inability to obtain micro data on the marginal output of land, we could only obtain indicators of land resource mismatch by indirect measurement methods. In future research, we will pay more attention to the impact of the misallocation of land resources on the sustainable development of enterprises and industries, and explore new paths for the sustainable development of the economy, society, and the environment.

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Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Authors' contributions

All authors contributed to the scientific content and authorship of this manuscript. Conceptualization, Qin He and Juntao Du; Data curation, Qin He; Methodology, Juntao Du; Writing – original draft, Juntao Du; Writing – review & editing, Juntao Du.

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Figures

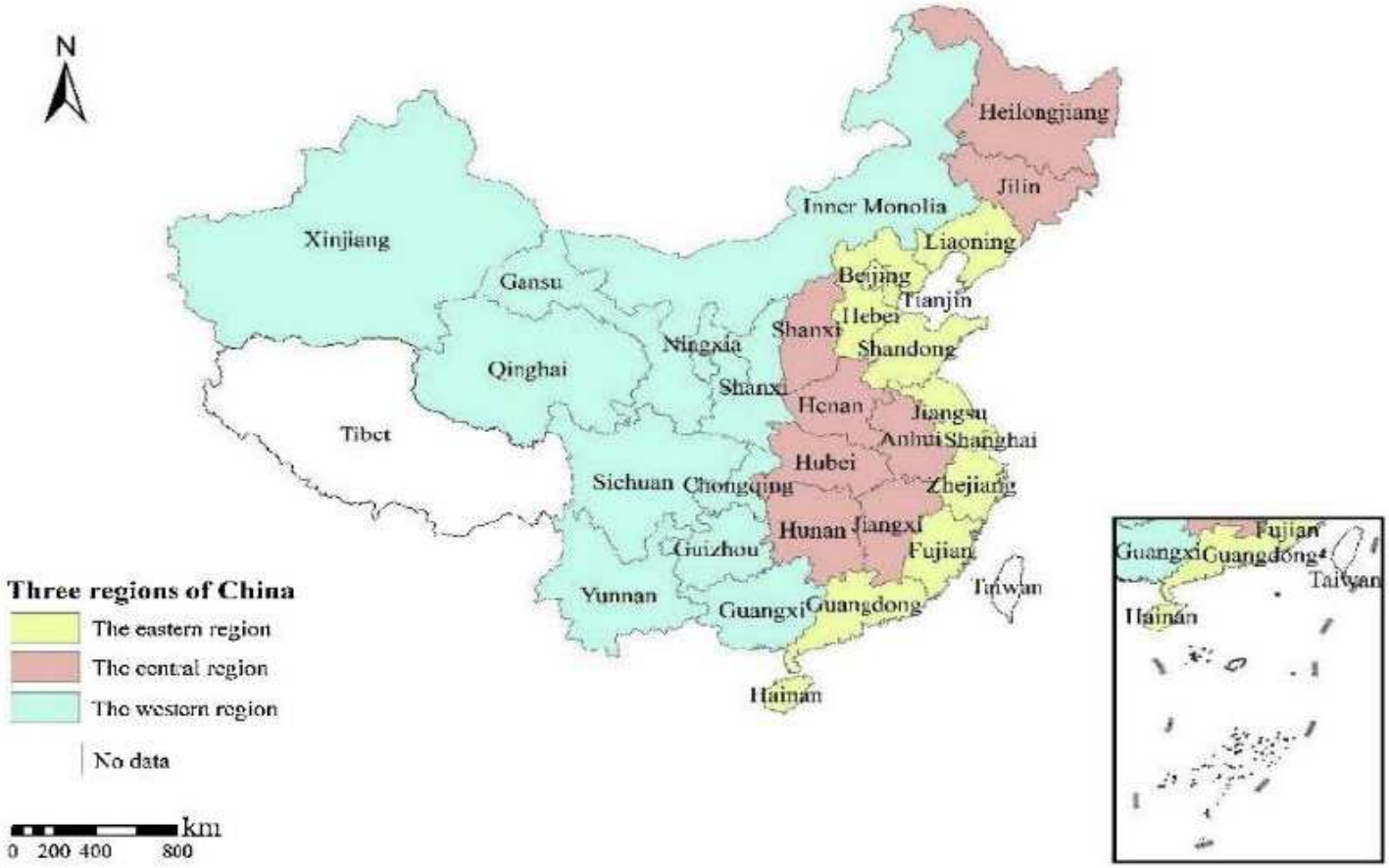

Figure 1

The distribution of the eastern, central, and western regions of China. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

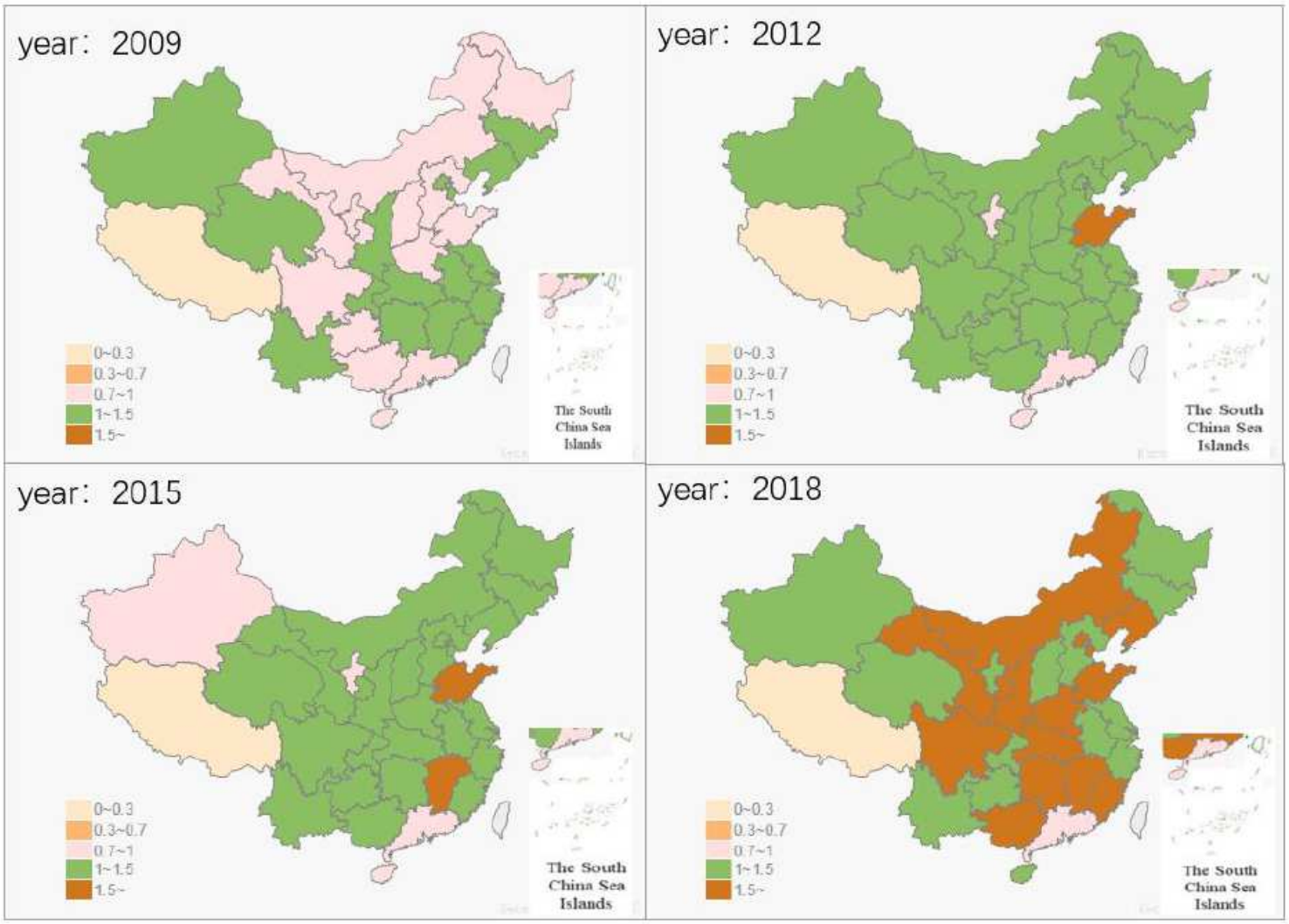

Figure 2

The trend of IGGE from 2009 to 2018. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

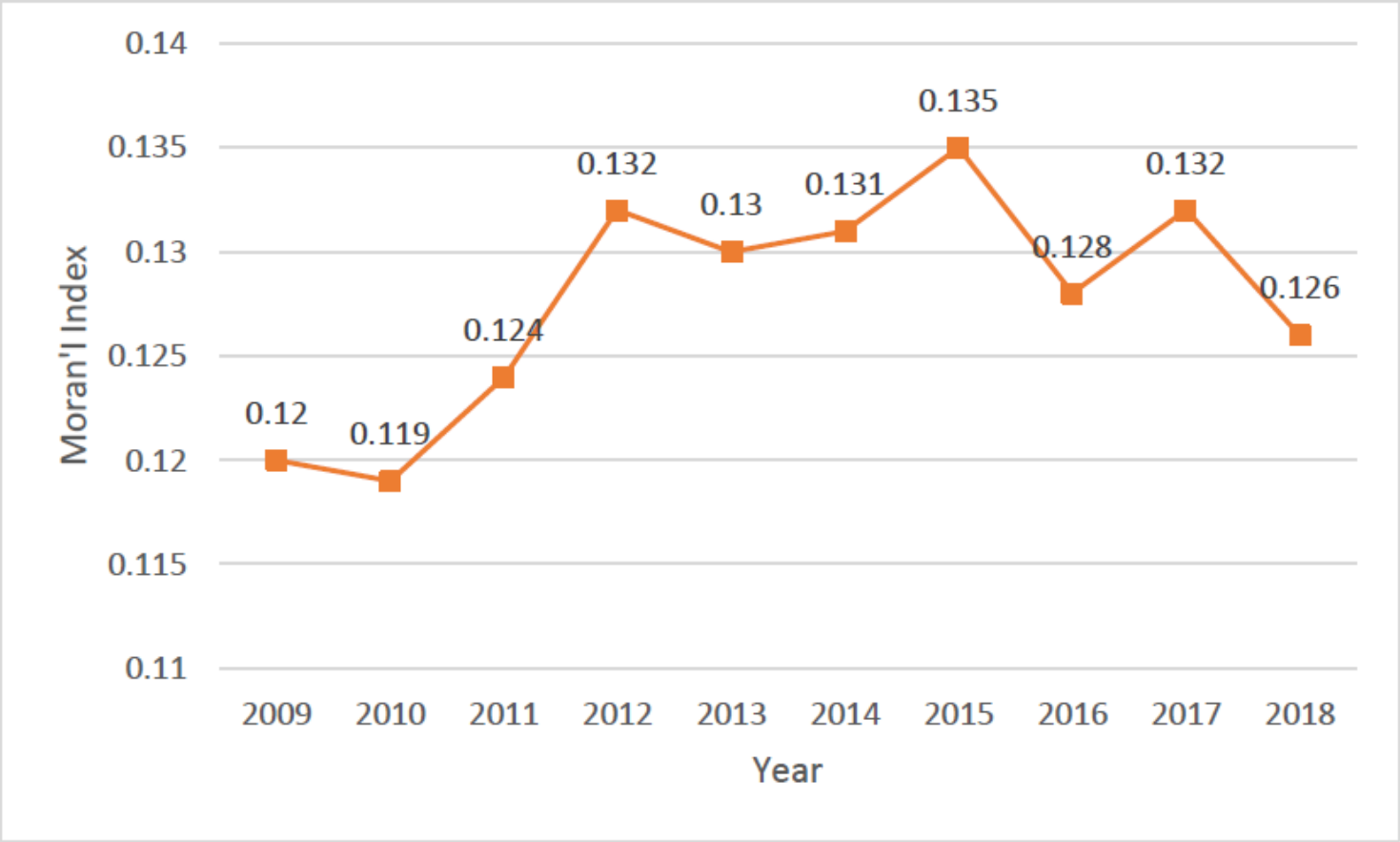

Figure 3

The value of global Moran's I.

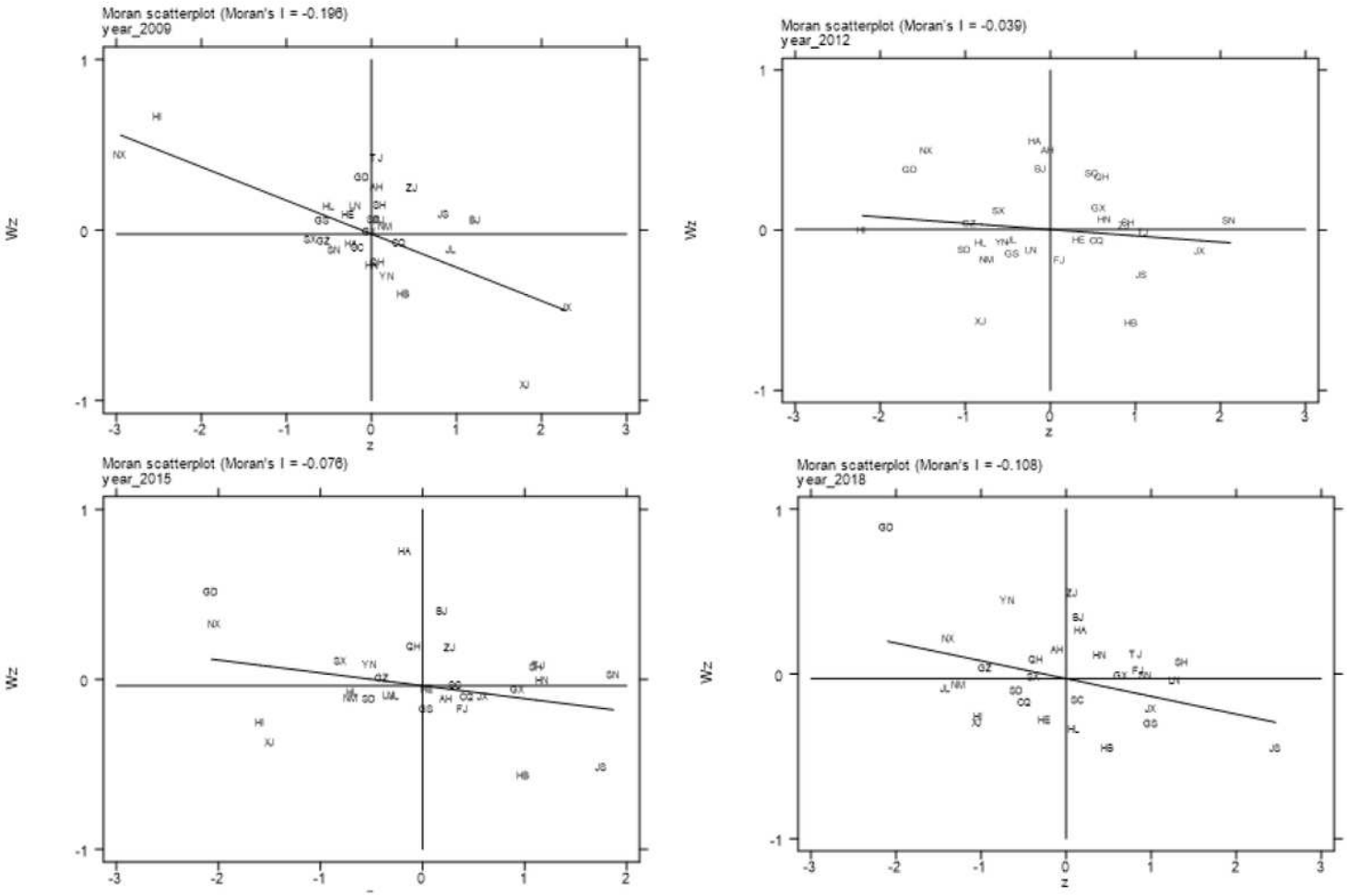

Figure 4

Local Moran's I value.