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Urban Green Innovation Efficiency in China: Spatiotemporal Evolution and Influencing Factors

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Abstract: Investigating urban green innovation efficiency (UGIE) is imperative because it is correlated with the development of an ecological civilization and an innovative country. Spatiotemporal evolution and influencing factors of UGIE are two important scientific problems that are worth exploring. This study presents an indicator system for UGIE that includes input, expected output, and unexpected output, and employs a super-efficiency slacks-based measure (super-SBM) to calculate UGIE in 284 cities at or above the prefecture level in China from 2005 to 2020. Then, we adopted spatial auto-correlation to identify its spatial differences among these cities and Geodetector to evaluate its influencing factors. The results are as follows: (1) The overall UGIE tended to rise, except in northeastern China, megacities, and super large-sized cities. (2) The UGIE of Chinese cities exhibited remarkable spatial differences and auto-correlation, and the "low-low" type enjoyed the most local spatial auto-correlations. (3) Sociocultural factors represented by the number of collections in public libraries became the most important factors affecting the UGIE in China.

Keywords: urban green innovation efficiency (UGIE); green innovation; spatiotemporal evolution; influencing factor; super-SBM; spatial auto-correlation; Geodetector; China

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1. Introduction

Economic downturn and environmental pollution are two problems facing the world today [1–5]. The fundamental way to actualize economic recovery and promote high-quality economic development lies in innovation [6–8]. In an effort to cope with environmental problems and maintain harmony between humans and nature, green development concepts must be implemented [9–11]. Hence, green innovation, which blends two critical concepts, green and innovation, is considered an ideal solution to the current pressures [12–14]. Along this line, a multitude of international organizations and governments, such as World Intellectual Property Organization, International Union for Conservation of Nature and Natural Resources, the United States, China, and EU states, attach great importance to green innovation [15–17]. Outside the international organizations and governments, green innovation has become a hot topic in academia concerning economics, management, geography, and environmental science [18].

Above all, the literature has paid attention to the influencing factors of green innovation. One of the influencing factors is environmental regulation, which has drawn extensive scholarly attention [19]. By a difference-in-difference analysis on the basis of propensity score matching (PSM-DID) model, Zhong and Peng [20] concluded that green innovation was positively impacted by environmental regulations. Zhao et al. [21], Guo et al. [22], and Nie et al. [23] reached the same conclusion after probing into dissimilar enterprises. On the contrary, some studies revealed that environmental regulation was not conducive to corporate green innovation. In their empirical study, Li and Li [24] demonstrated that environmental regulation negatively impacts corporate green innovation by reducing executive compensation. Other than this factor, other scholars have also looked at infrastructure construction [25], low-carbon city construction [26], enterprise nature [27], characteristics of enterprise managers [28], and credit financing [29].

Aside from that, the literature has also deeply probed into spillover effects of green innovation. Urban green innovation can have an impact on sustainable urban development from two aspects, namely, green infrastructure and environment public policy. Referring to green infrastructure, the improvement of urban green infrastructure can reduce the intensity of urban heat island effect [30] and heighten urban resilience [31], so as to slow down environmental pollution, balance the correlations between nature and human, and promote the balanced and stable development of urban society [32,33]. Regarding environmental public policy, green innovation can provide new ideas for the introduction of relevant public health policies. This can provide new development goals for urban governance and urban planning [34], thereby promoting the development of urban green economy, which facilitates the social sustainable development, and realizes sustainable development goals [35–37]. Apart from sustainable urban development, green innovation also has spillover effects on environment and economy [38]. Some studies have exhibited the positive environmental effects of green innovation. For instance, Wang et al. [39] employed a time-varying difference model and found that enterprises could suppress air pollution and bring environmental benefits by utilizing green technology innovations. Nonetheless, green innovation also has threshold and rebound effects [40]. When environmental regulations, R&D investment, and marketization levels are high, green technology innovation has a more remarkable and positive environmental impact [41], which may be offset by its rebound effect [42]. Singh et al. [43] and Chen et al. [44] argued that green innovation could elevate enterprises' economic performance by lessening corporate environmental governance costs, producing new sales revenue from the energy conservation and environmental protection market, and attaining differentiated competitive edges.

As indicated by systematic literature review, there has been fruitful research on green innovation which plays an indispensable role in theorizing green innovation and making relevant policies. Nevertheless, most research is dedicated to enterprises [45], and little attention has been paid to urban green innovation. Since cities are the basic administrative units for implementing national policies [46,47], exploring urban green innovation will enrich the research in this field and provide more valuable references for urban policy-making and planning. Previous researchers have chiefly employed green patents to indicate green innovation [48], which effectively reflects the level of green innovation. However, little is known about green innovation efficiency [49], a concept that integrates multiple factors, leaving urban green innovation efficiency (UGIE) a topic meriting further exploration. Last but not least, existing studies have been primarily dedicated to the influencing factors and spillover effects of green innovation, paying scant attention to its spatiotemporal evolution at a macro scale.

To sum up, assessing UGIE and exploring its spatiotemporal evolution and influencing factors are valuable scientific problems to be solved. This paper established three research objectives: (1) assessing UGIE, (2) exploring UGIE's spatiotemporal evolution, and (3) studying UGIE's influencing factors. To effectuate these three objectives, our study measured the UGIE among 284 Chinese cities at or above the prefecture level between 2005 and 2020 using a super-efficiency slacks-based measure (super-SBM), explored its spatial and temporal evolution using spatial auto-correlation, and evaluated the influencing factors with Geodetector. This study is innovative and outstanding to UGIE, in that we constructed an indicator system for UGIE, including expected output (green innovation represented by green patents), unexpected output (industrial sulfur dioxide emissions), and input (expenditures for urban science & technology, full-time equivalents of urban R&D personnel, and telecommunications business volume in urban areas). The reasons that the range of time studied was chosen from 2005 to 2020 are as follows: (1) It takes a certain time span to explore the spatial and temporal pattern of UGIE. The time span from 2005 to 2020 is as long as 16 years, which meets the needs of studying the spatial and temporal pattern, avoids the contingency of research results, and makes the research findings more credible. (2) This paper takes China's prefecture-level cities and above as the research object, with a multitude of samples, and the problem of data comprehensiveness needs to be considered. The data required in this paper covers all the research objects from 2005, so 2005 was chosen as the starting point of the study.

There are several aspects of this study that contribute to the knowledge base. In the first place, by using cities as the research object, the research field, together with corporate green innovation, is enriched. Aside from that, it further evaluates UGIE, thereby expanding the research in this field compared with the studies on its influencing factors and spillover effects. Furthermore, studying the spatiotemporal evolution and influencing factors of UGIE may shed light on its spatial patterns at a macro level.

The following is the organization of the remainder of this paper: Section 2 introduces the methods such as super-SBM, spatial auto-correlation, and Geodetector, as well as green patents, geographic information, and the data were employed to measure UGIE and its influencing factors; in Section 3, the results of the study are presented, including time series evolution characteristics, spatial differences, and influencing factors for China's UGIE; as part of Section 4, we present the research conclusions of this paper on the basis of the research findings and provide policy implications derived from the research conclusions.

2. Methods and Data

2.1. Methods

2.1.1. Super-SBM

Super-SBM is a method combining a super-efficiency model with a SBM model. It originated from the data envelopment analysis (DEA) model and was first proposed by Tone [50]. This paper chooses this method to measure UGIE for the following reasons: First and foremost, the data measured by this method can be greater than 1, which will effectively deal with the sequencing problem of relatively effective units. Apart from that, the measurement of green innovation efficiency involves the emission of environmental pollutants, which are undesirable outputs; this method can cope with the problem of undesirable output. In addition, all periods can be treated as reference, which can effectively cope with the problem of inter-period comparison [51,52]. The equation is as follows:

$$\min\rho* = \frac{\frac{1}{m}\sum_{i=1}^{m}\frac{x'}{x_{ik}}}{\frac{1}{r+p}\left(\sum_{s=1}^{r1} y^d y^d_{sk} + \sum_{q=1}^{r2} y^u y^u_{qk}\right)}$$
$$s.t.\begin{cases} x' \geq \sum\limits_{j=1,\neq k}^{n} x_{ij}\lambda_j; y^d \leq \sum\limits_{j=1,\neq k}^{n} y^d_{sj}\lambda_j; y^d \geq \sum\limits_{j=1,\neq k}^{n} y^d_{qj}\lambda_j \\ x' \geq x_k; y^d \leq y^k_d; y^u \geq y^u_k \\ \lambda_j \geq 0, i = 1,2,\cdots,m; j = 1,2,\cdots,n, j \neq 0 \\ s = 1,2,\cdots,r; q = 1,2,\cdots,p \end{cases} \quad (1)$$

In Equation (1), ρ^* is the UGIE value; x, y^d, and y^u stand for the necessary factors in the input matrix, expected output matrix, and unexpected output matrix; n represents the number of decision-making units, each with m kinds of inputs, r kinds of outputs and p kinds of unexpected outputs; λ refers to the weight vector.

As part of this paper, we reviewed the literature on the efficiency of green development and innovation [53,54] and used scientific & technological expenditure, urban R&D personnel equivalents, and the volume of telecommunications business as inputs, green patents as expected outputs, and industrial sulfur dioxide emissions as unexpected outputs to measure the UGIE.

2.1.2. Spatial Auto-Correlation

Spatial auto-correlation is a paramount index that reflects the correlation between a certain geographical phenomenon or an attribute value in a regional unit and the same phenomenon or attribute value in a neighboring regional unit. It is a measure of the degree of value aggregation in a spatial domain. A common method to test spatial auto-correlation is to use the Moran's I to measure this clustering property, which can be divided into global Moran's I and local Moran's I [55,56]. Moran's I can be expressed as follows:

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

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2 \quad (3)$$

where I represents the global Moran's I, $I \in$ [-1, 1]. Chinese cities have a striking positive spatial correlation if $I > 0$. The greater the value, the stronger the regional agglomeration; otherwise, there is a noticeable negative spatial correlation, and the smaller the value, the greater the regional dispersion [57]. There are n research units; x_i and x_j denote the UGIE of units i and j; $\overline{x}$ stands for the mean of all units. The spatial weight matrix for units i and j is designated as W_{ij}. If spatial units i and j share a common boundary, W_{ij} = 1; otherwise, W_{ij} = 0.

$$Z(I) = \frac{[1 - E(I)]}{\sqrt{Var(I)}} \quad (4)$$

In Equation (4), $Z(I)$ represents the significance level of the global Moran's I; $E(I)$ is the mathematical expectation of the global Moran's I; $Var(I)$ represents its variance.

UGIE's local Moran's I is adopted to identify regional agglomeration and dispersion by analyzing local spatial auto-correlation. In the case of the i^{th} unit, the local Moran index's I is expressed as follows:

$$I_i = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \overline{x})(x_j - \overline{x})}{S^2} \quad (5)$$

In Equation (5), the significance level of the local Moran's I can be determined by $Z(I)$ using the equation above. A spatial auto-correlation can be classified into four types on the basis of the significance level and the symbol of $Z(I)$: in the case of noticeably positive I_i and $Z(I) > 0$, the type is considered "high-high", which displays a high UGIE of the study area and its adjacent areas; in the case where I_i is statistically significant and $Z(I) < 0$, then the type is "low-low", which exhibits a low UGIE of the study area and its adjacent areas; When I_i is remarkably negative and $Z(I) > 0$, we have a "high-low" type, indicating a high UGIE of the study area but a low UGIE of its adjacent areas; a "low-high" type is defined as $I_i > 0$ and $Z(I) < 0$, indicating a low UGIE of the study area but a high UGIE of its adjacent areas [58].

2.1.3. Geodetector

Geodetector predominantly analyzes the association between geographical research objects from the perspective of spatial differentiation, including the four parts of risk detection, factor detection, ecological detection, and interaction detection. In this study, the factor detection part is selected to detect the factors that may affect the efficiency of urban green innovation in China. In a Geodetector analysis, causal correlations between variables are detected by examining their spatial heterogeneity [59]. The reason behind this is that when a dependent variable is influenced by an independent variable, their spatial distributions should be similar [60]. The equation is as follows:

$$q = 1 - \frac{1}{n\sigma^2}\sum_{i=1}^{m} n_i \sigma_{x,\,i}^2 \quad (6)$$

In Equation (6), q is the extent to which an influencing factor explains one of the driving factors of UGIE, and its value range is [0, 1]. Increasing the value of this influencing factor will have a more noticeable impact on green innovation; when it is equal to 0, the factor has no effect on UGIE; $i = 1, 2, 3, \ldots m$ corresponds to the layers of the factor x; σ^2 and $\sigma^2_{x,\,i}$ describe the variance of the research object and layer i.

2.2. Data

This study drew its data from three diverse sources.

Geographic information: A vector administrative boundary map of Chinese cities is based upon the 1:4 million Chinese geospatial data provided by the National Geomatics Center of China (http://www.ngcc.cn/ngcc/, accessed on: 23 November 2022).

Green patents and environmental regulation: Crawlers were employed to obtain the green patent data from Chinese cities (including all cities at a prefecture level and above, leagues, autonomous prefectures, regions, and some provincial counties) during the period between 2005 and 2020 using the Patent Retrieval and Analysis System of the China National Intellectual Property Administration (pss-system.cnipa.gov.cn, accessed on: 23 November 2022) [61,62]. Environmental regulation is one of the influencing factors of UGIE adopted in this study. Crawlers were adopted to retrieve the terms "environmental protection" and "ecological civilization" from the work reports of each city government, with the word frequency ratio adopted to indicate this factor [63].

Other data: Indicators other than green patent data employed to calculate UGIE and other than environmental regulation adopted to analyze the influencing factors of UGIE were from the "Statistical Yearbook of Chinese Cities" on a big data platform (https://data.cnki.net/, accessed on: 23 November 2022).

In Table 1, we present a summary of the descriptive statistics used in this study.

Table 1. Statistics describing the data.

	Variable	Units	Sample Size	Mean	Standard Deviation	Maximum	Minimum
Input	Scientific and technological expenditure	10,000 yuan	4544	81,460.51	307,731.48	5,549,817.00	34.00
	Full-time equivalent of urban R&D personnel	Person/year	4544	11,138.68	22,886.45	336,280.00	99.58
	Telecommunications business volume	10,000 yuan	4544	382,710.04	713,001.44	13,964,015.00	3180.00
Expected output	Green patent	PCS	4544	346.98	1177.02	24,435.00	0
Unexpected output	Industrial sulfur dioxide emissions	tons	4544	47,212.10	53,846.74	683,162.00	65.00
influencing factors	Per capita GDP	yuan	4544	42,560.81	32,075.71	256,877.00	2396.00
	Proportion of tertiary industry	%	4544	39.91	10.17	83.87	8.58
	Employees' average salary	yuan	4544	44,864.77	23,771.06	320,626.31	6409.73
	Number of books in public libraries	1000 books	4544	2757.94	6460.93	82,150.00	39.00
	Green coverage rate of built-up areas	%	4544	38.22	7.60	82.32	0.38
	Environmental regulation	%	4544	0.25	1.15	35.10	0.0000005

3. Results

Figure 1 is the spatial expression of the UGIE of Chinese cities from 2005 to 2020. On the basis of this result, we analyzed its spatiotemporal evolution.

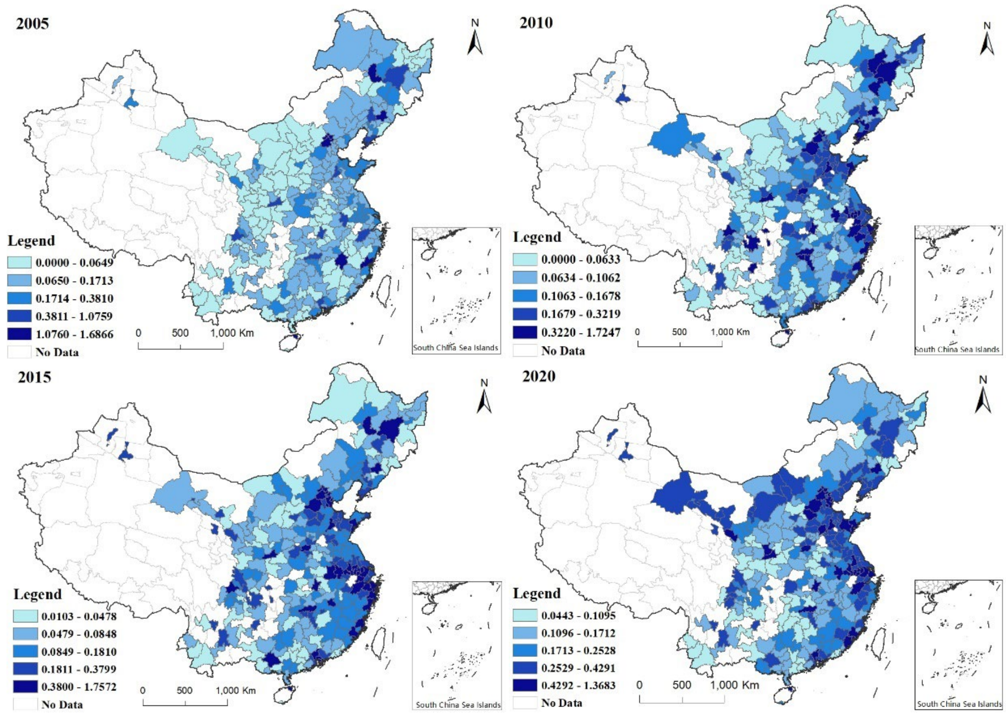
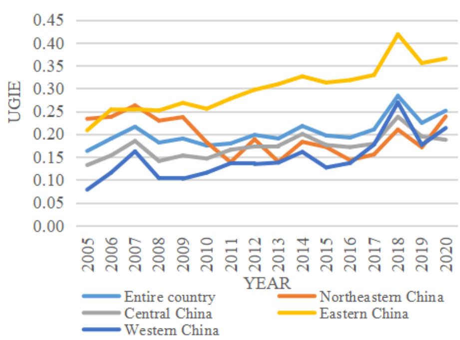


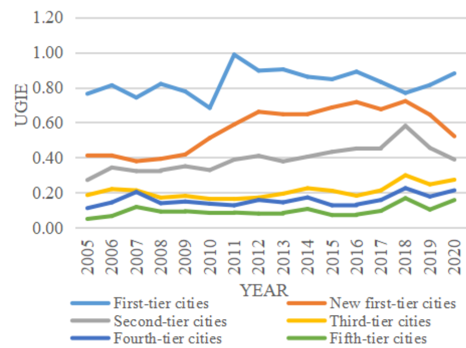
Figure 1. Spatial expression of the UGIE in Chinese cities from 2005 to 2020.

3.1. Spatiotemporal Analysis of UGIE

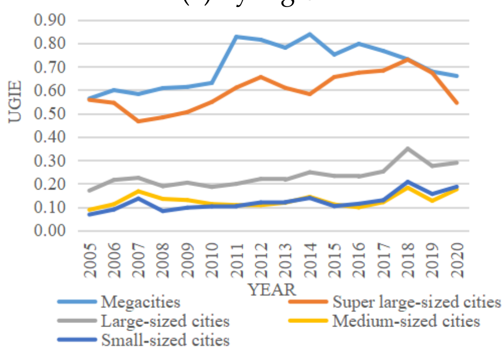
We divided the cities by regions, economic levels, scales, and administrative levels, and conducted a spatiotemporal analysis of UGI for each type of city. The Figure 2 below illustrates how UGIE evolved over time in diverse types of cities.



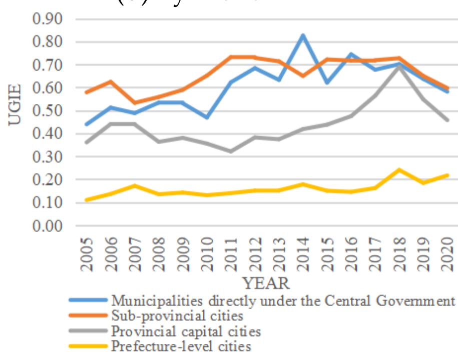
(**a**) By region



(**b**) By economic level



(**c**) By scale



(**d**) By administrate level

Figure 2. UGIE evolution over time in different types of cities.

There are four regions in China: eastern China, central China, western China, and northeastern China (Figure 2a). The national UGIE and that of the other three regions than the northeastern China tended to rise with fluctuations. From 2005 to 2020, the national average UGIE augmented from 0.16 to 0.25, the eastern China from 0.21 to 0.37, the central China from 0.13 to 0.19, and the western China from 0.08 to 0.21. The level of the northeastern China first dropped from 0.23 in 2005 to 0.14 in 2011 and then rose to 0.24 in 2020.

As exhibited in Figure 2b, cities in China can be classified as first-tier (T1), new first-tier (NT1), second-tier (T2), third-tier (T3), fourth-tier (T4), and fifth-tier (T5) cities on the basis of their economic standing [64]. From 2005 to 2020, the UGIE in various cities was on the rise as a whole, with T1 cities from 0.76 to 0.88, NT1 cities from 0.41 to 0.52, T2 cities from 0.27 to 0.39, T3 cities from 0.19 to 0.27, T4 cities from 0.11 to 0.21, and T5 cities from 0.05 to 0.16. The UGIE of various cities over the years remained "T1 > NT1 > T2 > T3 > T4 > T5". To put it simply, cities with higher economic levels had higher UGIE.

As illustrated in Figure 2c, in accordance with size, Chinese cities can be categorized as megacities, super large-sized cities, large-sized cities, medium-sized cities, and small-sized cities [65,66]. From 2005 to 2020, the overall UGIE of large-sized cities, medium-sized cities, and small-sized cities displayed an upward trend, with large-sized cities increasing from 0.17 to 0.29, medium-sized cities from 0.09 to 0.18, and small-sized cities from 0.07 to 0.19. The UGIE of mega cities first rose from 0.56 in 2005 to 0.83 in 2011 and then dropped to 0.66 in 2020, and super large-sized cities declined with fluctuations.

By administrative level, Chinese cities are divided into municipalities directly under the central government, sub-provincial cities, provincial capital cities, and prefecture-level cities (Figure 2d). From 2005 to 2020, the UGIE of the four types was all on the rise, municipalities from 0.44 to 0.58, sub-provincial cities from 0.58 to 0.60, provincial capitals from 0.36 to 0.46, and prefecture-level cities from 0.11 to 0.22.

The overall UGIE of Chinese cities tended to rise, except for cities in the northeastern China, megacities, and super large-sized cities. Northeastern China may be suffering from a serious deficiency of innovation power, population loss, and economic recession owing to the large number of resource-based cities in the region. For megacities and super large-sized cities, the possible reason is that after a long period of speedy growth in the UGIE, the input factors have continued to rise at a high level in recent years. Nevertheless, the growth rate of green patent output is much lower than that of input factors, which will give rise to a decline in their UGIE.

3.2. Spatial Differences of UGIE Methods

Table 2 presents the global spatial auto-correlation analysis of UGIE from 2005 to 2020 using ArcGIS. The global Moran's I was positive each year, which exhibits an obvious positive spatial correlation in the UGIE of Chinese cities. The UGIE between adjacent cities exhibited obvious mutual influence. This is because the development of a city's economy, politics, and culture not only affects, but also is affected by, the development of surrounding areas. The global Moran's I exhibited an overall downward trend, which adequately demonstrates that the mutual influence between cities was gradually weakening.

We probed deep into the local spatial auto-correlation of UGIE from 2005 to 2020 using ArcGIS. Figure 3 is the local auto-correlation LISA graphs for the years 2005, 2010, 2015, and 2020. There appeared to be four types of UGIE: "high-high", "high-low", "low-low", and "low-high". The "high-high" type, which indicates a high UGIE of the city and its adjacent areas, thereby forming high-value agglomerations, was few but tended to increase gradually, especially in the Shandong Peninsula, Yangtze River Delta, and Fujian Province. The "low-low" type, which indicates a low UGIE of the city and its adjacent areas, thereby forming low-value agglomerations, was widespread and continued to increase. The "high-low" type, which means a high UGIE of the city but a low GIE of its adjacent areas, was scattered, showing a trend of rising first and declining later. Cities of this type were chiefly distributed around "low-low" cities and regions, especially in Sichuan province, Hubei province, Hunan province, and Chongqing city. The "low-high" type, which means a low UGIE of the city but a high UGIE of its adjacent areas, tended to decrease gradually. Cities of this type were primarily situated around "high-high" cities and regions, moving from the northeastern region to provinces such as Shandong, Jiangsu, Zhejiang, Guangdong, and other eastern coastal areas. The "low-low" cities were the most prevalent and widest, have the largest number and the widest distribution, which suggests that there are remarkable spatial differences and that Chinese cities need to ameliorate their UGIE.

Table 2. The global Moran's I of the UGIE in China for the period 2005 to 2020.

Year	Moran's *I*	*Z*	*P*
2005	0.839472	194.820024	0.000000
2006	0.398908	92.738179	0.000000
2007	0.383123	89.158748	0.000000
2008	0.343885	79.906000	0.000000
2009	0.439900	102.222139	0.000000
2010	0.434089	100.901174	0.000000
2011	0.474058	110.061865	0.000000
2012	0.412294	95.695346	0.000000
2013	0.583437	135.383752	0.000000
2014	0.505103	117.233627	0.000000
2015	0.558978	129.681991	0.000000
2016	0.397948	92.343242	0.000000
2017	0.275546	63.994639	0.000000
2018	0.417706	96.943150	0.000000
2019	0.322348	74.873375	0.000000
2020	0.298893	69.544354	0.000000

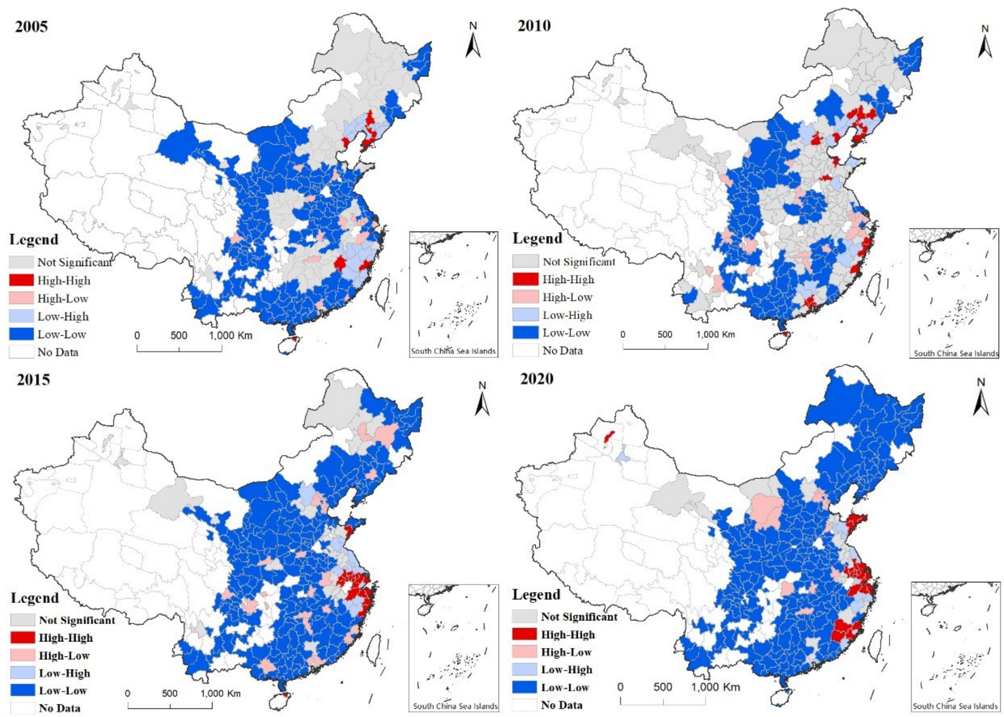


Figure 3. The LISA cluster map shows the distribution of UGIE in China during the period 2005 to 2020.

3.3. Factors Influencing UGIE

Green innovation activities are susceptible to dissimilar factors, such as the economy, social culture, and the environment [67]. In the present study, we referred to the human-environment system theory [68] and examined the impact of six indicators on UGIE from economy, social culture, and the environment, including GDP per capita, the percentage of tertiary industries, the average salary of employees, the number of collections in public libraries, green coverage in urban areas, and environmental regulation. To be more specific, GDP per capita and the percentage of tertiary industries represent economic factors [69]; the average salary of employees and the number of collections in public libraries stand for sociocultural factors [70]; green coverage in urban areas and environmental regulation denote environmental factors [71]. The q values of the six indicators accounting for the impact on UGIE are displayed in Table 3.

Table 3. The q values of the six indicators accounting for the impact on UGIE.

Year	Per Capita GDP	Proportion of the Tertiary Industry	Employees' Average Salary	Number of Books in Public Libraries	Green Coverage Rate of Built-Up Areas	Environmental Regulation
2005	0.234234	0.143033	0.129622	0.276431	0.117488	0.051209
2006	0.249351	0.148223	0.149788	0.371352	0.156064	0.040549
2007	0.110866	0.074132	0.043579	0.210214	0.081358	0.013898
2008	0.151793	0.228060	0.067947	0.264173	0.113793	0.039646
2009	0.140779	0.169141	0.057503	0.306027	0.155877	0.044165
2010	0.198637	0.166415	0.089685	0.367861	0.161783	0.029893
2011	0.125201	0.260233	0.057728	0.389024	0.099634	0.068049
2012	0.101482	0.266220	0.135082	0.395433	0.165547	0.056643
2013	0.232934	0.236228	0.157921	0.358745	0.139985	0.035539
2014	0.099977	0.224735	0.237462	0.353937	0.209525	0.068190
2015	0.255777	0.170466	0.207788	0.419229	0.138497	0.103801
2016	0.238861	0.180310	0.256084	0.463337	0.078980	0.018999
2017	0.315553	0.044466	0.282414	0.491418	0.126669	0.029775
2018	0.230754	0.096187	0.174961	0.281490	0.063241	0.074646
2019	0.255173	0.140651	0.182871	0.338003	0.081837	0.064565
2020	0.286007	0.154677	0.145605	0.235364	0.083734	0.042640

Note: All results were significant at 1%.

The number of collections in public libraries exerted the uppermost impact on UGIE. Since it represents a typical sociocultural factor, it is thereby safe to conclude that sociocultural factor is the primary influencing factor of UGIE. The possible reason is that green innovation primarily comes from universities, enterprises, and research institutions, which promote and are promoted by social culture and the input of factors affecting green innovation, thereby directly ameliorating the UGIE. Aside from that, since the 1980s, economic activities have exhibited a cultural turn [72]. The role of culture in economic growth has gradually become apparent. In addition, the economic process has become a sociocultural process as well. As a consequence, aside from traditional factors, sociocultural factors have an increasing impact on innovation [73]. GDP per capita and the percentage of tertiary industries, which represent economic factors, also imposed a substantial influence on the UGIE and remained stable over the years, illustrating that economic growth is fundamental to the UGIE. The influence of the two indicators representing environmental factors is less noticeable than other factors, which means that the UGIE is less affected by the environment.

4. Conclusions and Implications for Policy

4.1. Conclusions

Using a super-SBM model, we evaluated the UGIE of 284 cities at or above the prefecture level in China for the period from 2005 to 2020. On this basis, we explored its spatiotemporal evolution and influencing factors using spatial auto-correlation and Geodetector, respectively. The conclusions are as follows:

Temporal evolution: The overall UGIE of Chinese cities tended to rise from 2005 to 2020, except for cities in the northeastern China, megacities, and super large-sized cities.

Spatial differences: There were significant spatial differences and auto-correlation in China's UGIE from 2005 to 2020. Among the "high-high", "high-low", "low-low", and "low-high" types in local auto-correlation, "high-high" cities were few but tended to increase gradually, especially in Shandong Peninsula, Yangtze River Delta, and Fujian Province. The "low-low" type was the most frequent, which demonstrates that the UGIE of Chinese cities needs to be improved.

Geodetector: The number of collections in public libraries, which represents socio-cultural factors, made more remarkable contributions than other factors, hence the most important factor affecting the UGIE of Chinese cities.

4.2. Policy Implications

The UGIE pursues both economic and environmental benefits [74–76]. As such, it shall be a consideration for governments in urban planning and construction.

To begin to fill the gap in UGIE between cities of dissimilar types, each city is advised to choose a suitable development path to ameliorate its UGIE and promote high-quality economic development in line with its actualities, regional conditions, economic conditions, population size, and administrative levels. Since the UGIE of megacities, and due to declining super large-sized cities, large-sized and medium-sized cities warrant substantial support from the government to give full play to their role in driving the UGIE across the country. It is imperative for cities in the northeastern region to cultivate innovation factors, optimize and upgrade industries, and inject endogenous power into their UGIE.

Apart from that, in view of the obvious auto-correlation of China's UGIE, all regions are advised to strengthen cooperation by breaking the geographical constraints. Cities with high UGIE should give full play to their demonstration effect, expand their radiation and driving force, facilitate the flow of green innovation factors, and push the development of surrounding cities and regions ahead. It is essential for cities with low UGIE to fit into the larger economic and geographical pattern and absorb and undertake the resources and factors flowing out of advanced areas to promote their development.

Last but not least, as sociocultural factors have become a primary factor in UGIE, cities should not only concentrate more on developing social and cultural undertakings, but also attract labor forces and human resources. It is imperative for the city authority to ensure the supply of cultural products, create a distinctive urban culture, and develop economic, social, and cultural undertakings. Aside from that, it is essential for the city authority to optimize the talent team, make proper policies to introduce talent and attract them to settle down, thereby providing human resources to ameliorate the UGIE.

4.3. Limitations and Prospects

In this study, we exhibited the temporal evolution of UGIE by diverse types of cities during the research period. Although this result is policy enlightening, the limitation is that the UGIE has not been predicted. As a result, a Markov model and grey relational analysis model can be further used to make up for this limitation. We investigated the spatial differences in China's UGIE using a spatial auto-correlation model. In the future, efforts may be made to analyze the spatial evolution of UGIE using the Dagum Gini coefficient and kernel density estimation from a dynamic perspective. Since UGIE is affected by various factors, and dissimilar regions may have diverse factors affecting UGIE as a consequence of their dissimilar background conditions, researchers may choose heterogeneous regions to examine the influencing factors of UGIE in the future.

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