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Spatio-Temporal Evolution Characteristics and Spatial Interaction Spillover Effects of New-Urbanization and Green Land Utilization Efficiency

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Abstract: In the context of vigorously promoting new-urbanization, effectively improving the green use efficiency of urban land is an inevitable requirement to achieve high-quality economic and social development. Based on the panel data from 2011 to 2018 of 297 prefecture-level and above cities in China, this paper uses the entropy weight method and the super-efficient SBM-GML model to estimate the spatio-temporal evolution characteristics of new-urbanization and urban green land utilization efficiency. Then, the spatial simultaneous-equation and the generalized spatial three-stage least square method (GS3SLS) are employed to empirically investigate the spatial interaction spillover effects between the new-urbanization and the green land utilization efficiency. The results indicate that: (1) The level of new-urbanization and the green land utilization efficiency in Chinese cities have common and complex temporal and spatial dynamic evolution characteristics. (2) There are mutual inhibition effects between new-urbanization and green land utilization efficiency, and the level of new-urbanization is in a comparatively leading role. (3) Both the level of new-urbanization and green land utilization efficiency have obvious spatial spillover effects. (4) The level of new-urbanization of surrounding regions promotes the green land utilization efficiency of local regions, and the improvement of the green land utilization efficiency of surrounding regions also promotes the level of new-urbanization of local regions. As environmental pressure increasingly becomes a constraint on urban development, these findings are helpful to clarify the regional relationship between urban construction and green development and promote the harmonious development of new-urbanization and green land utilization efficiency.

Keywords: new-urbanization; green land utilization efficiency; temporal and spatial evolution; spatial simultaneous-equation; GS3SLS



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1. Introduction

1.1. Research Motivation

For more than two hundred years after the industrial revolution, the world has experienced a magnificent and rapid urbanization process. A considerable part of the progress of human society benefits from urbanization, but it also causes the continuous deterioration of the land environment. Urban land is a supporter of urbanization. Under the background of vigorously promoting urbanization, governments of various countries have also clarified the long-term goal of green land use. In the 21st century, urbanization in all countries worldwide is bound to develop in-depth and maintain strong growth potential. Nearly 70% of the world's population will live in cities by 2050 [1]. Compared with urbanization in population, urban land is expanding more rapidly, about twice of population growth [2]. Studies have shown that the extension of the city will be largely focused on developing countries in the coming decades [3].

As the world's largest developing economy, China has witnessed rapid growth in urbanization over the past 40 years of reform and opening-up, making outstanding contributions to economic and social development [4–6]. With the advancement of urbanization, the expansion of urban construction land has continuously encroached on cultivated land, and forest land [7], and some cities expand outward in the form of “spreading the pie”. At present, China's urban construction land increases year after year, but the efficiency of urban land utilization is not high, and pollution problems frequently occur [8,9]. There are irrational structures for land utilization and waste from land resources, and the inconsistency between the development of regional urbanization, The protection of agricultural land and ecological is becoming increasingly prominent. Improving the efficiency of urban land utilization has become the internal requirement to promote sustainable regional construction and the development of national environmental civilization. China presented the concept of new-urbanization in The National New Urbanization Plan (2014–2020) [10]. Specifically, new-urbanization is urbanization with the basic characteristics of urban–rural overall planning, urban–rural integration, industrial interaction, economy and intensification, ecological livability, and harmonious development. It is the urbanization of coordinated development and mutual promotion of large, medium, and small cities, small towns, and new rural communities. There are real differences between new-urbanization and traditional urbanization [11]. In terms of objectives, compared with traditional urbanization, the goal of new-urbanization is the development of urban–rural integration with the comprehensive transformation of economy, society, environment, and culture, while traditional urbanization emphasizes urban and social development, ignoring the development needs of society, culture, and other aspects to a certain extent. In terms of content, although the two are basically the same in outline, their emphasis is very different. New-urbanization emphasizes a people-oriented, or people-centered, view. Traditional urbanization emphasizes the urbanization of land.

Green land utilization efficiency is the land utilization efficiency considering pollution factors [12]. The evaluation of urban land utilization efficiency should not only pay attention to the economic benefits of urban land, but also consider the social and environmental benefits. The land utilization efficiency calculated according to the input-output factors such as land and manpower can well explain the utilization of land resources in a city at the level of optimal allocation and intensive use. At present, China is in the critical period of improving the quality and efficiency of new-urbanization construction, so it is urgent to carry out a relevant investigation into the mechanism of new-urbanization and green land utilization efficiency to change the current situation of extensive use of urban land, to realize the best allocation of urban land resources and the smooth progress of new-urbanization.

From the perspective of spatial layout, the level of new-urbanization and the efficiency of green land use have a prominent feature of taking a city as a unit, which is manifested as the aggregation of urban development resources and land ecological industries within cities, and there are apparent differences between different cities [10,13]. From the perspective of cities, internally, there is a complex interconnection mechanism between new-urbanization and green land utilization efficiency; externally, with the increase in cross-regional flow of resources and the intensification of inter-regional competition for ecological resources, the new-urbanization and green land utilization efficiency of a specific city are unavoidably influenced by neighboring cities. Therefore, we can raise some questions: Do new-urbanization and green land utilization efficiency have the same spatio-temporal evolution characteristics? What kind of interaction mechanism exists between new-urbanization and green land utilization efficiency within a city? From the perspective of inter-city interaction, what is the interaction mechanism between new-urbanization and green land utilization efficiency in neighboring areas? Given these problems, it is necessary to use specific statistical methods and theories for analysis.

Currently, China is in a phase of rapid growth in terms of new-urbanization. Urban construction and expansion are based on resource consumption and pollution. With the

economic restructuring and economic development of China entering a new normal, it is urgent to provide new drivers for the efficiency of green land utilization. The national power shortage in 2021 in China also reflects the importance of this problem: What is the relationship between urban development and environmental protection? How can we correctly understand the internal mechanism between them? The relationship between China's new-urbanization and green land utilization efficiency has an important reference value. Based on the above assumption, this paper uses data for more than 200 Chinese cities at the prefecture-level and above for 8 years to undertake the following research. Firstly, non-parametric kernel density estimation and Moran index are used to examine the spatio-temporal evolution characteristics of new-urbanization and green land utilization efficiency in China. Secondly, the spatial interaction spillover (hereinafter referred to as "inter-spillover") effect between new-urbanization and green land utilization efficiency is tested by using spatial simultaneous-equations (hereinafter referred to as "SS-equations") of space and the GS3SLS estimation method. Relevant conclusions have practical implications for urban construction and green development in the world.

Figure 1 shows the research framework of this study. Specifically, in the first section, through the introduction of the empirical facts and the summary of the existing literature, the core issues of the research are put forward, that is, the spatio-temporal evolution characteristics of the new-urbanization and the green land utilization efficiency and the correlation between the two; in the second section, based on the analysis of the relationship between key variables, the research hypotheses of this paper are proposed, and the empirical model and data source and pretreatment are introduced; the third section empirically analyzes the spatio-temporal evolution characteristics of new-urbanization and green land utilization efficiency in China; the fourth section empirically analyzes the spatial inter-spillover effects between new-urbanization and green land utilization efficiency and carries out the robustness test; and the fifth section draws some basic conclusions and provides relevant policy implications.

1.2. Literature Review and Contribution

The existing literature shows that urbanization influences green development in complex ways. There are many previous studies on the impact of urbanization on green development that focus mainly on the following angles. Influenced by rapid urbanization, the LUCC (land-use/land-cover change) has changed the environment and natural ecosystems [14,15]; for example, this process affects mesoscale weather patterns, local climatic states, biodiversity, water reserve, and carbon cycle [16–20]. Referring to the research methods of environmental pollution and socio-economic development, some scholars construct the Environmental Kuznets Curve (EKC) based on environmental pollution and urbanization levels. D.F.Huang verified the inverted N-shaped relationship between industrial waste-water and urbanization, the N-shaped relationship between industrial sulfur dioxide and urbanization, and the U-shaped relationship between industrial dust and urbanization by using the panel data of 29 Chinese regions from 1999 to 2008 [21]. Zhao et al. discussed the impacts of population urbanization and land urbanization on air pollution [22]. With data from a Landsat-TM (Thematic Mapper) in high-resolution, Long et al. Found that, under the pressure of rapid urbanization, land use transformation has many negative impacts on the local ecosystem and environment, and they believed that while meeting the needs of socio-economic development for construction land, the protection of the service function of regional ecosystems and the maintenance of the stability of the service function of regional ecosystems are fundamental for the sustainable development of construction land [23]. In recent decades, China's LUCC has experienced a series of complex changes, and the ecosystem service values (ESV) decreased by 0.45% and 0.10% during periods of 1988–2000 and 2000 to 2008, respectively [24]. Sustainable land utilization planning must be combined with landscape patterns to provide helpful guidance for space regulation in specific regions to defend and improve ecosystem services [25]. As a very fragile environment, the LUCC of Karst will cause significant environmental changes. In the coming decades, urbanization

and the LUCC may lead to further environmental deterioration. Therefore, environmental protection should be a precedence for the development of Karst areas [26]. However, there is little literature on the reverse impact of green development on urbanization.

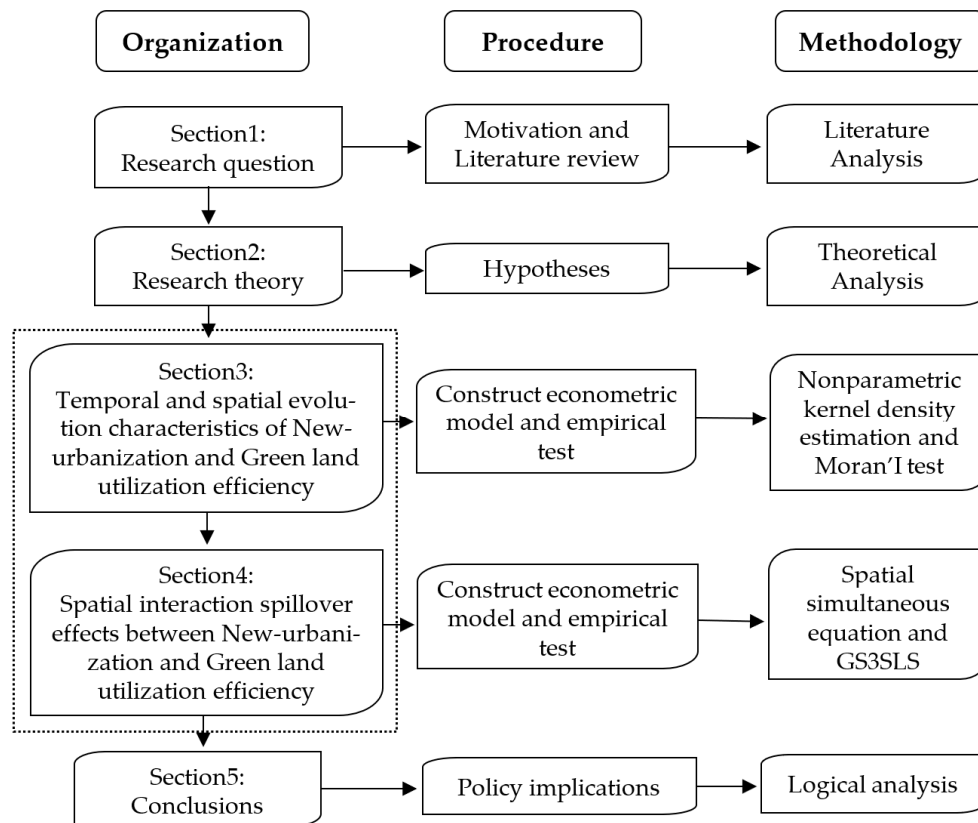


Figure 1. Research framework.

Researchers generally hold that the development of urbanization has spatial characteristics. Previous studies believe that spatial urbanization is the carrier of urbanization, and the advancement of urbanization will inevitably be reflected in space, including urban centripetal growth and spatial agglomeration [27,28]. Zhang et al. quantified impervious surfaces (IS) to investigate the spatial evolution and regional differentiation characteristics of urbanization in China, and they found that the overall performance of the percentage of urban IS shows a declining trend from the northwest region, southwest region, the Yellow River's middle reaches, northeast region, the Yangtze River's middle reaches, and the southern and northern coastal regions of China to the eastern coastal regions of China [29]. Based on the data of time series, the study of ISA (impervious surface area) shows that the megacities of China have expanded their ISA by five times the size of the U.S. megacities over the past three decades. Megacities in China expand outward from the urban core in a concentric ring structure, while megacities in the United States increase mainly within cities in patch-filling patterns. Megacities of China are in the development progress, and population and economic conditions significantly affect the mode and speed of urban expansion, while megacities of America are in the developed progress, and population and economic conditions are not imperative factors to promote the ISA expansion [30]. The spatial pattern of urban expansion in major Gulf areas expands and fills from the periphery to the edge; among them, the New York and the Tokyo Bay area experience the largest filling progress, followed by the San Francisco Bay area, and in the past, these areas have been ahead of the Guangdong–Hong Kong–Macao Greater Bay area [31].

The development of green land utilization efficiency also has spatial features. A large number of studies are based on the geographical effect of regional green total factor pro-

ductivity (mainly with the DEA model). The Xu et al. research found that the network of ecological profit distribution in the region presents a characteristic core-edge construction, and there is an obvious graded construction between parts with different orientations and roles [32]. The regional ecological efficiency of China is in the process of long-term fluctuation, but it is generally improved, with noticeable regional differences and widening gaps [33]. There is spatial autocorrelation in the distribution of green land utilization efficiency, and there is a spatial agglomeration effect between ecological efficiency and provincial financial development [34]. Chen et al.'s research shows that industrial aggregation, pollution, and environmental efficiency have obvious effects on space spillage, and aggregation has an obvious inverted U-shaped connection with sulfur dioxide discharge, soot emission, and wastewater emission, and a significant U-shaped connection with environmental efficiency [35]. Ren et al. have faith in that overall green land utilization efficiency in China are still not at a high level, with great variance among different areas; namely, the ecological efficiency in the eastern provinces is the highest, followed by the central provinces, and the gap between the western and central provinces is closing bit by bit [36].

This paper's research contents and marginal contributions are as follows. Based on the publicly available data of 297 China's cities at prefecture-level and above from 2011 to 2018, we calculate the new-urbanization index and green land utilization efficiency with the entropy weight method and the super SBM-GML (DEA) model, respectively. After analyzing the spatio-temporal evolution characteristics of the new-urbanization and green land utilization efficiency, we employ the simultaneous spatial equation and the GS3SLS estimation method to analyze the spatial inter-spillover effects between the two. The empirical results show that: (1) The level of new-urbanization and the green land utilization efficiency in Chinese cities have common and complex temporal and spatial dynamic evolution characteristics. (2) There are mutual inhibition effects between new-urbanization and green land utilization efficiency, and the level of new-urbanization is in a comparatively leading role. (3) Both the level of new-urbanization and green land utilization efficiency have significant spatial spillover effects. (4) The level of new-urbanization of surrounding cities promotes the green land utilization efficiency of the local city, and the improvement of the green land utilization efficiency of surrounding cities also promotes the level of new-urbanization of the local city.

2. Research Design and Variable Preprocessing

2.1. Theoretical Analysis and Research Hypothesis

The development of new-urbanization and green land utilization efficiency with cities as the unit will inevitably have temporal and spatial trends. Urban green land utilization efficiency is a comprehensive mapping of the urban production factor input system and the urban land use output system in urban space. President Xi Jinping's statement that "clear waters and green mountains are mountains of gold and silver" illustrates the dialectical connection between protection for the ecological environment and sustainable socio-economic development, and it is an important thought to guide ecological civilization construction of China. With the deepening of this thought, in the process of socio-economic development, it is also urgent to cease the traditional high pollution and extensive way to adapt to the new-era requirements of the efficient, green, moderate, and intensive practice in terms of the input and utilization of urban land resources. The 2018 National Conference on Ecological and Environmental Protection pointed out that green development is an inevitable obligation for the construction of a high-quality modern socioeconomic system, and green has become the contemporary urban economic development theme. The concept of new-urbanization has emerged in the wave of green development. It is characterized by urban-rural harmonization, urban-rural integration, industrial contact, conservation, intensification, ecological expedient, and harmonious development. It is also characterized by synchronized development and reciprocal promotion of cities of different sizes, small towns, and new-type rural

communities. It can be seen that new-urbanization and green land utilization efficiency should also have common temporal and spatial trends. Based on the theoretical analysis above, we can propose the following hypothesis:

Hypothesis 1 (H1). *New-urbanization and green land utilization efficiency in Chinese cities have common and complex temporal and spatial dynamic evolution characteristics.*

Since the reform and opening-up, China has experienced sustained high-speed growth. Rapid industrialization and urbanization will inevitably bring pollution problems. The environmental Kuznets curve is applicable in China. At present, all regions in China are still in the left-hand stage of the curve; that is, pollution emissions further increase with the rise of per capita GDP. According to the theory of sustainable development, the goal of government public policy is not only to increase GDP, but to improve social welfare. On the one hand, environmental pollution has a significant adverse impact on residents' subjective well-being; on the other hand, the high GDP at the cost of pollution plays a certain role in promoting the welfare of Chinese residents. How does the Chinese government balance economic development and environmental governance? In terms of the past governance models, local governments were keen on economic construction and did not hesitate to develop the economy extensively, with little motivation to pay attention to environmental quality. The long-term accumulated environmental pollution problem is gradually emerging, which not only causes huge economic losses but also brings health losses to the people. In recent years, the central government has paid more and more attention to environmental protection and formulated a series of laws and regulations. However, China's pollution situation is complex and has regional differences. A unified environmental regulation may not be in line with the local conditions of various regions. In addition, private enterprises generally believe that the existing environmental protection inspection and the fine system has brought a certain degree of burden to enterprise operation. Even pillar enterprises, such as a large number of coal and steel enterprises in many cities, have to be shut down due to environmental protection-related policies. Based on the theoretical analysis above, we can put forward the following hypothesis:

Hypothesis 2 (H2). *There are mutual inhibition effects between new-urbanization and green land utilization efficiency.*

With the increase in cross-regional flow of resources and the intensification of inter-regional competition for innovative resources, the new-urbanization and green land utilization efficiency are unavoidably influenced by adjacent regions. From the perspective of new-urbanization, firstly, the level of new-urbanization is closely related to regional development strategies such as urban agglomerations and Bay areas. Many policy orientations of China in recent years promote the level of urbanization to have strong features of agglomeration and correlation in geographical space, showing a trend of gradual growth; secondly, the improvement of the new-urbanization level in a specific region helps to benefit the surrounding regions through knowledge and talent mobility, demonstration and innovation effects, forming a space development impetus from the centre to the periphery, and promoting the new-urbanization development in the neighboring regions; thirdly, as the impact of development policies formulated by local governments often covers an economic zone, city cluster, or province, and new-urbanization, as the main goals of national development in recent years, also reflects the differences among different regions in terms of policy supports, the levels of new-urbanization in different regions are thus also spatially correlated. From the perspective of green land utilization efficiency, on the one hand, the improvement of green land utilization efficiency in adjoining regions can improve the green land utilization efficiency of local regions through the demonstration and dissemination effect and the innovation effect of knowledge; on the other hand, the green land utilization efficiency is highly related to the region geographical environment, and as the geographical environment of adjacent regions is significantly similar to that of

local regions, and other objective environments also have a significant degree of geographical correlation, the trend of development of the green land utilization efficiency in adjacent cities has a certain extent of the similarity. Based on the theoretical analysis above, we can propose the following hypothesis:

Hypothesis 3 (H3). *Both the new-urbanization level and the green land utilization efficiency have significant spatial spillover effects.*

The spatial interaction mechanism between new-urbanization and green land utilization efficiency is complicated. First of all, as the main driving factor of urban development and construction, the development of new-urbanization in the surrounding regions also brings opportunities for the local development, which is mainly manifested in bringing large amounts of capital and technology diffusion dividends to the local region, thereby realizing innovation-driven economies of scale, knowledge spillover, and environmental effects to optimize the driving force of urban green development and promote green land utilization efficiency [37]. Meanwhile, China's urban construction often lacks independence, and with environmental protection indicators, such as pollution emissions, being delegated to each region and overall planning being carried out within the region, "competition" among cities for development indicators are inevitable, resulting in the urbanization of surrounding cities and the lack of local urbanization resources for green development. Secondly, due to the promulgation or deepening of environmental laws and regulations, the improvement of green land utilization efficiency of surrounding cities may be accompanied by the outward relocation of industrial enterprises, and the urbanization of local cities will be further developed in the process of undertaking these industries. Improving the efficiency of green land utilization in adjacent regions also helps to benefit the local region through human capital and knowledge flow, demonstration, and innovation effects. In contrast, the local city is not affected by the reduction in production capacity brought by forced green transformation. Therefore, the local new-urbanization can draw nutrients from the green development of surrounding cities. Based on the theoretical analysis above, we can propose the following hypothesis:

Hypothesis 4 (H4). *The new-urbanization of surrounding cities promotes the local green land utilization efficiency, and the improvement of the green land utilization efficiency of surrounding cities also promotes the local new-urbanization.*

Figure 2 comprehensively shows the hypotheses H2, H3 and H4 in this paper.

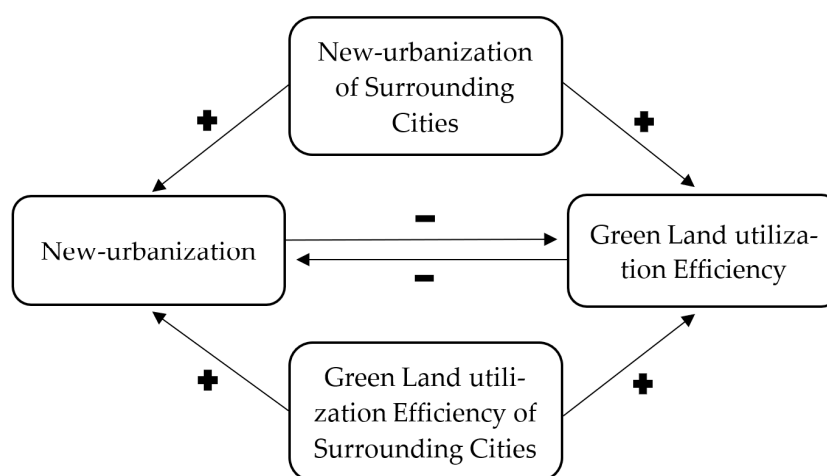


Figure 2. Interactive and spillover mechanism of new-urbanization and urban green land utilization efficiency in China.

It should be noted that, in model settings and measurement methods, this paper eliminates the impact of conduction between core variables in terms of the spatial interaction effect, thus only the direct relationship between the two factors is considered. For example, the new-urbanization of surrounding cities promotes the level of local new-urbanization, which is transmitted to inhibit the local green land utilization efficiency. The impact of the above transmission chain is not considered in this paper.

2.2. Model Setting and Measurement Method

At first, this paper analyzes the spatio-temporal evolution characteristics of new-urbanization and green land utilization efficiency by non-parametric kernel density estimation and Moran's I index.

Kernel density estimation is used to estimate the unknown density function in probability theory. It belongs to one of the non-parametric methods. Kernel density estimation is a common non-parametric method used by scholars to solve uneven distribution. Kernel density estimation solves the shortcomings of rough histograms and low estimation accuracy as the earliest non-parametric kernel density estimation method. It uses a smoothing method to replace the histogram with a continuous density curve, and then it can better describe the distribution form of random variables.

If the density function of the random variable regional systemic financial risk index x is assumed to be $f(x)$, the probability density at point x can be estimated by the following formula:

$$f(x) = \frac{1}{Nh} \sum_{i=1}^N K\left(\frac{X_i - x}{h}\right) \quad (1)$$

In the above formula, N is the number of observed values of urban regional systemic financial risk index, h is the bandwidth, and K is the kernel function, which is a weighting function or smooth conversion function. The kernel function has many types, such as Gaussian kernel, triangular kernel, etc., where X_i is the observed value of the total cost index of economic transformation of independent and identically distributed random variables, and x is the mean value of samples.

The bandwidth h in the probability density estimation formula will determine the smoothness of the density curve. If the bandwidth h is larger, the curve will be smoother. Therefore, the selection of bandwidth h will determine the shape of the density curve to a certain extent. In practical research, if there are more samples, the requirements for bandwidth h should be more minor, but not too small. That is, bandwidth h is a function of sample N , and the following conditions should be met:

$$\lim_{N \rightarrow \infty} h(N) = 0 \quad \lim_{N \rightarrow \infty} Nh(N) = N \rightarrow \infty \quad (2)$$

Spatial autocorrelation describes the cluster status of regional economic activity distribution from the whole regional space. The measurement indicators of global spatial autocorrelation are:

$$Moran' I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_{i=1}^n (Y_i - \bar{Y})^2 / n} * \frac{1}{\sum_{i=1}^n \sum_{j=1}^n w_{ij}} \quad (3)$$

In Equation (3), $\bar{Y} = \frac{\sum_{i=1}^n Y_i}{n}$, Y_i is the attribute value of unit i of the space, and W_{ij} ($i, j = 1, 2, \dots, n$) is the element of spatial weight matrix W . Moran's I coefficient reflects the correlation degree of attribute values of regional units in the hole. Similar to the correlation coefficient, the value range of the Moran's I coefficient is $[-1, 1]$. The sign represents the directionality of similarity, and the absolute value means the strength of correlation. It is generally believed that the closer the distance between two spatial units, the stronger the correlation between them, which is manifested as the positive or negative correlation of attribute values.

Then, the relationship between new-urbanization and green land utilization efficiency is considered. According to the hypotheses proposed above, there is an interaction between new-urbanization and the green land utilization efficiency. Therefore, a fixed effects panel regression model based on simultaneous-equations can be established [38], with the form as follows:

$$N_urb_{it} = \alpha_0 + \alpha_1 L_eff_{it} + \alpha X_{it} + \pi_i + \varepsilon_{it} \quad (4)$$

$$L_eff_{it} = \beta_0 + \beta_1 N_urb_{it} + \beta Z_{it} + \mu_i + \sigma_{it} \quad (5)$$

In Equations (4) and (5), i represents an individual city, and t represents a year; N_urb_{it} and L_eff_{it} are, respectively, the level of new-urbanization and the green land utilization efficiency of a sample city; X_{it} and Z_{it} are the covariates that may affect the new-urbanization and the green land utilization efficiency, respectively, including openness degree (ope), transportation development level (tra), capitalization degree (com), capital allocation efficiency (cap), innovation level (inv), import and export volume (m&x), and centrality of scientific research personnel (rd); π_i and μ_i represent the controlled individual city; and ε_{it} and σ_{it} are the error terms.

The traditional fixed effects panel model has two disadvantages. The first disadvantage is that the influence of surrounding cities on variables in spatial dimension is ignored; that is, the impact of the new-urbanization level and the green land utilization efficiency in surrounding cities on the local city's new-urbanization level and green land utilization efficiency is ignored. To solve this problem, previous studies mainly employed traditional econometric spatial models such as the spatial lag model (SLM), the spatial error model (SEM), and the spatial Durbin model (SDM). Still, they ignored the spatial interaction among parameters. Therefore, this paper establishes SS-equations to analyze the relationship between core variables comprehensively. The second disadvantage is that the possible correlation between the endogenous variables and the random perturbation terms of each equation is not considered. For the second problem, the estimation error of the two-stage least square method is used to construct the statistics of the random perturbation covariance matrix of the model to carry out the generalized least square estimation of the whole model, namely the generalized spatial three-stage least square method (GS3SLS), which is a complete information estimation method of the simultaneous-equation model. The method was proposed by Theil and Zellner in 1962 [39], and the main steps of applying this method are as follows: (1) the model system required to be identifiable, and all defining equations (i.e., identities) are removed; (2) least-squares estimation is made on the simplified formula of the model; (3) the above estimators are taken as instrumental variables to perform the least squares estimation (i.e., two-stage least squares estimation) on the model structural formula, and the estimation error is calculated; and (4) the two-stage estimation error is used to construct the statistics of the variance of the perturbation term to carry out the generalized least squares estimation. Under certain conditions, the estimation results of the GS3SLS method have better asymptotic validity than the two-stage least squares estimation.

Based on the analysis above, this paper adopts the SS-equations based on the generalized three-stage least square estimation method to investigate the spatial inter-spillover effect between new-urbanization and the green land utilization efficiency [40]. The forms of equations are as follows:

$$N_urb_{it} = \alpha_0 + \alpha_1 \sum_{j \neq i}^n W N_urb_{jt} + \alpha_2 \sum_{j \neq i}^n W L_eff_{jt} + \alpha_3 L_eff_{it} + \alpha X_{it} + \varepsilon_{it} \quad (6)$$

$$L_eff_{it} = \beta_0 + \beta_1 \sum_{j \neq i}^n W L_eff_{jt} + \beta_2 \sum_{j \neq i}^n W N_urb_{jt} + \beta_3 N_urb_{it} + \beta Z_{it} + \sigma_{it} \quad (7)$$

In Equations (6) and (7), W is the spatial weight matrix. In view of the intricacy of spatial inter-spillover, this paper builds a geographical-distance matrix. The linear distance between two samples are calculated according to their central latitude and longitude

coordinates, and its reciprocal is taken as the weight based on the dimensionless processing. If the distance between the two samples' centres exceeds 30, the weight is assigned to 0; that is, the two samples are identified as non-adjacent. According to the spatial–econometric theory, in Equations (6) and (7), α_1 represent the spatial spillover strength and orientation of the new-urbanization level in surrounding samples; β_1 represents the spatial spillover strength and orientation of the green land utilization efficiency in surrounding samples; α_2 and β_2 are used to test the spatial interaction between the new-urbanization level and the green land utilization efficiency, where α_2 describes the impact strength and orientation of the green land utilization efficiency in surrounding samples on the local new-urbanization level, and β_2 describes the impact strength and orientation of the new-urbanization level in surrounding samples on the local green land utilization efficiency; and α_3 and β_3 describe the endogenous relationship between the new-urbanization level and the green land utilization efficiency.

2.3. Variable Description and Data Source

2.3.1. Variable Description and Processing

The core variables of this paper include the new-urbanization level (N_{urb}) and the green land utilization efficiency (L_{eff}). The time and space dimensions are 297 sample cities from 2011 to 2018. The new-urbanization level in this paper is calculated by the entropy weight method [41], and it contains 24 specific variables, which can be classified into four dimensions: population urbanization, economy urbanization, land urbanization, and society urbanization. The weights of 24 sub-variables are objectively weighted by the entropy weight method, and the specific steps are as follows. The first step is to normalize index values. There are 2376 (297×8) objects to be evaluated and 24 evaluation indicators in this paper, and the forward processing matrix is as follows:

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,24} \\ x_{2,1} & x_{2,2} & \cdots & x_{2,24} \\ \vdots & \vdots & \ddots & \vdots \\ x_{2376,1} & x_{2376,2} & \cdots & x_{2376,24} \end{bmatrix} \quad (8)$$

The matrix X is normalized with the following equation (where the negative indicators are processed with the negative normalization method):

$$z_{i,j} = \frac{x_{i,j} - \min\{x_{1,j}, x_{2,j}, \cdots, x_{2376,j}\}}{\max\{x_{1,j}, x_{2,j}, \cdots, x_{2376,j}\} - \min\{x_{1,j}, x_{2,j}, \cdots, x_{2376,j}\}} \quad (9)$$

The second step is to calculate the proportion of the i -th sample of the j -th indicator and regard it as the probability used in the relative entropy calculation. Based on the previous step, the probability matrix P is calculated, and each element in P is as follows:

$$P_{i,j} = \frac{z_{i,j}}{\sum_{i=1}^{2376} z_{i,j}} \quad (10)$$

The third step is to calculate the information entropy of each indicator as well as the information utility value, obtaining the entropy weight of each indicator by normalization. For the j -th indicator, its information entropy can be calculated by:

$$e_j = -\frac{1}{\ln 2376} \sum_{i=1}^{2376} p_{i,j} \ln(p_{i,j}) \quad (11)$$

At this point, the larger the value of e_j , the larger the information entropy of the j -th indicator is, and the smaller the corresponding information amount is. The information

utility value is defined as $d_j = 1 - e_j$. The entropy weight of each indicator is obtained by normalizing the information utility value:

$$W_j = \frac{d_j}{\sum_{j=1}^{2376} d_j} \quad (12)$$

According to the above steps, the weights of 24 evaluation indicators can be obtained in this paper, as shown in Table 1. Finally, the new-urbanization level of each sample city in each period is obtained by adding all corresponding indicators according to their weights.

Table 1. New-urbanization indicator system.

Primary Indicator	Secondary Indicator	Weight
Population urbanization (0.20991)	The proportion of urban population	0.04797
	The proportion of urban population (negative indicator)	0.05940
	Urban population density	0.04633
	The proportion of employees in the tertiary industry	0.05619
Economy urbanization (0.27383)	GDP per capita	0.04925
	The proportion of the total output value of the secondary industry in GDP	0.05700
	The proportion of total output value of secondary and tertiary industries in GDP	0.04871
	Public revenue	0.01882
	Per capita disposable income of urban residents	0.05367
	Total retail sales of consumer goods per capita	0.04634
Land urbanization (0.13700)	The proportion of built-up area	0.01977
	Urban road area per capita	0.05150
	Green area per capita	0.02731
	Per capita real estate and residential investment	0.03840
Society urbanization (0.37926)	The proportion of education expenditure in financial expenditure	0.04337
	The proportion of expenditure on science and technology in government expenditure	0.05816
	Public transport vehicles per 10,000 people	0.02817
	Per capita public library collection	0.03191
	Number of doctors per 1000 people	0.05412
	Number of secondary schools and primary schools	0.04731
	Number of full-time teachers in secondary and primary schools	0.05015
	Per capita water supply	0.02670
	Per capita electricity consumption	0.02720
	Per capita gas supply	0.01213

This paper adopts the DEA (Data Envelopment Analysis) model based on super SBM-GML to study the green land utilization efficiency. The DEA was put forward in 1978 to assess the relative efficiency of a multi-input and output decision-making unit group [42–46]. Tonerrespectively proposed the new DEA model called “SBM” in 2001 and the upgraded model called “super-efficiency SBM” in 2002, which can not only consider the slack variable but also classify the decision-making units with efficiency value

over 1 [47,48]. The Malmquist index of DEA was first proposed by Malmquist and named after it [49], and Caves further optimized the index model [50], which is used to measure variations in total factor productivity between two periods and to introduce the directional function of distance containing some undesired productions into the Malmquist index to assist in the analysis of undesirable productions. In order to facilitate cross period comparison and overcome the problem of no feasible solution, Oh combines previous studies and finally puts forward the GML index (global Malmquist–Luenberger) [51].

Based on the model specification above and the research objectives of this paper, the input indicators are selected as follows: social fixed-asset investment, total employees, urban built-up land area, and total energy consumption. The output indicators are determined: GDP is taken as the desired output, representing total urban output value; wastewater, exhaust gas, and soot discharge are regarded as undesirable productions, representing pollution discharge. Table 2 shows the input and output indicators, respectively.

Table 2. Input and output indicators for calculating green land utilization efficiency.

Primary Indicator	Secondary Indicator	Tertiary Indicator
Input indicator	Capital	Fixed-assets investment
	Labor	Total employees
	Land	Built-up area
	Energy	Total energy consumption
Output indicator	Desired output	GDP
	Undesired output	Wastewater discharge
		Exhaust gas emission
		Soot emission

For covariates, this paper selects seven covariates that may influence the core variables and have a weak overlap with the core variables [52,53]. The variable of openness degree (ope) is measured by the relative proportion of FDI (foreign direct investment) in the GDP of the city in that year. The variable of transport development level (tra) is the logarithm of the total passenger volume of the city divided by the total population. The variable of capitalization degree (com) is measured by the standardized market value of listed companies in the city. For the measurement of the capital allocation efficiency (cap), this paper first uses the perpetual inventory method to ascertain the capital stock [54], which is used as the input and GDP as the output to obtain the efficiency value with the DEA method, and the efficiency value is divided by the weighted average inter-bank lending rate of the year to obtain the final capital allocation efficiency after normalization. The variable innovation level (inv) is measured by the logarithm of the number of inventions of the city in that year plus one. The import and export trade volume (m&x) is measured by the relative proportion of total import and export trade in the GDP of the whole city. The centrality of scientific research personnel (rd) is calculated by the node degree centrality of employees in the scientific research comprehensive technical service industry of a specific city with the social network analysis method.

2.3.2. Data Sources and Descriptive Statistics

Table 3 reports the sources of all variables in this paper. All data are from publicly acquired platforms. The interpolation method is used to complete some missing values according to the variation trend of variables. Softwares such as GeoDa and Stata16 help complete data processing in this paper. The former is a free software package analyzing spatial data and modelling. In this paper, the GeoDa software is used to establish the spatial distance weight matrix based on latitude and longitude distance [55] and the Moran's I test, which is a spatial autocorrelation measure developed by Patrick Alfred Pierce Moran [56,57].

Table 3. Variable data sources.

Variable	Abbr.	Source
New-urbanization	N-urb	Entropy weight method
Green land utilization efficiency	L-eff	DEA Analysis
Openness degree	ope	China City Statistical Yearbook
Transport development level	tra	China City Statistical Yearbook
Capitalization degree	com	Wind
Capital allocation efficiency	cap	DEA Analysis
Innovation level	inv	CNRDS
Import and export trade volume	m&x	Statistical Yearbook of each city
centrality of scientific research personnel	rd	Social Network Analysis

Table 4 shows the descriptive statistics of variables. To reflect the differences among cities, descriptive statistics of eastern regions, central regions, and western regions of China are presented, respectively. It can be seen that cities in eastern China obviously have a higher level of new-urbanization, and the green land utilization efficiency in central China is slightly better compared with cities in other regions. In order to reflect the differences between cities in different periods, the descriptive statistics of sample cities from 2011 to 2014 and from 2015 to 2018 are displayed, respectively. It can be seen that both the new-urbanization level and the green land utilization efficiency have been greatly improved in the long run.

Table 4. Descriptive statistics of variables.

	Unit	Items	Summary	Eastern	Central	Western	2011–2014	2015–2018
N	-	-	2376	904	896	576	1188	1188
N-urb	-	Mean	0.235	0.254	0.223	0.222	0.227	0.242
		Std	0.049	0.060	0.034	0.037	0.044	0.052
L-eff	-	Mean	1.660	1.652	1.702	1.608	1.445	1.876
		Std	0.528	0.470	0.541	0.584	0.364	0.576
ope	ratio	Mean	0.019	0.019	0.026	0.005	0.017	0.020
		Std	0.027	0.019	0.036	0.011	0.017	0.034
tra	ratio	Mean	2.740	2.715	2.660	2.904	2.954	2.527
		Std	0.784	0.867	0.713	0.728	0.769	0.740
com	-	Mean	0	0.320	−0.064	−0.402	−0.062	0.062
		Std	1	0.789	0.967	1.168	1.000	0.996
cap	ratio	Mean	0	0.100	0.050	−0.235	−0.528	0.528
		Std	1	1.024	0.916	1.048	0.821	0.875
inv	Ln(n + 1)	Mean	4.722	5.663	4.423	3.712	4.297	5.148
		Std	1.864	1.743	1.524	1.848	1.791	1.839
m&x	ratio	Mean	0.229	0.482	0.081	0.062	0.256	0.201
		Std	0.648	0.990	0.115	0.123	0.746	0.532
rd	-	Mean	0.043	0.043	0.038	0.050	0.044	0.042
		Std	0.146	0.152	0.112	0.178	0.164	0.124

3. Temporal and Spatial Evolution Characteristics of New-Urbanization and Green Land Utilization Efficiency

3.1. Characteristics of the Temporal Dynamic Evolution

Based on the non-parametric kernel density estimation formula, this paper uses Stata 16.0 to draw the kernel density curves of new-urbanization levels and green land utilization efficiency of Chinese cities in 2011, 2013, 2016, and 2018 (see Figures 3 and 4) at the global scale and the regional scale, respectively (global scale: 297 cities; regional scale: 113 cities in eastern China, 112 cities in central China, and 72 cities in western China) to characterize the

temporal dynamic evolution characteristics of new-urbanization and green land utilization efficiency in China.

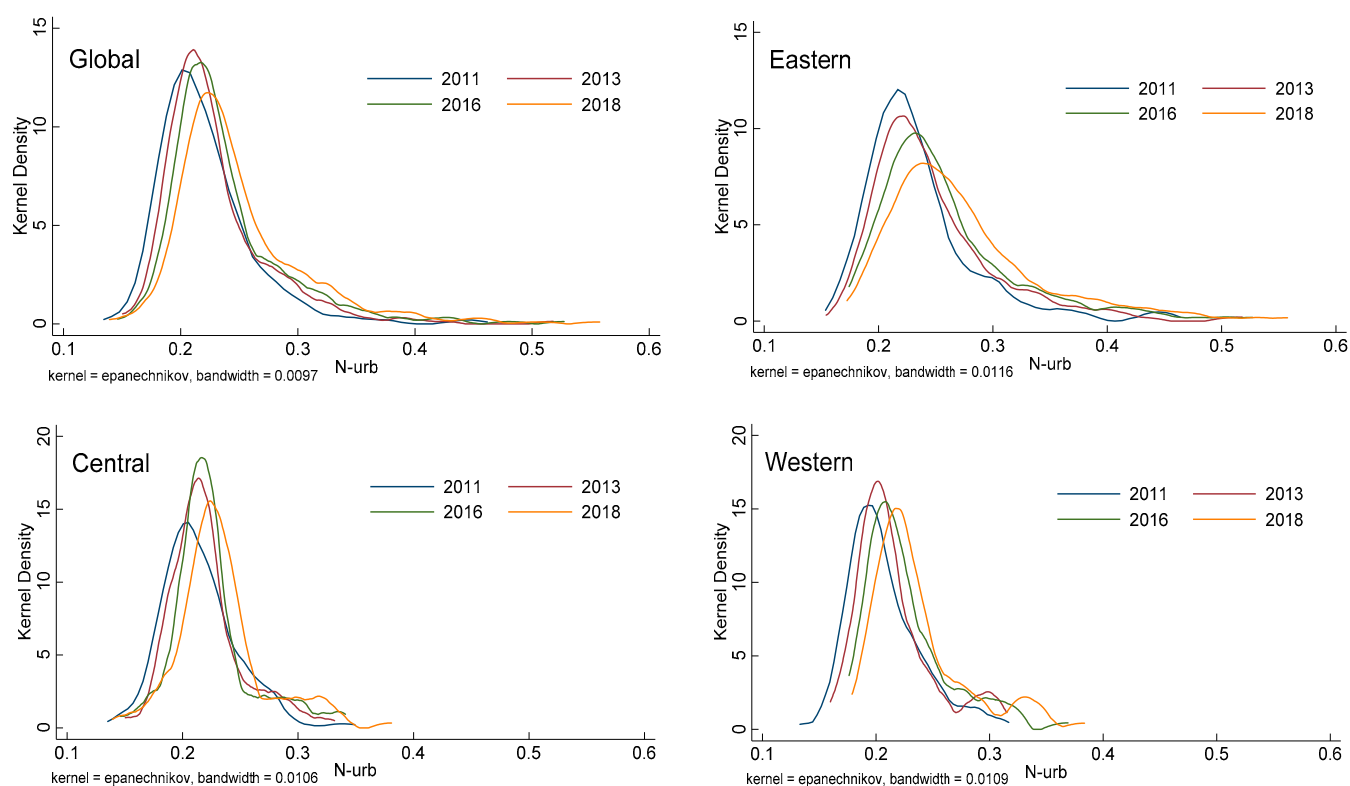


Figure 3. Temporal dynamic evolution characteristics of the new-urbanization in China.

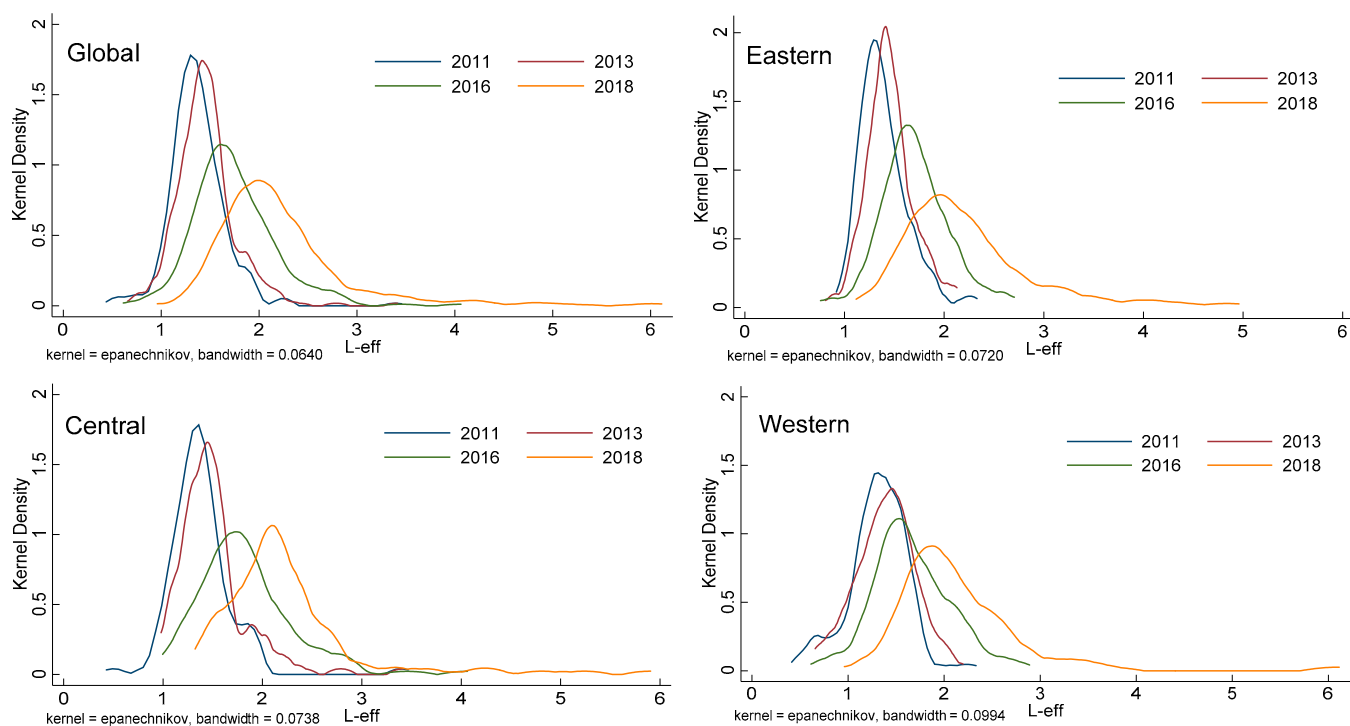


Figure 4. Temporal dynamic evolution characteristics of the green land utilization efficiency in China.

3.1.1. Global Temporal Dynamic Evolution Characteristics

The global scale can describe the temporal evolution characteristics of new-urbanization and green land utilization efficiency in China from a global perspective. (1) From the gravity position of the annual kernel density curve, the centres of gravity in periods of 2011 to 2013, 2013 to 2016, and 2016 to 2018 all move to the right, indicating that during the study periods, the level of new-urbanization and the value of green land utilization efficiency in Chinese cities show an upward evolution characteristic as a whole. (2) From the height of the main peak of the curve, in terms of the level of new-urbanization, the peak shows a trend of first rising and then falling, indicating that the difference in the level of new-urbanization between cities shows a trend of first expanding and then narrowing; in terms of green land utilization efficiency, the peak shows a downward trend, indicating that the difference of green land utilization efficiency between cities continues to narrow. (3) From the number of curve peaks, there is no multi-peak coexistence in the new-urbanization level and green land utilization efficiency, indicating that there is no multi-polar differentiation pattern. (4) From the left and the right tailing of the curve, the new-urbanization level and green land utilization efficiency show that the tailing of the right side is greater than the left side, and the tailing on the right side has a trend of lengthening and thickening, indicating that during this period, the new-urbanization level and green land utilization efficiency of cities in high-level regions have increased, and the proportion of cities in high-level regions has increased. It can be seen that, on a global scale, the new-urbanization level and green land utilization efficiency of Chinese cities have different dynamic evolution characteristics of development level, efficiency difference, and polarization degree in different times, and the dynamic evolution features of the two are consistent.

3.1.2. Regional Temporal Dynamic Evolution Characteristics

At the regional scale, the temporal evolution characteristics of green land utilization efficiency in different regions of China can be described from the perspective of three regions. (1) Judging from the gravity centre position of the annual curve of kernel density, the new-urbanization level and green land utilization efficiency of the three regions moved significantly to the right from 2011 to 2018, indicating that the core variables of the three regions all show an upward evolution feature during this period. (2) From the perspective of the height of the main peak of the curve, in terms of the level of new-urbanization, the peak of the eastern region curve continues to decline from 2011 to 2018, indicating that the gap in the level of new-urbanization among eastern cities has a narrowing evolution trend, and the curve peaks of the central regions and western regions rose first and then fell during the research period. It shows that the new-urbanization level gap between the central and western cities shows an evolution characteristic of first expanding and then narrowing. In terms of green land utilization efficiency, the curve peaks of the three regions maintain a downward trend, and the gap of green land utilization efficiency among the three regions shows a narrowing trend during this period. (3) From the number of curve peaks, in terms of the level of new-urbanization, there is a coexistence of one main peak and one secondary peak in the central and the western regions, indicating that cities in the two regions have the characteristics of two-level differentiation. In terms of green land utilization efficiency, only the central region had an insignificant secondary peak in 2011, and there is no multi-polarization pattern. (4) From the left and right tailing of the curve, the new-urbanization level and green land utilization efficiency of the cities in the three regions show that the tailing of the right side is greater than the left side, and the tailing on the right side has a trend of lengthening and thickening, indicating that during this period, the new-urbanization level and land green land utilization efficiency of cities in high-value areas have increased, and the proportion of cities in high-value areas has increased. It can be seen that under the regional scale, the temporal dynamic evolution process of China's new-urbanization level and green land utilization efficiency in different regions and different periods is the result of the superposition and symbiosis of regional characteristics and period characteristics.

3.2. Spatial Evolution Characteristics

3.2.1. Global Spatial Evolution Characteristics

The global Moran's I and the Z -value of the new-urbanization level and the green land utilization efficiency of Chinese cities from 2011 to 2018 are calculated by using the global Moran index formula and the GeoDa software (see Figure 5). In terms of the level of new-urbanization, the results show that the global Moran's I values are all positive, between 0.067–0.391, and the Z -values are between 2.616–9.701, both of which pass the 5% significance test. Therefore, the spatial distribution of the new-urbanization levels in Chinese cities has a significant positive global spatial auto-correlation during the study period, and the new-urbanization of the local city will be affected by that of its neighboring cities. Overall, except for the decline of the global Moran's I in 2013, the global spatial correlation of China's urban new-urbanization level has evolved from a weak correlation to a strong correlation. Regarding the green land utilization efficiency, the results show that the global Moran's I values are all positive, ranging from 0.028–0.259, and the Z -values are between 1.083–6.567. Except for 2012 ($p = 0.120$), all of them pass the 5% significance test. In conclusion, the spatial distribution of urban green land utilization efficiency in China has a significant positive global spatial auto-correlation during the sample period, and the green land utilization efficiency of a local city will be affected by that of its neighboring cities. Overall, the global spatial correlation of urban green land utilization efficiency in China presents the evolution characteristics of alternating strong and weak correlations. At the global scale, there is an obvious spatial auto-correlation between the new-urbanization level and the green land utilization efficiency in Chinese cities.

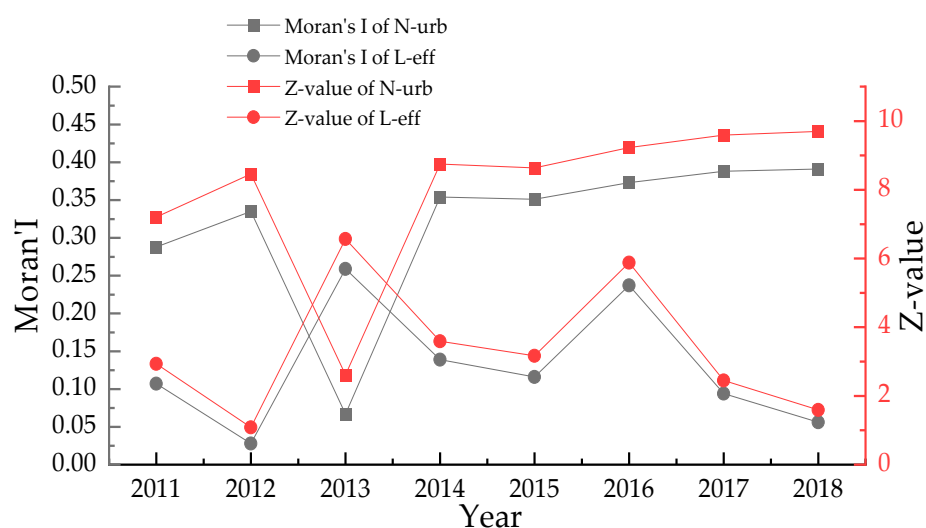


Figure 5. Global Moran's I and Z -value evolution characteristics of new-urbanization level and green land utilization efficiency in China.

3.2.2. Regional Spatial Evolution Characteristics

The global Moran's I can prove that there is global spatial auto-correlation between the new-urbanization level and the green land utilization efficiency in Chinese cities from a macro perspective. However, it cannot visualize the characteristics of the regional spatial pattern. Therefore, it is necessary to identify the regional spatial pattern characteristics of urban core variables in China with the help of regional spatial auto-correlation (see Figures 6 and 7). The specific regional spatial pattern and distribution quantity can be classified into four categories. (1) The high–high aggregation type (H–H) indicates that the core variables' values of the local city are high, and those of its surrounding regions are also high, showing a high level of spatial equilibrium correlation aggregation state of “high in the centre, high in the surrounding”. (2) The low–low aggregation type (L–L) indicates that the values of the core variables of the local city are low, and those of the

surrounding regions are also low, showing a low-level spatial equilibrium correlation aggregation state of “low in the centre and low in the surrounding”. (3) The low–high aggregation type (L–H) indicates that the values of the core variables of the local city are low, but those of the surrounding regions are high, which is displayed as the spatial disequilibrium correlation aggregation state of “low in the centre, high in the surrounding”. (4) The high–low aggregation type (H–L) indicates that the core variables’ values of the local city are high, but those of the surrounding regions are low, which is displayed as the spatial disequilibrium correlation aggregation state of “high in the centre, low in the surrounding”.

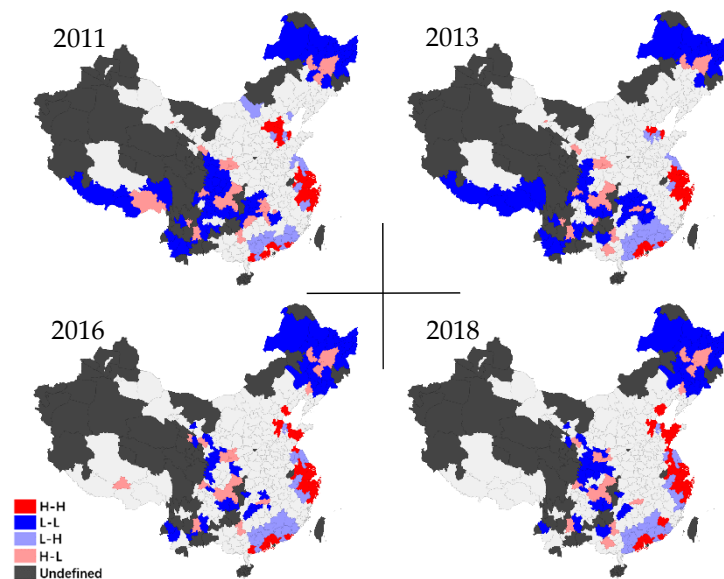


Figure 6. Evolution characteristics of regional spatial patterns of new-urbanization levels in Chinese cities.

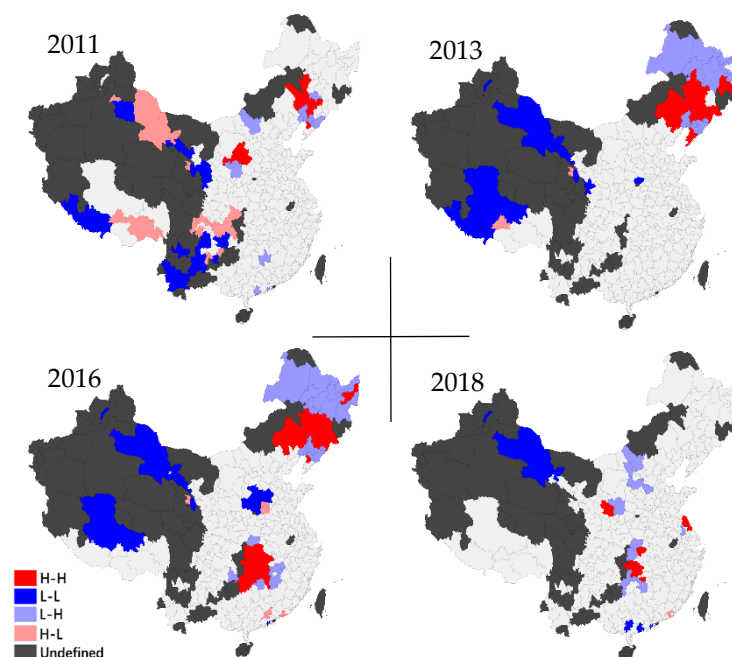


Figure 7. Evolution characteristics of regional spatial patterns of the green land utilization efficiency in Chinese cities.

By observing Figure 6, we can find that the level of new-urbanization in Chinese cities has a complex local spatial pattern. From an evolutionary perspective, as time goes by, the number of low–low aggregation type (L–L) cities in the central regions and western regions gradually decreases, indicating that the urban development in the central regions and western regions is effective; the diffusion trend of the L–L cities in northeast China shows that the urbanization process in northeast China needs to be improved. The evolution of other areas is not apparent. From the perspective of regional distribution, the midwest and northeast China are dominated by the L–L and H–L types of cities, indicating that there are still phenomena such as slow urbanization and core cities siphoning the development capacity of surrounding cities in China’s midwest and northeast, and the development momentum and equity still need to be strengthened in those regions. Developed regions such as the Pearl River Delta, the Yangtze River Delta, and the Beijing–Tianjin–Hebei region are obviously dominated by the H–H and the L–H types of cities for a long time. Firstly, there is a geographical spatial proximity spillover effect among China’s developed cities, as they have high economic, social, and cultural similarity, close spatial distance, and low transportation cost, and with frequent connections and mutual circulation of urbanization resources, a spatial pattern of “strong cooperation” has emerged. Secondly, through observing the distribution of the L–H type cities, it can be found that the development resources of relatively backward cities in developed areas are “plundered” by developed cities, which is particularly obvious in the Pearl River Delta. The ideal of “being rich first drives wealth later” has been replaced by “strong alliances” or “strong–strong mutual protection”.

By observing Figure 7, it can be found that the intensity of the local spatial pattern of green land utilization efficiency in China is relatively weak. From the evolutionary perspective, with the passing of time, central and western China and northeast China showed the high–high aggregation (H–H) and low–high aggregation (L–H) types of cities during the research period. Then, they were not obvious, indicating that there has been a short-term aggregation development and resource concentration of green land utilization efficiency in the central regions and western regions and northeast regions. The evolution of cities in other regions is not apparent. From the perspective of regional distribution, the western region has long been dominated by low-level aggregation (L–L) type cities, indicating that cities in the western region have insufficient land green development capabilities and are also vulnerable to the homogeneity of the surrounding cities with low levels of green development.

In general, from the spatial evolution characteristics, it can be found that there is spatial proximity peer effect in the new-urbanization and green land utilization efficiency of Chinese cities. When the core variables of the adjacent cities around the local city are at a high (low) level, the local city is also more likely to become a high (low) level city, or it is more difficult for the local city to “highlight” and transfer to a low (high) level city. Therefore, the new-urbanization and the green land utilization efficiency of Chinese cities have formed the spatial pattern of “the low is always low and the high is always high”.

To sum up, there are common and complex temporal and spatial dynamic evolution characteristics of the new-urbanization and the green land utilization efficiency in Chinese cities. This paper verifies Hypothesis 1.

4. Spatial Inter-Spillover Effects of the New-Urbanization and the Green Land Utilization Efficiency of Chinese Cities

4.1. Parameter Estimation Results

In this paper, the relationship between the level of new-urbanization and the green land utilization efficiency is initially analyzed by using the simultaneous-equation based on fixed effects panel regression models (4) and (5). Table 5 shows parameter estimation results according to the model specification.

Table 5. Benchmark regression results.

Items	Explained Variable: N-urb			Explained Variable: L-eff		
	(1)	(2)	(3)	(4)	(5)	(6)
N-urb	-	-	-	1.799 *** (8.30)	3.031 *** (8.99)	8.904 *** (12.58)
L-eff	0.016 *** (8.30)	0.011 *** (8.99)	0.008 *** (12.58)	-	-	-
ope	-	-0.084 *** (-3.57)	-0.016 (-1.49)	-	1.989 *** (5.06)	0.821 ** (2.29)
tra	-	0.003 *** (3.63)	-0.002 *** (-3.93)	-	-0.074 *** (-5.16)	-0.121 *** (-6.76)
com	-	0.003 *** (4.36)	0.003 ** (2.20)	-	-0.031 ** (-2.36)	0.115 *** (2.85)
cap	-	-0.003 *** (-4.18)	0.003 *** (6.42)	-	0.089 *** (7.75)	0.027 ** (2.01)
inv	-	0.013 *** (26.74)	0.006 *** (11.19)	-	-0.004 (-0.44)	0.143 *** (7.39)
m&x	-	0.030 *** (27.50)	-0.010 *** (-7.06)	-	-0.108 *** (-5.25)	0.187 *** (3.91)
rd	-	0.008 ** (1.99)	0.003 ** (2.05)	-	-0.097 (-1.38)	-0.075 (-1.38)
Cons	0.209	0.141	0.200	1.238	1.163	-0.832
N	2376	2376	2376	2376	2376	2376
FE	No	No	Yes	No	No	Yes
R ²	0.0282	0.6307	0.4119	0.0282	0.1053	0.3097
F	68.83 ***	505.27 ***	181.33 ***	68.83 ***	34.81 ***	116.12 ***

Notes: ***, ** stand for significant levels of 1%, 5%, respectively, and the values in brackets are T-values.

As shown in Table 5, there is a significant interaction between the level of new-urbanization and the green land utilization efficiency. Columns (1) and (4) represent the case in which individuals are not controlled, and the covariates are not considered; Columns (2) and (5) represent the situation in which individuals are not controlled, but the covariates are taken into account, and Columns (3) and (6) represent the cases where individuals are controlled, and the covariates are considered at the same time. It can be seen from Columns (1)–(3) that the green land utilization efficiency promotes the level of new-urbanization. It can be seen from Columns (4)–(6) that the new-urbanization level plays a reverse role in promoting green land utilization efficiency.

As mentioned earlier, the fixed effects regression model based on simultaneous-equations not only ignores the impact of the new-urbanization level and green land utilization efficiency in the surrounding regions on those of the local city but also does not consider the possible correlation between the endogenous variables and random disturbances in each equation. Therefore, according to Models (6) and (7), this paper uses the SS-equations and the GS3SLS to estimate the parameters of the spatial inter-spillover effect between the new-urbanization level and the green land utilization efficiency in Chinese cities. According to the setting of geospatial matrix W , the parameters of the models are estimated. Table 6 shows the results.

Table 6. Parameter estimation results of SS-equations and the GS3SLS.

Items	Explained Variable: N-urb	Explained Variable: L-eff
	(1)	(2)
$W \times N\text{-urb}$	0.940 *** (4.00)	2.173 * (1.65)
$W \times L\text{-eff}$	0.106 *** (4.27)	1.037 *** (21.53)
N-urb	-	-5.298 *** (-7.80)
L-eff	-0.109 *** (-4.94)	-
ope	0.031 (0.89)	0.382 (1.25)
tra	0.008 *** (4.96)	0.047 *** (3.87)
com	0.002 * (1.82)	0.011 (0.89)
cap	-0.004 *** (-4.19)	-0.021 ** (-2.49)
inv	0.014 *** (18.43)	0.081 *** (7.76)
m&x	0.024 *** (13.08)	0.128 *** (4.97)
rd	0.001 (0.17)	-0.006 (-0.10)
Cons	-0.082	0.117
N	2376	2376
R ²	0.9295	0.9309
F	4974.16 ***	3482.31 ***

Notes: ***, **, and * stand for significant levels of 1%, 5%, and 10%, respectively, and the values in brackets are T-values.

As shown in Table 6, there is an obvious spatial inter-spillover effect between the new-urbanization level and the green land utilization efficiency in Chinese cities. The results in Column (1) reflect that the new-urbanization level of surrounding regions positively influences the local new-urbanization level; the green land utilization efficiency of surrounding regions promotes the local new-urbanization level; the local green land utilization efficiency has a negative impact on the level of new-urbanization. The parameter estimation results of Column (2) reflect that the new-urbanization level of surrounding regions has a promoting effect on the local green land utilization efficiency; the efficiency of green land utilization of surrounding regions promotes the green land utilization efficiency of the local city; the level of local new-urbanization has a negative impact on the local green land utilization efficiency. In addition, the coefficients can be compared as the significance has passed the test and the economic meanings are the same. The promotion effect of the green land utilization efficiency in surrounding regions on the local new-urbanization level is slightly less than the negative impact of local green land utilization efficiency on the local new-urbanization level. The promotion effect of the new-urbanization level in surrounding regions on the local green land utilization efficiency is significantly less than the negative effect of the new-urbanization level on the local green land utilization efficiency.

4.2. Empirical Results Analysis

4.2.1. General Interaction Effect between New-Urbanization and Green Land Utilization Efficiency

Through spatial-econometric estimation, we find mutual inhibition effects between new-urbanization level and green land utilization efficiency. The new-urbanization level will be significantly reduced by 0.109 ($p = 0.000$) for every unit increase in green land utilization efficiency. For each unit of increase in the new-urbanization level, the green land utilization efficiency will decrease significantly by 5.298 ($p = 0.000$). In general, there is an interactive effect between the level of new-urbanization and green land utilization efficiency, and the marginal effect of the new-urbanization level on the green land utilization efficiency is more obvious, that is, the new-urbanization level takes a comparatively leading role in the reciprocal promotion relationship. China's urbanization development is still in the left-hand stage of the environmental Kuznets curve; pollution emissions increase further with the rise of per capita GDP, and industrialization features are obvious. With the population shifting from primary industry to secondary industry, heavy industrial and chemical companies develop speedily, and the discharge of industrial wastes increases. The demand for green development has also adversely affected the process of urbanization.

4.2.2. Spatial Spillover Effects between New-Urbanization and Green Land Utilization Efficiency

Through spatial-econometric estimation, this paper finds that both new-urbanization and efficiency of green land utilization have significant spatial spillover effects. The local new-urbanization level will increase significantly by 0.940 ($p = 0.000$) for each unit of increase in the new-urbanization level of surrounding regions. The new-urbanization level of adjacent cities can promote the development of local new-urbanization through industrial external expansion radiation and common market effect. The local green land utilization efficiency is significantly increased by 1.037 ($p = 0.000$) when surrounding regions' green land utilization efficiency increases by 1. The improvement of the green land utilization efficiency of surrounding regions can promote the efficiency of green land utilization of local regions through the demonstration and innovation effect and the effect of knowledge spillover.

4.2.3. Spatial Interaction between New-Urbanization and Green Land Utilization Efficiency

Through spatial-econometric estimation, we can find that the new-urbanization level of surrounding regions has a promotion effect on the green land utilization efficiency of local regions, and the development of the green land utilization efficiency of surroundings also promotes the level of local new-urbanization. The green land utilization efficiency of

local regions increases by 2.173 ($p = 0.093$) when the new-urbanization level of surrounding regions increases by one unit. As one of the pivotal factors of urban development and construction, the diffusion of new-urbanization to surrounding regions brings green innovation resources and knowledge spillover. The underdeveloped cities should consolidate their own development resources and actively accept the exogenous support of surrounding regions for local green development. When the green land utilization efficiency of surrounding regions increases by 1, the new-urbanization level of local regions increases by 0.106 ($p = 0.000$) significantly. Improving the green land utilization efficiency of surrounding regions leads to the optimisation of the environment of economic development and the development of the innovation ecosystem, which can have a radiation effect on the local new-urbanization. Low new-urbanization level cities need to promote its industrial structure, take the initiative to carry out mild green transformation by utilizing the diffusion mechanism of surrounding regions and relieve the environmental pressure in the process of urbanization.

4.3. Robustness Test

Based on the research of spatial inter-spillover effects between new-urbanization and green land utilization efficiency, this part examines the impact of adjusting the width of distance band and adjusting the type of spatial weight matrix on the robustness of analysis conclusions.

4.3.1. Distance-Band Robustness Test

In the process of constructing spatial effect models, the establishment of spatial weighted matrix is the first step, where the setting of the distance band is the most important part. The “number of neighbors” considered in the test of a single sample will increase with the increase in the distance band and vice versa. In order to verify the effects of adjustment of the spatial matrix range, we reduce the range from the initial setting ($W : 0$ to 30) to more minor ($W : 0$ to 20) and increase to bigger ($W : 0$ to 40), as shown in Table 7. At this time, fewer or more neighboring cities in the sample city will enter the spatial matrix, and the other settings are consistent with those in Equations (6) and (7).

Table 7. Robustness test results of distance band adjustment.

Items	W: 0 to 20		W: 0 to 40	
	Explained Variable: N-urb	Explained Variable: L-eff	Explained Variable: N-urb	Explained Variable: L-eff
	(1)	(2)	(3)	(4)
$W \times N\text{-urb}$	0.525 ** (2.37)	2.325 * (1.66)	1.071 *** (5.26)	1.111 (0.69)
$W \times L\text{-eff}$	0.119 *** (4.24)	1.019 *** (23.53)	0.063 *** (2.65)	1.060 *** (20.35)
N-urb	-	-5.472 *** (-12.93)	-	-4.538 *** (-4.26)
L-eff	-0.141 *** (-6.63)	-	-0.070 *** (-3.20)	-
ope	0.071 *** (1.54)	0.491 (1.60)	0.008 (0.26)	0.622 * (1.82)
tra	0.010 *** (5.21)	0.056 *** (4.47)	0.008 *** (5.64)	0.050 *** (3.68)
com	0.003 * (1.70)	0.013 (1.08)	0.002 *** (2.65)	0.008 (0.69)
cap	-0.004 *** (-3.17)	-0.020 *** (-2.58)	-0.005 *** (-5.61)	-0.019 * (-1.78)
inv	0.014 *** (14.39)	0.078 *** (9.23)	0.014 *** (21.81)	0.071 *** (4.85)
m&x	0.024 *** (10.79)	0.129 *** (6.29)	0.024 *** (16.31)	0.108 *** (3.17)
rd	0.001 (0.13)	0.002 (0.03)	0.003 (0.50)	-0.022 (-0.34)
Cons	0.049	0.138	-0.104	0.192
N	2376	2376	2376	2376
R ²	0.1519	0.9523	0.9786	0.9338
F	356.09 ***	5124.91 ***	15989.13 ***	3518.62 ***

Notes: ***, **, and * stand for significant levels of 1%, 5%, and 10%, respectively, and the values in brackets are T-values.

According to Table 7, we can find that the estimation result is still robust, and adjustment of the distance band does not bring a different result from the initial setting ($W : 0$ to 30) estimation result. Firstly, there is a mutual inhibition effect between the new-urbanization and the green land utilization efficiency, and the new-urbanization is in a relatively advantageous position ($W : 0$ to 20 , $\alpha_3 = -0.141$, $\beta_3 = -5.472$; $W : 0$ to 40 , $\alpha_3 = -0.070$, $\beta_3 = -4.538$). Secondly, both the level of new-urbanization and the green land utilization efficiency have significant spatial spillover ($W : 0$ to 20 , $\alpha_1 = 0.525$, $\beta_1 = 1.019$; $W : 0$ to 40 , $\alpha_1 = 1.071$, $\beta_1 = 1.060$). Finally, the new-urbanization level of surrounding regions has a promoting effect on the efficiency of green land utilization of local regions, and the promotion of the green land utilization efficiency of surrounding regions also has a promoting effect on the indigenous new-urbanization level ($W : 0$ to 20 , $\alpha_2 = 0.119$, $\beta_2 = 2.325$; $W : 0$ to 40 , $\alpha_2 = 0.063$, $\beta_2 = 1.111$).

4.3.2. Robustness Test of Adjusting the Spatial Weighted Matrix Type

The specification of the spatial weight matrix may influence the test result of the spatial estimation. The spatial weight matrix usually includes two forms: one is a quantitative matrix with the reciprocal of the distance between samples as the weight; the other is a qualitative weight matrix which divides the distance between samples into two parts according to the “neighbor relationship” and “non-neighbor relationship”. In the estimation above, the distance weighted matrix of numerical-type is initially used to characterize the proximity of the connection among samples. In this part, the distance weight matrix of adjacent is used, which means the distance among adjacent sample cities is 1, and the distance among other sample cities is 0. The spatial effects between the new-urbanization level and the green land utilization efficiency are investigated using the adjusted spatial weighted matrix in combination with different distance band settings. Table 8 shows the analysis results.

Table 8. Robustness test of adjusting the spatial weighted matrix type.

Items	W: 0 to 20 (Qualitative Weight Matrix)		W: 0 to 30 (Qualitative Weight Matrix)		W: 0 to 40 (Qualitative Weight Matrix)	
	Explained Variable: N-urb	Explained Variable: L-eff	Explained Variable: N-urb	Explained Variable: L-eff	Explained Variable: N-urb	Explained Variable: L-eff
	(1)	(2)	(3)	(4)	(5)	(6)
$W \times N\text{-urb}$	0.240 (0.91)	1.586 (0.52)	0.276 (0.78)	4.815 * (1.58)	1.550 *** (6.23)	11.301 *** (3.15)
$W \times L\text{-eff}$	0.097 *** (−0.91)	1.141 *** (13.69)	0.107 *** (8.07)	1.081 *** (12.94)	0.039 *** (3.07)	0.894 *** (10.00)
N-urb	-	−7.977 *** (−13.31)	-	−8.816 *** (−16.90)	-	−8.040 *** (−7.57)
L-eff	−0.069 *** (−6.81)	-	−0.090 *** (−11.31)	-	−0.057 *** (−5.67)	-
ope	0.001 (0.03)	0.464 (1.36)	0.036 (1.06)	0.437 (1.29)	−0.021 (−0.74)	0.444 (1.27)
tra	0.007 *** (6.64)	0.076 *** (5.63)	0.008 *** (6.11)	0.073 *** (5.48)	0.007 *** (6.48)	0.069 *** (4.95)
com	0.003 *** (3.09)	0.022 * (1.83)	0.003 *** (6.11)	0.026 ** (2.16)	0.003 *** (3.92)	0.024 * (1.91)
cap	−0.002 ** (−1.98)	−0.028 ** (−2.23)	−0.005 *** (−4.29)	−0.042 *** (−3.51)	−0.007 *** (−7.67)	−0.054 *** (−3.87)
inv	−0.002 *** (22.34)	0.108 *** (10.42)	0.014 *** (20.09)	0.124 *** (12.40)	0.014 *** (24.63)	0.115 *** (7.33)
m&x	0.028 *** (21.36)	0.213 *** (8.78)	0.027 *** (18.24)	0.238 *** (10.54)	0.028 *** (23.29)	0.216 *** (6.07)
rd	0.005 (0.92)	0.014 (0.22)	0.003 (0.53)	0.016 (0.25)	0.005 (0.99)	0.006 (0.09)
Cons	0.156	0.480	0.048	−0.047	−0.188	−1.381
N	2376	2376	2376	2376	2376	2376
R ²	0.9838	0.9698	0.9589	0.9729	0.9900	0.9768
F	21611.99 ***	9652.20 ***	8485.45 ***	11001.47 ***	33120.49 ***	12386.61 ***

Notes: ***, **, and * stand for significant levels of 1%, 5%, and 10%, respectively, and the values in brackets are T-values.

According to Table 8, we can find that the estimation result is still full of robustness, and the specification of adjusting the spatial weighted matrix does not bring a different result from the initial setting ($W: 0$ to 30 , quantitative weight matrix) estimation result. Firstly, there is a mutual inhibition effect between the level of new-urbanization and the green land utilization efficiency, and the level of new-urbanization is in a relatively advantageous position ($W: 0\text{--}20$ contiguity, $\alpha_3 = -0.069$, $\beta_3 = -7.977$; $W: 0\text{--}30$ contiguity,

$\alpha_3 = -0.090$, $\beta_3 = -8.816$; W: 0–40 contiguity, $\alpha_3 = -0.057$, $\beta_3 = -8.040$). Second, both the new-urbanization level and the green land utilization efficiency have significant spatial spillover effects (W: 0–20 contiguity, $\alpha_1 = 0.240$, $\beta_1 = 1.141$; W: 0–30 contiguity, $\alpha_1 = 0.276$, $\beta_1 = 1.081$; W: 0–40 contiguity, $\alpha_1 = 1.550$, $\beta_1 = 0.894$). Finally, the new-urbanization level of surrounding regions has a promoting effect on the green land utilization efficiency of local regions, and the increase in the green land utilization efficiency of surrounding regions also has a promoting influence on the local new-urbanization level (W: 0–20 contiguity, $\alpha_2 = 0.097$, $\beta_2 = 1.586$; W: 0–30 contiguity, $\alpha_2 = 0.107$, $\beta_2 = 4.815$; W: 0–40 contiguity, $\alpha_2 = 0.039$, $\beta_2 = 11.301$).

In a word, the conclusions reached through the SS-equations and the GS3SLS are effective and robust. We can accept hypotheses H2–H4.

5. Conclusions and Implications

There is a complicated interaction and spillover mechanism between the new-urbanization level and the green land utilization efficiency, and the spatial inter-spillover effects of the two deserve further investment due to the significant spatial distribution features. This paper uses the entropy weight method and super-efficiency SBM-GML(DEA) model to calculate the new-urbanization level and the green land utilization efficiency of 297 cities in China from 2011 to 2018, respectively. Based on the analysis method of spatio-temporal evolution characteristics, SS-equations and the GS3SLS, this paper draws the following conclusions.

First, the new-urbanization level and the green land utilization efficiency in Chinese cities have common and complex spatio-temporal evolution characteristics. (1) From the perspective of global temporal dynamic evolution, the new-urbanization level and the green land utilization efficiency in Chinese cities show an upward trend as a whole, and the differences show a trend of continuous narrowing. The new-urbanization level and the green land utilization efficiency of cities in high-value regions have increased, and the proportion of cities in high-value regions has also increased. (2) From the perspective of regional and temporal dynamic evolution, the new-urbanization level and the green land utilization efficiency of the three regions all have prominent upward evolution characteristics, and the level gap shows a narrowing evolution trend. The new-urbanization level of central and western cities shows a two-level differentiation feature. The new-urbanization level and the green land utilization efficiency of high-value cities in the three regions have increased, and the proportion of high-value cities has also increased. (3) From the perspective of the global spatial pattern evolution, there is a significant positive global spatial auto-correlation in the spatial distribution of the new-urbanization level and the green land utilization efficiency in Chinese cities. The global spatial correlation of the new-urbanization level has evolved from a weak correlation to a strong correlation, and the global spatial correlation of the green land utilization efficiency presents the evolution characteristics of alternating between strong and weak correlation. (4) From the perspective of regional spatial pattern evolution, there is spatial proximity peer effect in Chinese cities' new-urbanization level and green land utilization efficiency. When the core variables in the adjacent cities around the local city are at a higher (lower) level, the local city is also more likely to become a higher (lower) level city, or it is more difficult for the local city to "highlight the encirclement" to transfer to a low (high) level city. Therefore, Chinese cities' new-urbanization and green land utilization efficiency have formed the spatial pattern of "the low is always low and the high is always high".

Secondly, there are spatial inter-spillover effects between the new-urbanization level and the green land utilization efficiency in Chinese cities. (1) There are mutual inhibition effects between the new-urbanization level and the green land utilization efficiency, and the former is in a comparatively leading role. (2) Both the new-urbanization level and the green land utilization efficiency have obvious spatial spillover effects. (3) The new-urbanization of surrounding regions has a promotion effect on the green land utilization efficiency of

the local, and the increase in the green land utilization efficiency of surrounding regions also has a promotion effect on the new-urbanization of local cities.

The conclusions of this paper can provide a reference for strategies of developing new-urbanization and green land utilization efficiency in various countries and regions. First, it is essential to balance the new-urbanization level and green land utilization efficiency development between regions, breaking the spatial pattern of “the low is always low, and the high is always high”. Developing cities in backward areas should learn from the experience and practice of green utilization and management of land resources of neighboring cities, eliminating backward industries or carrying out green renewal. Cities in advanced regions should use their own advantages to help neighboring cities carry out industrial renewal and pollution control in land development and improve the green efficiency of new-urbanization and land use, playing a leading effect in promoting the progress of urbanization.

Second, the government should actively optimize the layout of new-urbanization and enhance the positive traction of the new-urbanization construction on urban land utilization efficiency. At the present stage, the development of new-urbanization did not play a positive role in green land use within a city. The urban construction land area is not necessarily better for being bigger. Factors such as the suitability of land spatial development and resource and environmental carrying capacity should be fully considered. The government should continue to push forward regional national spatial planning, promoting “multiple planning compliance”. In addition, the government should encourage the scientific connection and hybrid nesting of various functional areas within a city, optimizing the allocation of urban land resources, clearing and disposing of approved but idle land, revitalizing the inefficient stock of construction land so as to fundamentally guarantee to ensure the intensive, circular, and efficient improvement of urban land utilization in the process of new-urbanization.

Third, the government should optimize the industrial structure between and within cities. New technologies, such as information technology and digitalization, should be adopted to transform traditional industries, form an industrial structure dominated by high-end manufacturing and producer services, and foster a modern industrial system with high added value. Land use targets should favor tertiary industry with lower pollution, lower energy consumption, and higher efficiency. The local governments should step up efforts to attract investment, encourage enterprises to concentrate on layout and scale operations, give full play to the advantages of scale economies, and increase the efficiency of each unit of land.

Fourth, the allocation effect and the baton role of green land utilization efficiency should be brought into play. From the competitive perspective of regional green development, it is an alternative to promote local new-urbanization by promoting the urban green land utilization efficiency to absorb industrial and innovative factors. In general, countries and regions need to implement domestic and foreign strategies such as land-use policy, urban development, green technology, environmental protection, and the supply side according to their own actual national conditions from the above perspective, improving the pertinence of countermeasures and gradually improving the level of urbanization and green development capacity.

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