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Research Article

Investigating the Spatiotemporal Disparity and Influencing Factors of Urban Construction Land Utilization Efficiency: Empirical Evidence from Panel Data of China

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This paper corrected the long-term misunderstanding of the land utilization efficiency concept. The Undesirable-Window-DEA model, Dagum Gini coefficient, and spatial panel autoregressive model with fixed effect were used to explore the spatial heterogeneity and influencing factors of urban construction land utilization efficiency in China from 2004 to 2016. The results show the following: (1) China's overall utilization of urban construction land is still at a low level. It decreased first and then rose, with a "flat V-shaped" evolution pattern. (2) During the study period, the Gini coefficient of urban construction land utilization efficiency for all provinces decreased first, then rose, and decreased again. The utilization efficiency Gini coefficients within provincial grouping were eastern region (0.063), central region (0.101), and western region (0.128). The Gini coefficients within provincial grouping were central versus western (0.121), eastern versus western (0.161), and eastern versus central (0.168). For the contribution to overall inequality of land utilization efficiency, the inequality within groups contributes the most (57.57%), and the inequality between groups accounts for about 25.62%. The overall efficiency is improved, with an evolution pattern of "difference narrowed–differences expanded–difference narrowed." (3) "economic development," "industrial structure," "research development investment," and "land urbanization level" have significantly positive effect on urban construction land utilization efficiency, while other factors have a negative effect, including "urbanization level of population," "urban population density," "cultivated field resources level," "government influence level," "land urbanization level," and "financial dependence level." This study could provide theoretical support for the implementation of cross-provincial/regional urban construction land quotes reallocation and differential construction land management policies.

1. Introduction

Under the background of increasing resource and energy constraints and environmental constraints, the traditional development path of combining excessive consumption with low efficiency of land resources has become unsustainable. Improving the efficiency of urban land use has become an inherent requirement for promoting regional sustainable development [1, 2]. The improvement of land use efficiency also has a sustainable development effect on the transformation of industrial structure [3]. The urban construction land quotas of province or region in China are allocated by the central government under the national total amount control principle. Such allocation operation ignores the different economic development levels and uneven natural resources distribution among provinces [4], combined with the lack of provincial-level construction land quote trading market, and legal provisions for the prohibition of interprovincial circulation of construction land quotas for nonstate major projects. The above reasons result in an inefficient allocation situation that provinces having higher construction efficiency need more quotas, while there are surplus quotas for those having lower utilization efficiency.

Due to the internal differences among resource endowments and socioeconomic contexts in China, it is necessary to explore spatial patterns and regional differences of land use efficiency among the eastern, central, and western parts of China [5]. The previous studies on China focus only on a single city or urban agglomeration [6, 7], the conclusions from which cannot be applied to the regional or national scales. How can the overall urban construction land utilization efficiency in China be improved? Should we implement the reallocation of construction land quotas through the market mechanism to maximize efficiency? These topics attracted researchers' interests and attention.

The existing literature mainly concentrated on theory research and evaluation of urban construction land utilization efficiency. (1) For theory research, the topics include the connotation and significance of urban construction land utilization efficiency [8–10], behavioral models of urban construction land users and their decision-making process [11], and the motivation and influence of authority in urban construction land utilization [12]. (2) Regarding evaluation and optimization of urban construction land utilization efficiency, researchers utilized various models to measure the utilization efficiency of urban construction land in a certain area [13, 14], depicted the temporal and spatial characteristics of utilization efficiency [15, 16], analyzed the influencing factors [17, 18], and introduced various countermeasures and policy recommendations [19]. In the existing research, land utilization efficiency is regarded as the total factor productivity or overall efficiency. For the evaluation of land utilization efficiency, the most used method is difficult to balance the evaluation efficiency index and cannot compare the dynamic trend of efficiency vertically and appropriately. In addition, most studies simplified the efficiency evaluation. Only a few of them combined spatial differences in urban construction land utilization efficiency with China's existing urban construction land quota allocation methods and management systems but still limitedly explain on practical issues.

Clarifying the utilization efficiency of urban construction land in China's provinces and spatial heterogeneity and influencing factors of urban construction land utilization efficiency in China is of great realistic significance for promoting the coordination of "resources-economy-environment" and achieving green development. This paper used the Undesirable-Window-DEA model to measure the utilization efficiency of urban construction land in China's provinces and quantitatively explored the spatial and temporal characteristics of construction land utilization efficiency by means of Dagum model; then a spatial panel model was applied to analyze the influencing factors of urban construction land utilization efficiency. The remaining part of this paper is organized into five sections. The related literature review is conducted in the second section. The third section introduces research methods and study data. The fourth section measures the land utilization efficiency in China and analyzes the spatial and temporal disparity and influencing factors. The fifth and sixth sections draw some conclusions and discuss the policies and suggestions for the redistribution of urban construction land quotas.

2. Literature Review

The existing research on urban construction land utilization efficiency mainly focuses on efficiency evaluation, temporal and spatial characteristics study, influencing factors, and improvement approaches.

2.1. The Land Utilization Efficiency Evaluation Indicators. Efficiency evaluation indicators are developed from a single economic indicator to a comprehensive indicator including economic, social, and ecological factors [20]. Shao et al. used the construction land area as input indicator and nonagricultural outcome as an output indicator to evaluate the output efficiency of construction land in various provinces in China during 1998–2008 [21]. Yang et al. selected the construction land area to represent land input, the whole society's fixed assets investment to represent capital input, and the number of employees in the secondary and tertiary industries to represent labor input, respectively. The added value of the secondary and tertiary industries, the average wage of employees, and construction maintenance funds are utilized as expected output indicators; industrial wastewater discharge, industrial waste gas emissions, and industrial solid waste emissions are considered as unexpected indicators; and then the urban land utilization efficiency of 16 cities in the Yangtze River Delta region is measured [22]. Zhong and Hu selected capital stock, nonagricultural industry employees, and urban construction land area as input indicators and used nonagricultural industry output value and green space area as output indicators to empirically analyze the utilization and allocation efficiency of urban construction land in 30 provinces and 275 prefecture-level cities in China from 2005 to 2012 [23].

Primary efficiency evaluation methods include coordination degree model, regression analysis method, and data envelopment method (DEA). Wang and Song established a coordination degree model to evaluate the comprehensive benefits and trends of land utilization of 14 cities in China [24]. Chen et al. used the C-D production function to measure the contribution rate to the regional economic growth of farmland used for nonfarming purposes in China's various regions from 1989 to 2001 [25]. Zhang and Wu applied DEA to measure the utilization efficiency of urban construction land in China from 2003 to 2014 and analyzed the spatial and temporal differences [26]. Wang et al. used the DEA model and the Malmquist productivity index to measure and analyze the overall and different types of land utilization efficiency and their changes in 21 development zones in Shanghai during 2006–2011 [27]. Yang et al. built the SBM-undesirable model to measure the land utilization efficiency of 16 cities in the Yangtze River Delta region [22].

2.2. The Influencing Factors of Land Utilization Efficiency. The studies of influencing factors vary due to the differences in research perspectives, but primary streams concentrate on capital, labor, land, management, and technology [23]. Zhao et al. used the Tobit model to examine how the construction land utilization efficiency in various provinces from 2003 to 2012 was impacted by many factors, including economic development level, the ratio of capital to labor, the industrial structure, the government's public finance expenditure and law-enforcement efficiency against land violations, and the fixed capital stock on the construction land [28].

The research methods of influencing factors mainly include panel data model, geographically weighted regression model, and spatial panel data model. Chen and Wu used the panel data model to examine the influencing factors of the economic efficiency of urban construction land in the Yangtze River Delta region from 1996 to 2008 [29]. Zhang and Jin examined the influencing factors of construction land utilization efficiency in 41 cities in the middle reaches of the Yangtze River between 2000 and 2014 by the means of geoweighted regression models [30]. Bei used the spatial panel data model to examine the urban construction land utilization efficiency in various provinces in China from 1999 to 2008 [31]. Wu et al. used the Tobit model to test the influence of the economic scale, investment scale, city size, industrial structure, population factor, spatial factor, and government regulation on Hunan Province's total factor productivity of urban land use during 2004–2014 [20].

2.3. The Characteristics of China Land Utilization Efficiency. The existing research proved that there is a spatial difference in urban construction land utilization efficiency, but whether the difference is convergence or diffusion is controversial due to the differences in research realms. Zhang measured the land utilization efficiency of 622 cities in China in 2010 using the Bootstrap-DEA model. The results showed that urban land utilization efficiency in China is relatively low, and there are significant regional differences. In addition, it is proved that the city scale, land acquisition, and land sale finance have a significantly negative impact on land utilization efficiency. It is believed that the key to improving the utilization efficiency of urban construction land is to enhance the land market's role [32]. Li et al. used GIS spatial analysis, Theil Index, and panel data model to study the spatial and temporal characteristics, regional differences, and influencing factors of urban construction land utilization efficiency of 31 provinces in China from 1999 to 2011 [33]. Lu et al. analyzed the variation tendency and spatial correlation of the urban land efficiency values of 28 cities in the Urban Agglomeration in the middle reaches of Yangtze River from 2003 to 2015 by the means of DEA. The results show significant spatial disparity of land utilization efficiency during the study period; however, the spatial spillover effect of urban land utilization efficiency is weak. The newly added urban land area has a negative effect on land utilization efficiency, while the coefficient of the influence of fiscal expenditure, foreign direct investment, and per capita GDP is significantly positive. The population factor has no significant effect on land utilization efficiency [34]. From the perspective of spatial and temporal heterogeneity, He et al. empirically analyzed the impact of urban form on land use efficiency. They used patch density, mean patch size, edge density, mean shape index, and patch cohesion index to describe urban morphology. They believed that there were great regional differences in urban morphology and land use efficiency between 2005 and 2015 in China. It was found that the influence of urban form on land use efficiency varies significantly with the region and city size. Although high patch density and large urban patch size have a positive effect on large-scale urban land use efficiency, it is not conducive to the improvement of land use efficiency in small cities [35].

2.4. The Three Issues of China Land Utilization Efficiency

2.4.1. The Connotation of Land Utilization Efficiency Evaluation Is Unclear. Most studies equate the overall production efficiency with land utilization efficiency. However, the overall production efficiency only takes the radial adjustment into account, and slack adjustment is not considered. Thus, the measurement result is the comprehensive utilization efficiency of total factor productivity. It could be called capital utilization efficiency or labor utilization efficiency, as well as land utilization efficiency [5, 36, 37]. He et al. used the added value of the secondary and tertiary industries per square kilometer as the indicator of land use efficiency and the dependent variable [35]. The added value of the secondary and tertiary industries per square kilometer is the result of the interaction of labor, capital, land, and other elements. It is obvious that other factors are not excluded when the added value of secondary and tertiary industries per square kilometer is used to measure the efficiency of land use contribution. That is to say, a local land area is small (denominator is small), but the added value of the secondary and tertiary industries is large. So, the efficiency of land use must be large. However, this concept does not consider the possibility that the local labor and capital investment are very large. Therefore, this is not land use efficiency.

2.4.2. The Limitation of Research Methods. Undesired output was not considered in the classical DEA model, and the effective index cannot be compared vertically. In addition, the model cannot solve the sorting problem that the decision unit efficiency is greater than 1. Undesirable-Windows-DEA model has both nondimensional and nonangle characteristics. It also satisfies the sorting problem of multiple decision-making units with efficiency greater than 1, while incorporating undesirable output into the evaluation index. Combined with *Malmquist* or *Luenberger productivity index*, the index of unit efficiency evaluation can be compared vertically and dynamically [38]. However, this method may lead to a bias in the efficiency growth index due to the inability to properly reflect the characteristics of technological progress [39]. In addition, the analysis of influencing factors is mainly based on the ordinary panel regressions, such as Tobit and Probit. Few kinds of research focus on spatial correlation.

2.4.3. The Evaluation Indicators Are Inadequate. The single indicator method only takes individual inputs and outputs into account and cannot fully reflect the efficiency of multiple input factors in land utilization. The comprehensive index method is subjectively determined by the weight of the index and is likely to cause bias in the evaluation results. Although some studies construct the evaluation system with multiple input and output indicators, they do not take the undesirable output into consideration. Energy consumption indicator is neglected in past research, which is contrary to the fact that undesirable output is mainly from energy input. Research content most focuses on simple efficiency evaluation and spatial differences of it. Few studies combine the regional differences in land utilization efficiency with the allocation patterns of urban construction land quotas and the spatial optimization of resources.

This paper redefined the efficiency of urban construction land utilization; namely, the efficiency of urban construction land utilization = (the actual investment in urban construction land–adjusted urban construction land investment)/the actual investment inland construction. We used the Undesirable-Windows-DEA model to evaluate the utilization efficiency of urban construction land in China's provinces. To our knowledge, no study yet has applied Undesirable-Window-DEA model to the land utilization research. The method takes the undesirable output into consideration, has the nondimensional and nonangle characteristics, and can effectively solve the sorting problem that the efficiency of multiple decision-making units is greater than 1. Additionally, the DEA window analysis method can measure the trend of the efficiency of all decision-making units in time series.

3. Methods and Data

3.1. Method. The Undesirable-Window-DEA model, Dagum Gini coefficient, and spatial panel autoregressive model with fixed effect were used to explore the spatial disparity and influencing factors of urban construction land utilization efficiency in China from 2004 to 2016. The analytic framework is seen in Figure 1.

3.1.1. The Measure of Land Utilization Efficiency. The measurement of urban construction land utilization efficiency of any time point in any region is an important prerequisite for analysis. The traditional DEA method is not suitable for efficiency evaluation considering undesired outputs. It cannot measure the trend of the efficiency of decision-making units (DMU) in time series and cannot deal with the sorting problem when the efficiency of the DMU is greater than 1. Charnes et al. proposed a DEA window analysis method with nonradial, dimensionless, and nonangle features [40]. Not only is it suitable for considering the efficiency evaluation under undesired output, but also it can compare the efficiency of different DMU in the same period and compare it with its own efficiency in other periods by the moving average method [41]. Therefore, this paper chooses the Undesirable-Window-DEA model to measure the overall production efficiency of urban construction land.

The basic idea of Undesirable-Window-DEA method is as follows: firstly, we should determine the window width d. It is generally believed that setting d to 3 or 4 can achieve the best balance between reliability and stability of efficiency measures [42]. If there are T time periods, it will establish $\mathrm{T}-\mathrm{d}+1$ windows to measure the efficiency of each DMU, and each DMU obtains d efficiency values in each window. Secondly, we adopt a moving average method to obtain the efficiency of DMU at each period. For DMU $\mathbf{i}$, starting from the time period $\boldsymbol{t}=1$ $(t=1, 2, \ldots, T)$, the d efficiency values are measured in the first window. Then we move to the second time period $\boldsymbol{t}=2$, and the $\mathbf{d}$ efficiency values are measured in the second window and so on until moving to the $\mathbf{T}-\mathbf{d}+1$ time period, and the d efficiency values are measured in the last window. Finally, the average efficiency value of all the windows that belong to the $\boldsymbol{t}$ period is taken as the effective value of DMU of $\mathbf{t}$ period. The operation process is shown in Table 1.

The Undesirable-Window-DEA method is mainly used to measure the overall efficiency of multiple input factors. Suppose that there are J DMUs, $\mathbf{X_{ij}}$ is the $\mathbf{i}$-th nonurban construction land input of $\mathbf{j}$ DMU ($\mathbf{i} \in \mathbf{I}, \mathbf{j} \in \mathbf{J}$), and $\mathbf{e_{rj}}$ is the $\mathbf{r}$-th urban construction land inputs of $\mathbf{j}$ DMU ($\mathbf{r} \in \mathbf{R}$). In this paper, we call nonurban construction land input and urban construction land inputs together as total factor production factor input. $\mathbf{y_{kj}}$ is the $\mathbf{k}$-th expected output of $\mathbf{j}$ DMU ($\mathbf{k} \in \mathbf{K}$), and $\mathbf{p_{hj}}$ is the $\mathbf{h}$-th unexpected output of $\mathbf{j}$ DMU ($\mathbf{h} \in \mathbf{H}$). For any DMU, the efficiency of total factor production factor input at the $\mathbf{n}$-th time periods in the $\mathbf{m}$-th window is measured by

$$
\begin{aligned}
&E_{mn} = \min \frac{1}{2}\left(\frac{1}{R}\sum_{r=1}^{R}\theta_r^{mn} + \frac{1}{H}\sum_{h=1}^{H}\phi_h^{mn}\right), \quad m = 1,2,\ldots,(T-d+1);\ n = 1,2,\ldots,d,\\
&\left(s.t.\ \sum_{j=1}^{d\times J}\lambda_j^{mn}X_{ij}^{mn} + s_i^{X-,mn} = X_{iq}^{mn}\right), \quad i = 1,2,\ldots,I;\ j = 1,2,\ldots,d\times J,\\
&\sum_{j=1}^{d\times J}\lambda_j^{mn}e_{rj}^{mn} + s_r^{e-,mn} = \theta_{rq}^{mn}e_{rq}^{mn}, \quad r = 1,2,\ldots,R,\\
&\sum_{j=1}^{d\times J}\lambda_j^{mn}y_{kj}^{mn} + s_k^{y+,mn} = y_{kq}^{mn}, \quad k = 1,2,\ldots,K,\\
&\sum_{j=1}^{d\times J}\lambda_j^{mn}p_{hj}^{mn} = \phi_h^{mn}p_{hq}^{mn}, \quad h = 1,2,\ldots,H,\\
&\lambda_j^{mn}, s_i^{X-,mn}, s_r^{e-,mn}, s_k^{y+,mn} \geq 0,
\end{aligned}
\tag{1}
$$

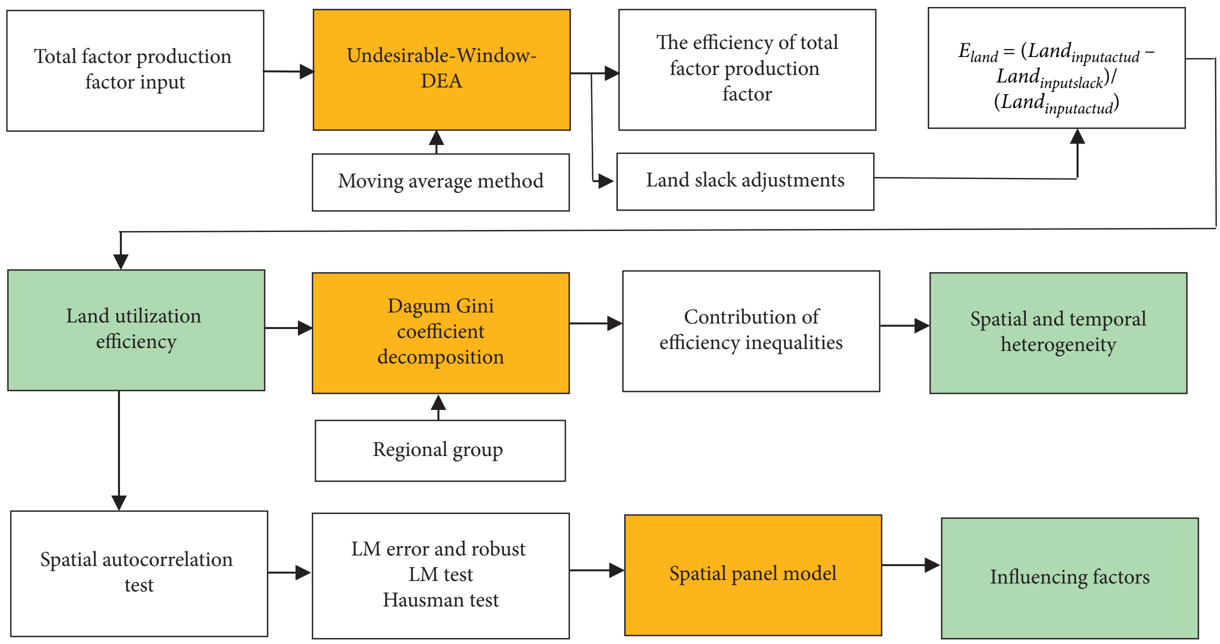


Figure 1: The flowchart and research method.

Table 1: The moving average method of efficiency for a DMU ($d = 3$).

	$t=1$	$t=2$	$t=3$	$t=4$	$t=5$	. . .	$t=T-4$	$t=T-3$	$t=T-2$	$t=T-1$	$t=T$
Window 1	$E_{1,1}$	$E_{1,2}$	$E_{1,3}$								
Window 2		$E_{2,1}$	$E_{2,2}$	$E_{2,3}$							
Window 3			$E_{3,1}$	$E_{3,2}$	$E_{3,3}$						
. . .						. . .					
Window $T-d-1$							$E_{T-d-1,1}$	$E_{T-d-1,2}$	$E_{T-d-1,3}$		
Window $T-d$								$E_{T-d,1}$	$E_{T-d,2}$	$E_{T-d,3}$	
Window $T-d+1$									$E_{T-d+1,1}$	$E_{T-d+1,2}$	$E_{T-d+1,3}$

$\mathbf{E}_{\mathbf{DMU},\,\mathbf{t}}$: average efficiency value of $\mathbf{E}_{\mathbf{m},\,\mathbf{n}}$ in windows which belong to the **t** period. $\mathrm{E}_{\mathrm{DMU},\,\mathrm{t}}$: efficiency value of DMU at the **t** period. $\mathbf{E}_{\mathbf{m},\,\mathbf{n}}$: the efficiency of DMU at the **n**-th ($n = 1, 2, \ldots, d$) time periods in the **m** window.

where E is the efficiency of total factor production factor input; θ_r is the total production factor input effect; φ_h is the total production factor output effect; λ_j is the ratio of the **j**-th DMU in the regenerated DMU set in the evaluation process. $s_i^{X-}, s_r^{e-}, s_k^{y+}$ are slack adjustments in the linear programming.

Equation (1) can measure the efficiency of total factor production factor input of each DMU and the slack adjustments of various input factors. *The existing literature equates the efficiency of total factor production factor input with urban construction land utilization efficiency, which will lead to the high utilization efficiency of urban construction land.* According to Hu and Wang [43], urban construction land utilization efficiency can be measured by

$$E_{\text{land}} = \frac{\text{Land}_{\text{input actual}} - \text{Land}_{\text{input slack}}}{\text{Land}_{\text{input actual}}}. \tag{2}$$

E_{land} is urban construction land utilization efficiency; $\text{Land}_{\text{input actual}}$– the input actual variable of urban construction land;$\text{Land}_{\text{input slack}}$ is the input slack adjustment of urban construction land, which can be obtained by equation (1).

3.1.2. The Measurement of Spatial and Temporal Disparity. We used the Dagum Gini coefficient decomposition to measure spatial and temporal disparity. The method of decomposition of the Gini coefficient in discrete space is proposed by Dagum [44]. The Dagum Gini coefficient is calculated using

$$G = \frac{\sum_{j=1}^{k}\sum_{h=2}^{k}\sum_{i=1}^{nj}\sum_{r=1}^{nh}\left|y_{ji} - y_{hr}\right|}{2n^2\overline{y}}. \tag{3}$$

G is the Gini coefficient, $y_{ji}(y_{hr})$ is individual income of $i(r)$ belonging to subgroup $j(h)$, $\overline{y}$ is the average income of all population, n is the number of all population, k is the number of subgroups, and $nj(nh)$ is the number of people in the j(h) subgroup. Dagum decomposed the Gini coefficient into three components: (1) G_w, contribution of within-group income inequalities to G; (2) G_b, the net contribution of the between-group inequalities to G measured on all population; (3) G_t, the contribution of the transvariation between the subpopulations to G. Detailed derivation and calculation process for each component is listed in [44], and the equation of Gini coefficient decomposition into three components is

$$G = G_w + G_b + G_t. \tag{4}$$

Decomposition of the Gini coefficient not only effectively solves the source of group disparities but also describes the distribution of subgroups and solves the problem of overlap between groups (shows the structure of inequality). In this paper, the Gini coefficient of urban land utilization efficiency is calculated and decomposed. All the regions involved in the evaluation were divided into three groups according to their geographical location and economic development level, namely, the eastern part of China, the central part of China, and the western part of China. *The detailed provinces/province-level municipalities included in each region are shown in* Table 2. It helps us to know if the urban construction land utilization efficiency gaps within groups generate the inequalities or if the urban construction land utilization efficiency gaps between groups engender the inequalities.

3.1.3. The Spatial Regression Models. Land use efficiency is affected not only by the endogenous features of land use patterns but also by the exogenous spatial spillover effect of land use efficiency on neighboring areas. The relative advantages of a location are enhanced by spatial spillover effects, and the land use efficiency is also thereby increased. To detect the effect of spatial spillovers, a spatial regression model is employed to calculate the relative contribution of each driving force and spatial effects toward land use efficiency. The advantage of spatial regression models over ordinary least squares (OLS) is that both the spatial heteroscedasticity and spatial dependence of error terms are considered. The estimation accuracy of spatial regression models can be ensured by effectively controlling spatial dependence in the form of lag and error dependence.

This paper assumes that a provincial land utilization efficiency is correlated with the value of neighboring provinces, and a global autocorrelation index, Moran's I, is calculated with values of all provinces to verify whether the pattern of land utilization efficiency is clustered, dispersed, or random. Once a significant spatial autocorrelation is detected, we will consider the use of spatial panel regression for exploring the relationship between land utilization efficiency and its potential influencing factors. The most used spatial panel models generally include a spatial autoregressive model (SAR) and space error Model (SEM). Each model can be divided into fixed effects and random effects. There are two criteria when choosing a model: (1) selecting SAR or SEM by robust LM error and robust LM test and (2) selecting fixed-effect model or random-effect model by Hausman test. In this study, the Hausman test-statistic showed P >0.05, indicating that the spatial fixed-effect model should be selected. The robust LM error and robust LM test show that the spatial autoregressive model is better. Therefore, we choose the spatial panel autoregressive model with fixed effect.

$$y_{it} = \rho W y_{it} + X_{it}\beta + \mu_i + \varepsilon_{it}. \tag{5}$$

Here, $i = 1, 2, \ldots, N$ are different regions; $t = 1,2, \ldots, T$ means time. y_{it} denotes urban construction land utilization efficiency, ρ denotes spatial autoregressive coefficient, W denotes spatial weights matrix, X_{it} denotes independent variable vector, μ_i denotes individual effects of spatial units, and ε_{it} denotes the error term.

3.2. Data. Due to the lack of data in Tibet and the difficulty of obtaining data in Hong Kong, Macau, and Taiwan, the scope of the study includes 30 provinces (municipalities, districts) in China. The time range for this study is from 2004 to 2016. The data in this paper are from China Statistical Yearbook (2005–2017), China City Statistical Yearbook (2005–2016), China Environmental Statistics Yearbook (2005–2017), China Energy Statistics Yearbook (2005–2017), and "Statistical Bulletin on National Science and Technology Funds Investment" (2005–2016). The total factor production factor input includes capital, labor, energy, and urban construction land. The variables required in equation (1) are shown in Table 3.

4. Results and Discussion

4.1. The Urban Construction Land Utilization Efficiency. Based on the methods introduced in Section 3.1.1, the utilization efficiency of urban construction land use in China's provinces from 2004 to 2016 is measured, and the spatial distribution maps of urban construction land utilization efficiency in China are shown in Figure 2.

4.1.1. National Level Dynamics of Land Use Efficiency. At the national level, the urban construction land utilization efficiency shows an upward trend. The national average land utilization efficiency was 0.777 in 2004 and 0.866 in 2016, with a total increase of 11.45%. The overall trend can be summarized into two phases: from 2004 to 2012, the national average land utilization efficiency showed a fluctuating downward trend, reached the bottom point (0.771) in 2012, and then rebounded to 0.866 in 2016. This dynamic change is a little different from the existing literature. In Hu's work [35], the land use efficiency demonstrates an upward trend from 2000 to 2015 at an average annual growth rate of 7.55% at national level. Our work has adopted a different measurement of land use efficiency. Although the land use efficiency from 2004 to 2016 has maintained an upward trend, the average annual growth rate is far less than 7.55%. At the same time, our data and methods also captured the decline in land use efficiency across the country in 2012. This shows that our land use efficiency measurement is sensitive enough to respond to changes.

4.1.2. Provincial Level Dynamics of Land Use Efficiency. Although the average level of land use efficiency is improved against the background of rapid urbanization and industrialization, the range of land use efficiency among provinces became larger from 2004 to 2016, illustrating the widening internal differences among provinces. There are significant differences in the efficiency and trends of urban construction land utilization at the provincial level. The average utilization efficiency of urban construction land in Zhejiang,

Table 2: The regional division of China in this study.

Eastern group	Central group	Western group
Beijing (BJ)	Shanxi (SX)	Chongqing (CQ)
Tianjin (TJ)	Neimenggu (NM)	Sichuan (SC)
Hebei (HE)	Jilin (JL)	Guizhou (GZ)
Liaoning (LN)	Heilongjiang (HL)	Yunnan (YN)
Shanghai (SH)	Anhui (AH)	Shaanxi (SN)
Jiangsu (JS)	Jiangxi (JX)	Gansu (GS)
Zhejiang (ZJ)	Henan (HA)	Qinghai (QH)
Fujian (FJ)	Hubei (HB)	Ningxia (NX)
Shandong (SD)	Hunan (HN)	Xinjiang (XJ)
Guangdong (GD)	—	—
Guangxi (GX)	—	—
Hainan (HI)	—	—

Table 3: Evaluation index of urban construction land utilization efficiency in China.

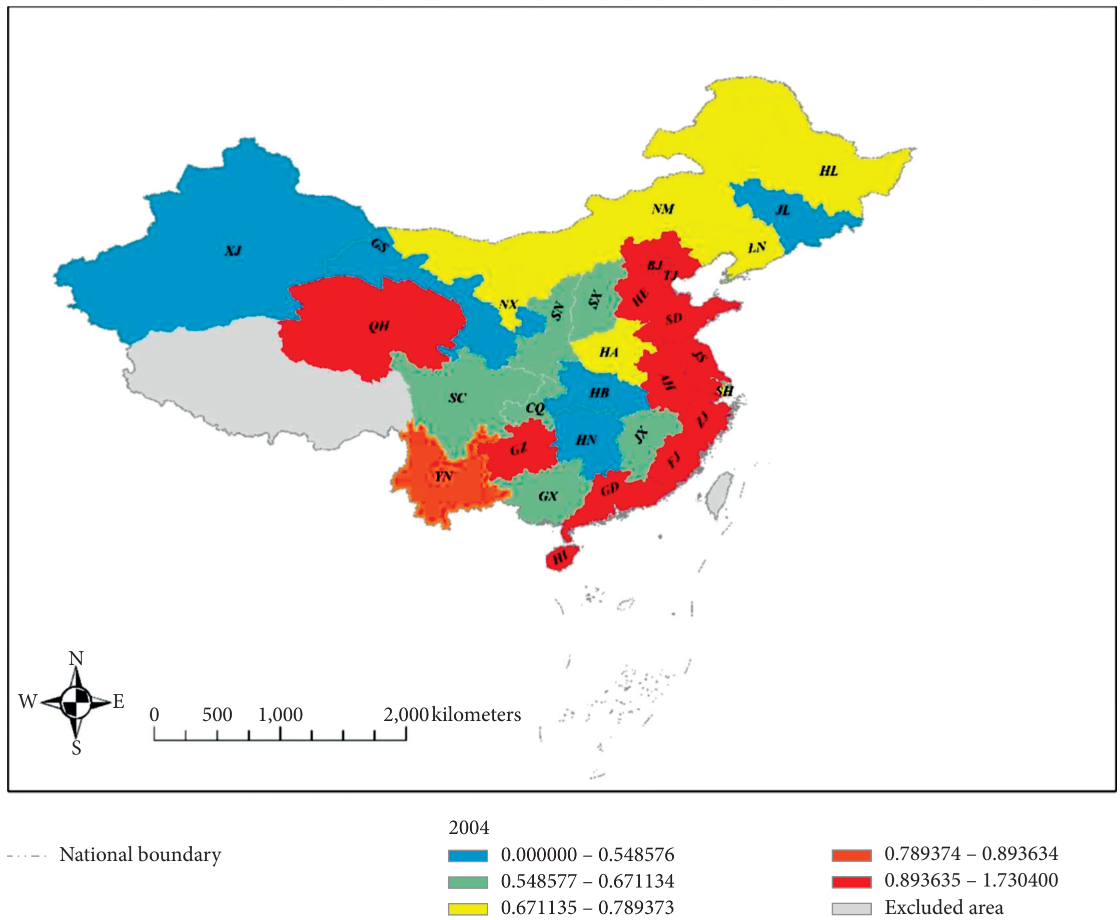
Indicators	Variables	Definition
The total factor production factor input	Urban construction land	Urban construction land area
	Capital	Fixed capital stock
	Labor	Number of urban employees at the end of the year
	Energy	Million tons of standard coal
Expected output	Economics	The output value of the secondary and tertiary industries
	Sociology	Disposable income of urban residents
	Ecology	The urban green space area
Unexpected output	Ecology	Industrial sulfur dioxide emission
		Discharge of industrial wastewater
		Discharge of industrial solid waste

Fujian, Guangdong, Hainan, and Qinghai is relatively higher (greater than 1), and the average utilization efficiency of Jilin, Gansu, and Xinjiang is relatively lower (less than 0.6). Compared with the results of literature 99 [35], the cities in the southeastern provinces such as Southern Jiangsu, Zhejiang, Fujian, and Guangdong provinces have maintained a high level of land use efficiency. The two works are consistent. During the study period, Guangdong has the highest average utilization efficiency (1.067), while Xinjiang has the lowest average utilization efficiency (0.490), with the former being 2.176 times of the latter. Some provinces' urban construction land utilization efficiency decreased overall, including Fujian, Shandong, Heilongjiang, Anhui, Guizhou, Yunnan, Gansu, and Qinghai, and the remaining provinces showed an upward trend. In Hu's work [35], cities in Beijing-Tianjin-Hebei region, Shandong, and Northern Jiangsu obviously had lower land use efficiency. This is inconsistent with the results we measured.

4.1.3. Regional Level Dynamics of Land Use Efficiency. The urban construction land utilization in eastern, central, and western cities shows a fluctuating upward trend from 2004 to 2016. The utilization efficiency of construction land in the eastern cities increased from 0.908 (2004) to 0.977 (2016), and the overall trend was fluctuating upward. The utilization efficiency of construction land in the central cities first increased from 0.648 (2004) to 0.711 (2008), with 2008 as the turning point, and then decreased to 0.654 (2011) and then climbed to 0.755 (2016); the overall trend was "rise-fall-rise." The utilization efficiency of urban construction land of the western cities first decreased and then increased. It fell from 0.730 to 0.652 during 2004–2011 and then began to rebound, reaching 0.81 in 2016. There are significant spatial differences in the urban construction land utilization efficiency in the eastern, central, and western cities. The average land utilization efficiency of these three regions is as follows: eastern (0.939) > western (0.700) > central (0.691). Overall, the land utilization efficiency in the eastern region is higher than those of the central and western regions in every year; from 2007 to 2010, the land utilization efficiency in central region was higher than that of western region; in 2011, the two were equal; in other years within the study period, the land utilization efficiency of central cities is lower than that of western cities.

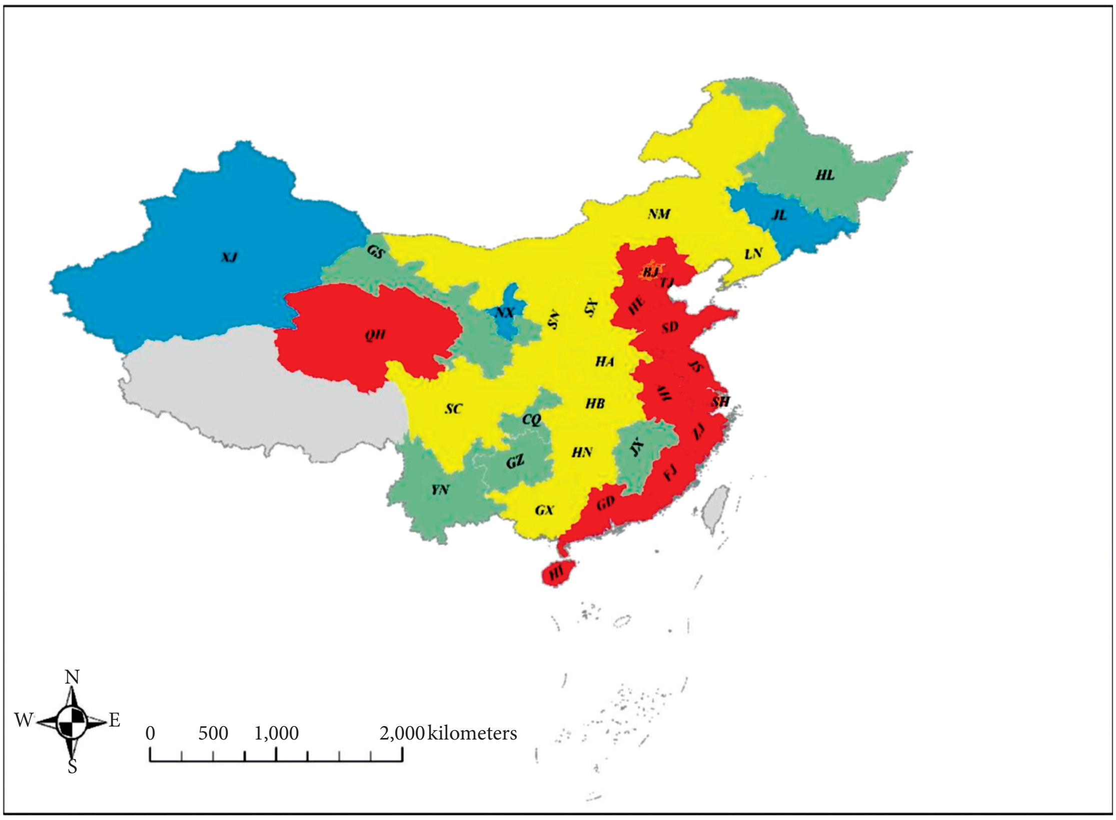
4.2. Spatial Disparity of Urban Construction Land Utilization Efficiency. Based on the methods introduced in 3.1, we calculated the Gini coefficient and decomposition results of urban construction land utilization efficiency of China and the eastern, central, and western cities of China from 2004 to 2016 (Table 4 and Figures 3 and 4).

4.2.1. Spatial Disparity of Urban Construction Land Utilization Efficiency. Firstly, the spatial differences among eastern, central, and western regions are significant, but there is a narrowing trend. During the study period, the overall regional Gini coefficient of urban construction land



(a)

Figure 2: Continued.



National boundary

2008

0.420191 – 0.548576

0.548577 – 0.671134

0.671135 – 0.789373

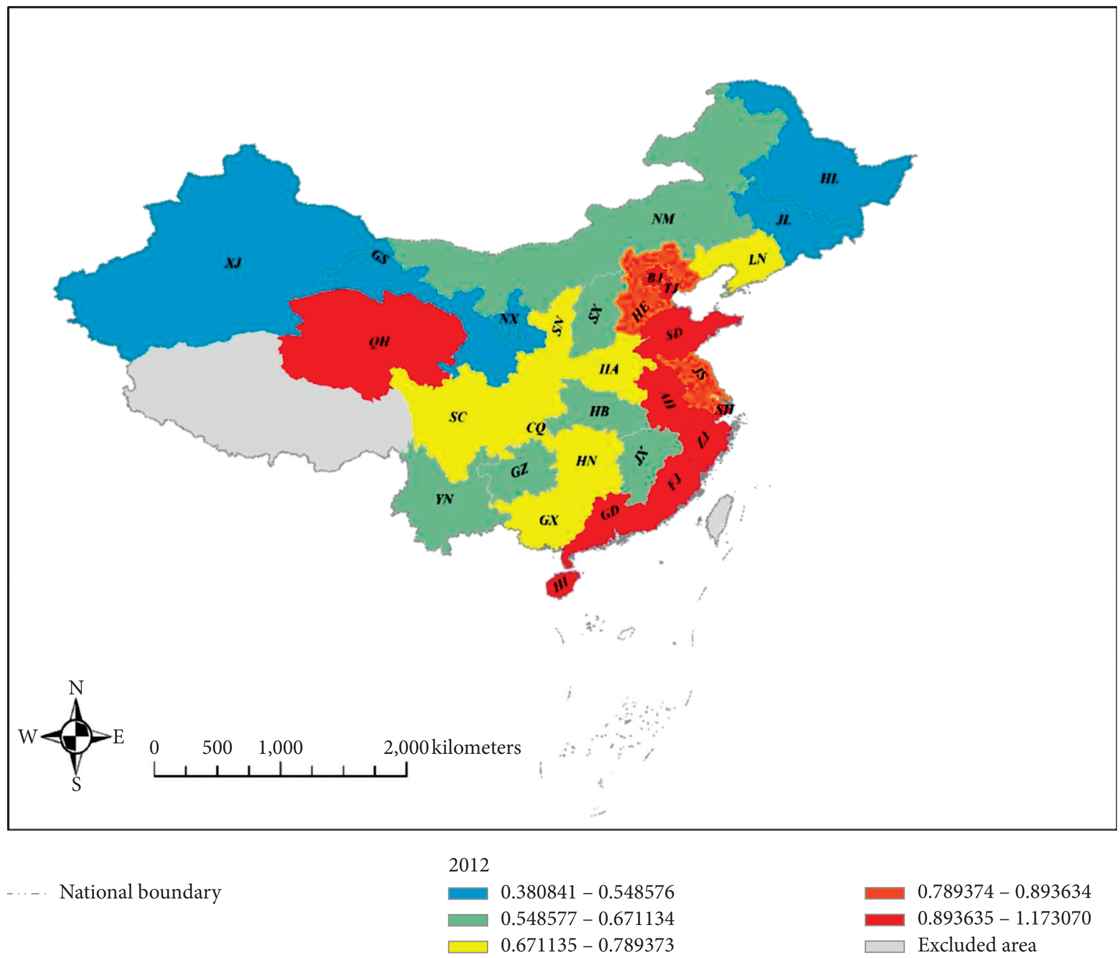
0.789374 – 0.893634

0.893635 – 1.730700

Excluded area

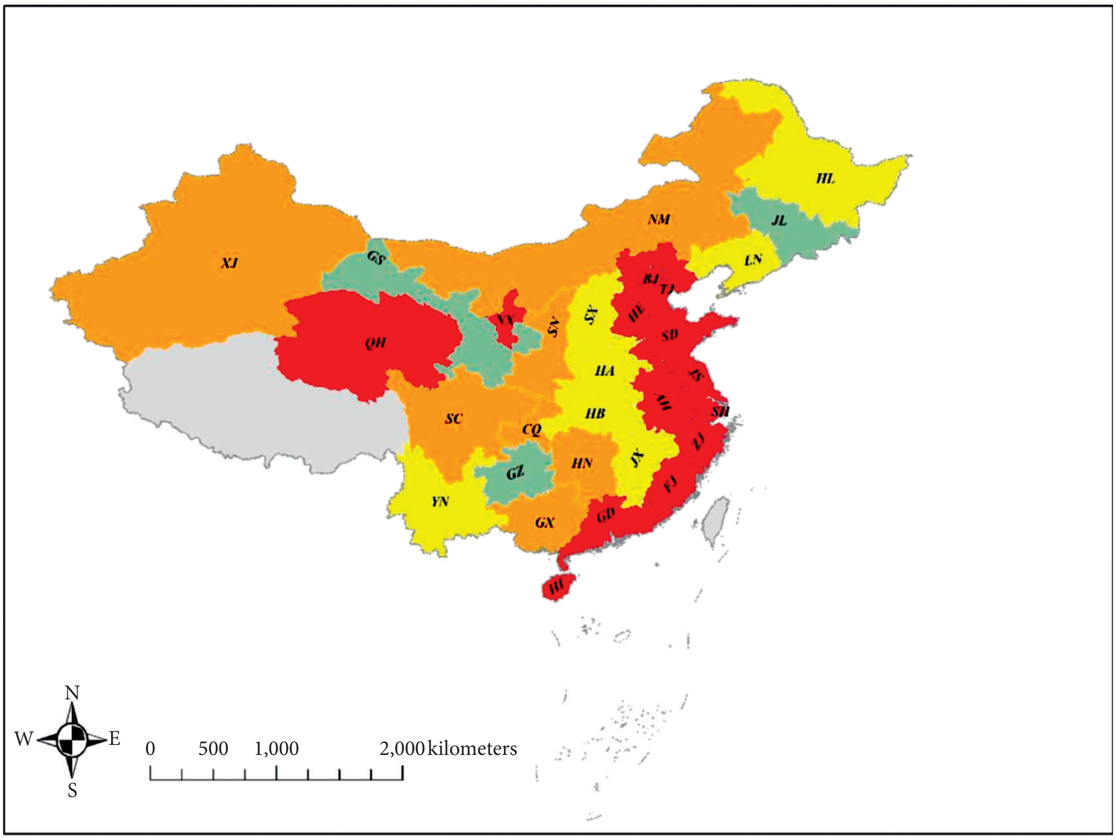
(b)

Figure 2: Continued.



(c)

Figure 2: Continued.



National boundary

2016

0.568294 – 0.671134

0.671135 – 0.789373

0.789374 – 0.893634

0.893635 – 1.173070

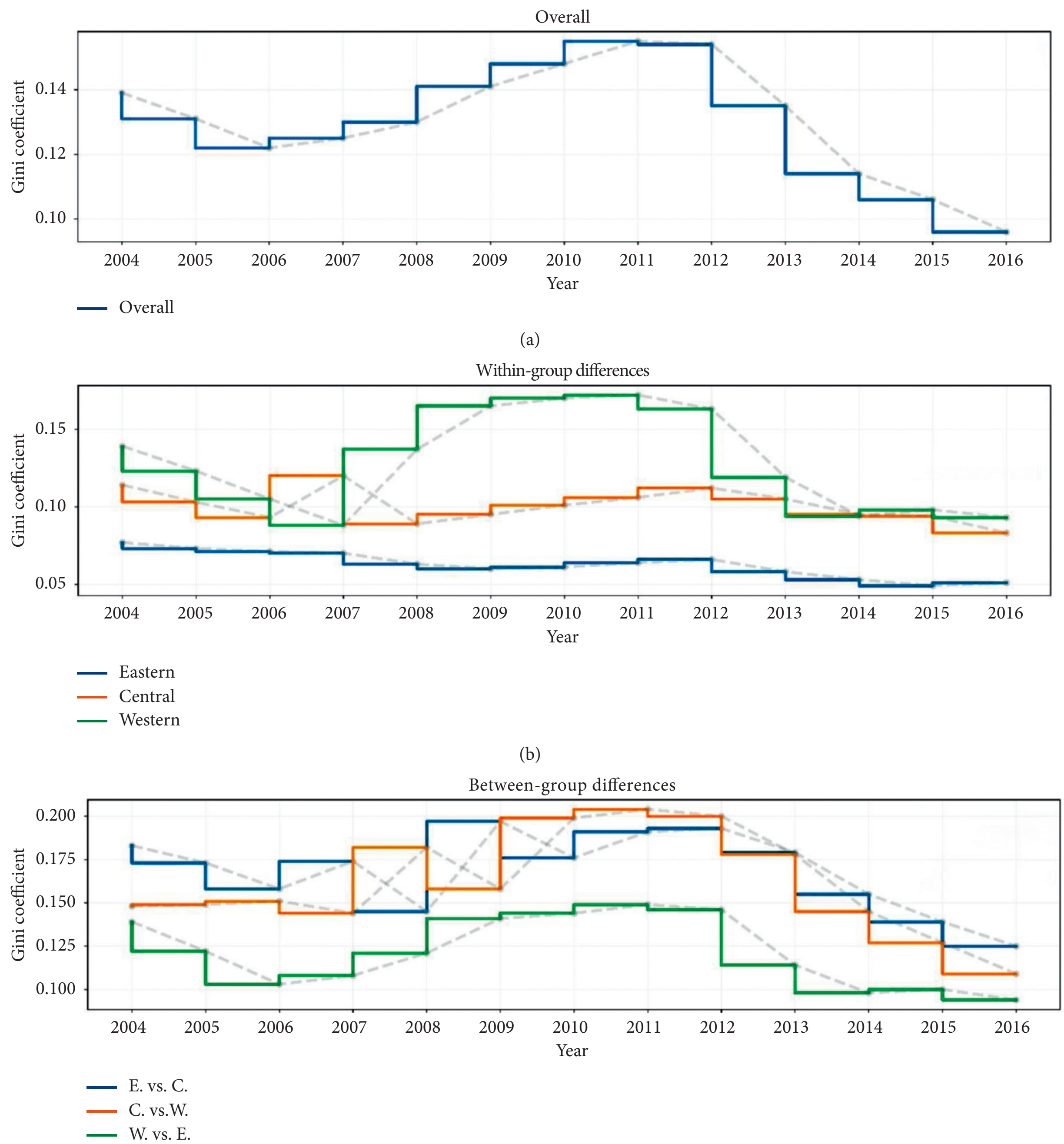
Excluded area

(d)

Figure 2: Urban construction land utilization efficiency of provinces in different years.

Table 4: Gini coefficient and decomposition results of urban construction land utilization efficiency.

Year		2004	2008	2012	2016	Mean
Overall Gini coefficient ID		0.139	0.13	0.154	0.096	0.13
Within-group differences	Eastern	0.077	0.063	0.066	0.051	0.063
	Central	0.114	0.089	0.112	0.083	0.101
	Western	0.139	0.137	0.163	0.093	0.128
Between-group differences	E. versus C.	0.183	0.145	0.193	0.125	0.168
	E. versus W.	0.148	0.182	0.2	0.109	0.161
	C. versus W.	0.139	0.121	0.146	0.094	0.121
Contribution (%)	Within	25.13	22.9	56.18	24.49	25.62
	Between	55.82	62.14	33.36	57	57.57
	Transvariation	19.05	14.96	10.46	18.51	16.81



(a)

(b)

(c)

Figure 3: Gini coefficient and decomposition of urban construction land utilization efficiency.

utilization efficiency was 0.131, with a peak value of 0.148 (2010) and a valley value of 0.096 (2016). The regional Gini coefficient decreased with an overall trend of "fall-increase-fall," which declined in the fluctuations from 0.139 (2004) to 0.096 (2016). The total decline was 30.94% and the average annual rate was 2.58%. Secondly, there are significant differences between the urban construction land utilization efficiency among the eastern, central, and western regions, but the differences show a convergence trend. The Gini coefficient of urban construction land utilization efficiency in the eastern, central, and western regions decreased from 0.077, 0.114, and 0.139 in 2004 to 0.051, 0.083, and 0.093 in 2016, respectively, with total decline percentages of 33.76%, 27.19%, and 33.09%, respectively. In terms of the average efficiency of urban construction land utilization within different regions, it is ordered as eastern region (0.063) < central region (0.101) < western region (0.128) < China (0.130). Obviously, intraregional differences are not the main source of spatial differences in urban construction land utilization efficiency. Thirdly, there are significant interregional differences among eastern, central, and western regions. Overall, the interregional Gini coefficients of urban construction land utilization efficiency are large, with the order of central versus western (0.121) < eastern versus western (0.161) < eastern versus central (0.168). However, interregional differences show a convergence trend. The Gini coefficients of central versus western, eastern versus central, and eastern versus western declined from 0.139, 0.183, and 0.148 in 2004 to 0.094, 0.125, and 0.109 in 2016, respectively. The total decline percentages were 32.37%, 31.69%, and 26.35%, respectively, with average annual rates of 2.69%, 2.64%, and 2.19%.

4.2.2. The Decomposition of Urban Construction Land Utilization Efficiency. First, the contribution rate of the interregional difference to the overall difference in urban construction land utilization efficiency is 57.57%, which is much higher than the intraregional difference contribution rate (25.62%) and the transvariation (16.81%). Second, the contribution rates of the intraregional difference, interregional difference, and transvariation to the overall difference in urban construction land utilization efficiency are generally between 21.23% and 25.13%, between 55.79% and 62.14%, and between 14.93% and 19.32%. It is worth noting that the contribution rates of the intraregional gap, interregional gap, and transvariation to the overall difference were mutated to 56.18%, 33.36%, and 10.46%, respectively, in 2012, but this change did not continue. In conclusion, interregional differences are the main source of spatial differences in urban construction land utilization efficiency.

4.3. Influence Factors of Urban Construction Land Utilization Efficiency. Based on the existing research results and data availability, this paper selected 14 indicators, and, after eliminating multicollinearity in variables, 10 variables were selected as the influencing factors of urban construction land utilization efficiency. A spatial panel autoregressive model with the fixed effect is established as

$$\begin{aligned} Y_{it} = {} & \rho WY_{it} + \beta_1 GDP_{it} + \beta_2 UP_{it} + \beta_3 IS_{it} + \beta_4 ID_{it} + \beta_5 RD_{it} \\ & + \beta_6 LU_{it} + \beta_7 CL_{it} + \beta_8 MK_{it} + \beta_9 GC_{it} + \beta_{10} LF_{it} + \varepsilon_{it}. \end{aligned} \tag{6}$$

In equation (6), i represents the study objects, and it includes 30 provinces (or cities and districts). t denotes the study period from 2004 to 2016.GDP represents the secondary and tertiary industries output. UP represents the urbanization level of population. IS represents the industry structure. ID represents the urban population density. RD represents the research development investment. LU is the land urbanization level. CL represents the cultivated field resources level. MK represents the marketization level of land. GC represents the government influence level. LF represents the land financial dependence level and ρ is the spatial lag regression coefficient. The spatial regression analysis of the sample data from 2004 to 2014 is conducted on MATLAB, and the significance of the coefficients is verified; see Table 5.

The influence factors "economic development," "industrial structure," "research development investment," and "land urbanization level" are all positively significant at 1% level. (1) The results indicate that a higher level of economic development is more likely to promote compact development, thereby reducing the consumption of urban construction land. (2) In addition, a more advanced industrial structure is more likely to increase the overall output and improve the urban construction land utilization efficiency. (3) The research development investment also plays an important role in promoting urban construction land utilization efficiency, in line with the general economic assumption that technological progress is conducive to the improvement of production efficiency. (4) Besides, the results also prove that the higher the land urbanization level, the larger the area in which urban construction land is actually used.

According to the results, other factors have a significantly negative impact on urban construction land utilization efficiency. Among them, the influence factors "urbanization level of population," "urban population density," "cultivated field resources level," and "government influence level" are significant at 1% level, and the influence factors "land urbanization level" and "financial dependence level" are significant at the 10% and 5% levels, respectively. (1) In the early stage of urbanization, the rapid population increased, and extensive land utilization not only reflected the low level of China's urbanization but also was not conducive to the improvement of urban construction land utilization efficiency. At present, a lot of Chinese cities are serving overload population more than that the urban space, resources, and land can afford, resulting in a population agglomeration effect less than its negative externalities. (2) The population load on land has not significantly promoted the compact development yet; thus, the population density has a negative effect on the urban construction land utilization efficiency at the current stage. (3) It is believed that people living in an area with rich cultivated land resources are easier to have a "mental account," which is more likely to result in extensive land use rather than intensive land use. (4)

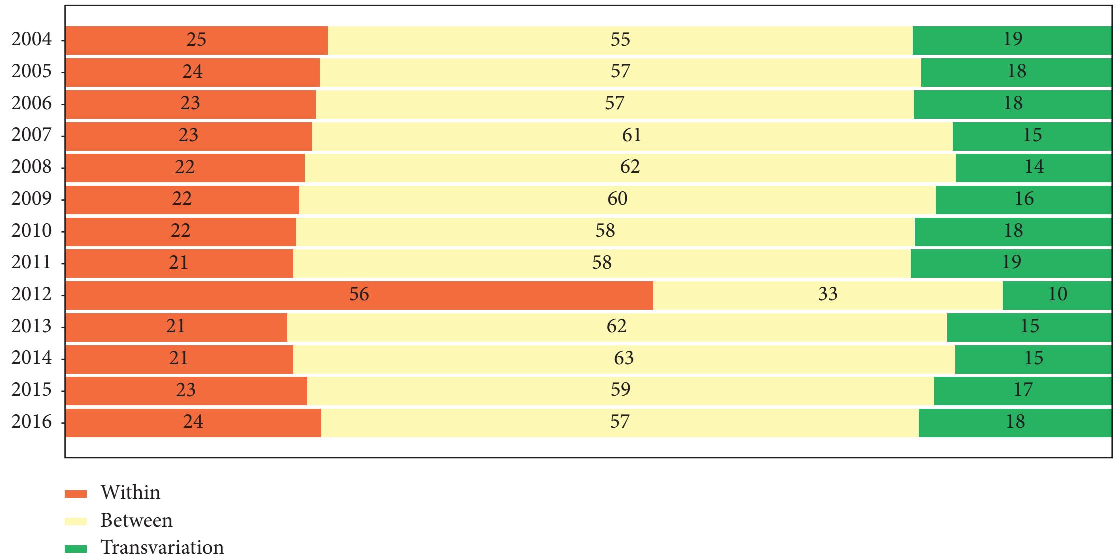


Figure 4: Gini coefficient and decomposition of urban construction land utilization efficiency.

Table 5: Estimation results of fixed-effect spatial lag panel model.

GDP	*UP*	*IS*	*ID*	*RD*	*Lu*	*CL*	*KM*	*GC*	*LF*	*W*∗dep.var.
0.393∗∗∗	−0.757∗∗∗	1.305∗∗∗	−0.295∗∗∗	0.030∗∗∗	0.220∗∗∗	−0.424∗∗∗	−0.061∗	−0.162∗∗∗	−0.064∗∗∗	−0.383∗∗
(12.674)	(−6.451)	(3.329)	(−5.348)	(3.095)	(4.255)	(−16.320)	(−1.891)	(−3.047)	(−2.288)	(−7.708)

Note: ∗ denotes significance of 10%; ∗∗ denotes significance of 5%; ∗∗∗ denotes significance of 1%; *t* values are given in parentheses.

The results show that government influence has a negative effect on urban construction land utilization efficiency, indicating that governments' current planning and management of land use are inefficient. (5) Unexpectedly, the increase of marketization level of land will inhibit the increase of urban construction land utilization efficiency. A possible reason is that there is already a large proportion of land sold in the completely market-oriented methods; therefore, further improving the marketization of the land trading market may not pay off well. (6) The results show that the higher the land financial dependence level is, the more likely the government is to develop in an incremental way, which is contrary to the intensive development concept.

5. Conclusions

First, China's urban construction land utilization efficiency is still at a lower level, with a fluctuating upward tendency, but the spatial difference is significant. During the study period, China's urban construction land utilization efficiency showed a volatility upward trend and decreased first and then rose, with a "flat V-shaped" pattern, and the average value increased from 0.777 to 0.866. The average land utilization efficiency of three major regions is as follows: eastern (0.939) > western (0.700) > central (0.691). The urban construction land utilization efficiency of Zhejiang, Fujian, Guangdong, Hainan, and Qinghai is greater than 1, while that of Jilin, Gansu, and Xinjiang is smaller than 0.6. Except for the decline in urban construction land utilization efficiency in Fujian, Shandong, Heilongjiang, Anhui, Guizhou, Yunnan, Gansu, and Qinghai, the remaining provinces were on the rise.

Second, the results revealed the spatial disparity of urban construction land utilization, and the interregional differences are the main source of urban construction land utilization efficiency. The regional Gini coefficient decreased with an overall trend of "fall-increase-fall," which declined in the fluctuations from 0.139 (2004) to 0.096 (2016). During the study period, the mean value of Gini coefficient of regional urban construction land utilization efficiency was as follows: eastern region (0.063) < central region (0.101) < western region (0.128), and the Gini coefficient decreased from 0.057, 0.114, and 0.139 to 0.051, 0.083, and 0.093, respectively; the interregional Gini coefficient of urban construction land utilization efficiency is large, with the order of central versus western (0.121) < eastern versus western (0.161) < eastern versus central (0.168). The Gini coefficients decreased from 0.139, 0.183, and 0.148 to 0.094, 0.125, and 0.109, respectively. In terms of the source and contribution rate of urban construction land utilization efficiency, the order is "interregional difference contribution rate (57.57%) > intraregional contribution rate (25.62%) > transvariation (16.81%). Except in 2012, the three major contribution rates for the other years of the study period were generally stable.

Third, the influence factors "economic development," "industrial structure," "research development investment," and "land urbanization level" had a significantly positive effect on urban construction land utilization efficiency, while other factors were proved to be not conducive to the efficiency improvement.

6. Policy Recommendations

The policy of restricting cross-regional reallocation of construction land utilization may lead to neither efficiency nor balance, and cross-regional reallocation of construction land utilization may act as a new driving force for the next round of Chinese economic growth [45, 46]. In 2018, the State Council issued a policy on the management of urban and rural construction land use quotas across administrative areas. The focus of this policy is to allow cross-provincial adjustment of urban and rural construction land use quotas in some poor areas. Compared with the original regulations prohibiting the interprovincial reallocation of urban construction land use quotas, this policy can reverse the efficiency loss. However, as the policy is still in the exploratory stage, the land use quotas adjustment is mainly determined by administrative means, which ignores the market mechanism, so there is still much room for improvement. It is easy to think that the economically developed areas will bring higher utilization efficiency, but our research on the influencing factors shows that the utilization efficiency is affected by many factors, and the level of economic development is not the only factor. This study provides a theoretical basis for the further improvement of the policy. Firstly, the scope of index adjustment should be further expanded in the future. Specifically, it is necessary to reconfigure urban construction land indicators through market trading mechanism, that is, under the premise of the same land use planning, to build a national trading center and trading platform, so that, on the basis of the initial allocation of construction land indicators (clear property rights), resources can be reconfigured through the center and platform (Pareto improvement of efficiency through the market). Secondly, the allocation and reallocation of urban construction land indicators should take into full account many factors affecting the efficiency of urban construction land use and consider the overall improvement of efficiency.

Under the premise of fully considering the fair development opportunities of the provinces and the initial allocation of urban construction land quotas, urban construction land indicators should be allowed for cross-provincial and regional transactions. Allowing the urban construction land quotas to be reallocated spatially through the nation trading center will not only help to improve the overall construction land utilization efficiency but also realize the regional coordinated development through the differential land rent and further solve the contradiction between economic development and cultivated land protection. In addition, other supporting policies or management, such as fiscal transfer payment, balancing policy of occupation, and compensation in cultivated land protection, should also be applied. For cities with lower urban construction land utilization efficiency, we should actively promote the transformation and upgrading of the agricultural industry structure and increase investment in science and technology research and development, especially those studying the transformation of urban construction land use. The city scale could be appropriately increased and expanded, but the absolute population size and population density have to be limited to a reasonable range. Besides, the red line of cultivated land protection must be implemented resolutely.

Data Availability

The data in this paper are from China Statistical Yearbook (2005–2017), China City Statistical Yearbook (2005–2016), China Environmental Statistics Yearbook (2005–2017), China Energy Statistics Yearbook (2005–2017), and "Statistical Bulletin on National Science and Technology Funds Investment" (2005–2016). They are freely available. Requests for access to these data should be made to Qingfeng Zhou (zhouqingfeng@hit.edu.cn).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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