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Research Article

Spatial Pattern Characteristics and Influencing Factors of Green Use Efficiency of Urban Construction Land in Jilin Province

Huisheng Yu,[1] **Ge Song**,[1] **Tong Li**,[1] **and Yanjun Liu**[2]

[1]*School of Humanities and Law, Northeastern University, Shenyang 110169, China*
[2]*School of Geographical Sciences, Northeastern Normal University, Changchun 130024, China*

Correspondence should be addressed to Ge Song; songgelaoshi@163.com

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How to explore the allocation and green utilization level of urban construction land resources has an important role in the sustainable development of the city. Taking 47 counties and cities in Jilin Province as an example, this paper evaluates the green utilization efficiency of urban construction land (GUEUCL) in 2011 and 2015 by using the unexpected output super-SBM model and explores the spatial-temporal differentiation characteristics and influencing factors of GUEUCL by using GIS and machine learning methods. The results show that (1) the GUEUCL in Jilin Province is low, mainly distributed in small- and medium-sized areas, with significant positive spatial correlation. The L-L concentration area is mainly distributed in the eastern region, but the degree of spatial concentration is small, the spatial structure characteristics of the two periods are different, and the spatial heterogeneity is large; (2) the internal factor decomposition shows the impact of pure technical efficiency on the comprehensive efficiency and the restriction ability is stronger than the scale efficiency, that is to say, the factors such as management and technology have a greater impact on the comprehensive efficiency; (3) the relative importance of external factors has always been ranked as socioeconomic factors, urban development factors, and natural science and technology factors. This paper focuses on the temporal and spatial characteristics of each county and city and the influencing factors, which provides a certain value reference for the pilot of ecological construction and the development of ecoenvironmental benefit economic system in Jilin Province.

1. Introduction

There are many theoretical research studies on urban land use efficiency at home and abroad. Economic geography, social behavior, and political economics all focus on the progress of land use efficiency research from their respective fields [1–5]. In recent years, the research focuses on the optimal allocation, intensive utilization, and efficiency evaluation of urban construction land [6–9], even the evaluation index, driving factor analysis, and improvement of management methods [10, 11]. Evaluation methods such as analytic hierarchy process, principal component analysis, and data envelopment analysis have the defects of subjectivity and information compression, which are not suitable for efficiency evaluation. Traditional data envelopment analysis ignores slack variables or unexpected output. In evaluation criteria, the unexpected output is only a single pollution index [6, 7], and the driving factors are mostly traditional statistical analysis [8, 9]. The research scale covers national [7], urban agglomerations [10], provincial [11], municipal [12], county [13], and village [14]. The county scale is the grassroots unit of China's administrative management and the best scale of land use, management, and planning [15].

With the rapid development of urbanization and industrialization, a large number of people gather in the city, and the urban space sprawl disorderly, inefficient expansion problems are serious. The urban development is also faced with resource constraints, environmental pollution, and ecological damage problems [16–23]. "Green" mainly emphasizes the importance of green development. Green development is an inevitable choice for countries in the world

to achieve sustainable urban development under the constraints of resources and environment. It is also an important guiding ideology and main realization path for China's current social and economic transformation. Therefore, the green utilization efficiency of urban construction land is a new model of land use in the new period of ecological civilization construction and is the extension and expansion of sustainable land use. Green utilization efficiency is a comprehensive index of the effective utilization of resources in current natural, economic, technological, and social conditions, based on the principle of minimizing resource and environmental consumption and maximizing the comprehensive economic, social, and environmental benefits of production. Land is a complex system of socioeconomic-natural environment, and the efficiency of traditional urban construction land use is limited from the socioeconomic perspective, ignoring the green development concept of land use efficiency following the principle of coordination of economic, social, and ecological benefits. Therefore, in the current background of urban sprawl, resource waste and environmental pollution and ecological civilization construction require "green development," and the GUEUCL has attracted wide attention of the state and society [24–33].

Based on theoretical perspective, many literature works study the efficiency of urban land use, mostly from the interests of all parties, lack of the core elements of urban land, and the single subject's interest goal orientation is serious. According to the theory of human land relationship, land use should not only maximize the economic benefits, but also minimize the adverse effects on the geographical environment and avoid exceeding the upper limit threshold of the self-recovery of the geographical environment. According to the theory of scale economy, resources need to eliminate the "short board effect" by optimizing the allocation and improving the level of production technology to form an ideal scale economy, rather than blindly investing in the number of resources in the theory of production frontier, and the most ideal situation for producers is to be able to reasonably allocate various resources and produce the most valuable products at a certain level of science and technology; the theory of sustainable land use mainly focuses on the long-term interests of land users, that is, the economic, social, and ecological sustainability of land use. In conclusion, the concept of green utilization efficiency of urban construction land is put forward, which refers to the green sustainable development system of comprehensive evaluation of the quality and benefit of urban construction land under the guidance of economic, social, and ecological benefits under the factors of urban construction land, labor, capital, etc., invested in a certain period of time.

From the perspective of geography and ecology, which attach importance to regional and sustainable development, this paper uses pollution load index as the comprehensive land pollution output evaluation of GUEUCL, through spatial analysis and machine learning methods, combined with many factors in urban construction land use, to identify and quantify the spatial-temporal pattern and driving factors of GUEUCL. The purpose of the study is as follows: (1) to interpret multitemporal images, extract urban construction land, evaluate GUEUCL by unexpected output super-SBM, and solve the problems of input-output variable relaxation, effective differentiation of multiple decision-making units, and unexpected output; (2) to explore the spatial correlation and heterogeneity of GUEUCL by using the methods of spatial autocorrelation and spatial variation function; (3) to make use of the evaluation model decomposition and support vector machine regression model to analyze the influencing factors of GUEUCL, which provide a valuable reference for formulating effective measures and improving the allocation and sustainable development of urban construction land resources.

2. Data and Methods

Jilin Province is located in the middle of Northeast China, between 121°38′–131°19′E and 40°50′–46°19′N, covering an area of 187400 km^2 (Figure 1), which belongs to the temperate continental monsoon climate. It is an important grain base, governing 47 counties and cities. In 2015, the GDP was 14063.13 billion yuan, the total population was 26.621 million, and the per capita disposable income was 24900.86 yuan. With the rapid development of industrialization and urbanization in Jilin Province, large-scale urban expansion has begun, resulting in low economic benefits of land, and the problems of urban construction land resource allocation and green utilization begin to appear, which have a potential threat to the sustainable development of Jilin Province and the national food security.

Jilin Province is the national ecological province construction pilot, and 2015 is defined as the node of the ecological construction development period in the outline of the overall planning of the ecological province construction of Jilin Province [34]. This paper studies the green use efficiency of urban construction land in Jilin Province, which can not only test the actual results of the planning, but also provide reference experience and practical value for the ecological construction improvement period in 2016–2030.

The data of this study include Landsat remote sensing image, DEM, environmental pollution, and socioeconomic data. Landsat remote sensing image is divided into two phases. Envi software is used to extract urban construction land, including large, medium, and small cities and built-up areas above county and town, factories and mines, large industrial areas, oil fields, salt fields, quarries, and other lands, as well as transportation roads, airports, and special land (since the output value of secondary and tertiary industries and rural residential areas is excluded). The interpretation accuracy of Landsat data extraction for construction land is more than 90%. The technical process and basis refer to "National Ecological Environment Monitoring and Evaluation Technical Plan"; DEM data use ArcGIS software to calculate the slope. Environmental pollution data include wastewater, chemical demand, ammonia nitrogen, sulfur dioxide, nitrogen oxide, and smoke; social and economic data include fixed asset investment, unit employees, GDP, total population, hospital beds, unit employees' wages, professional technicians, patents, and non-agricultural population. Other indicators in this paper are

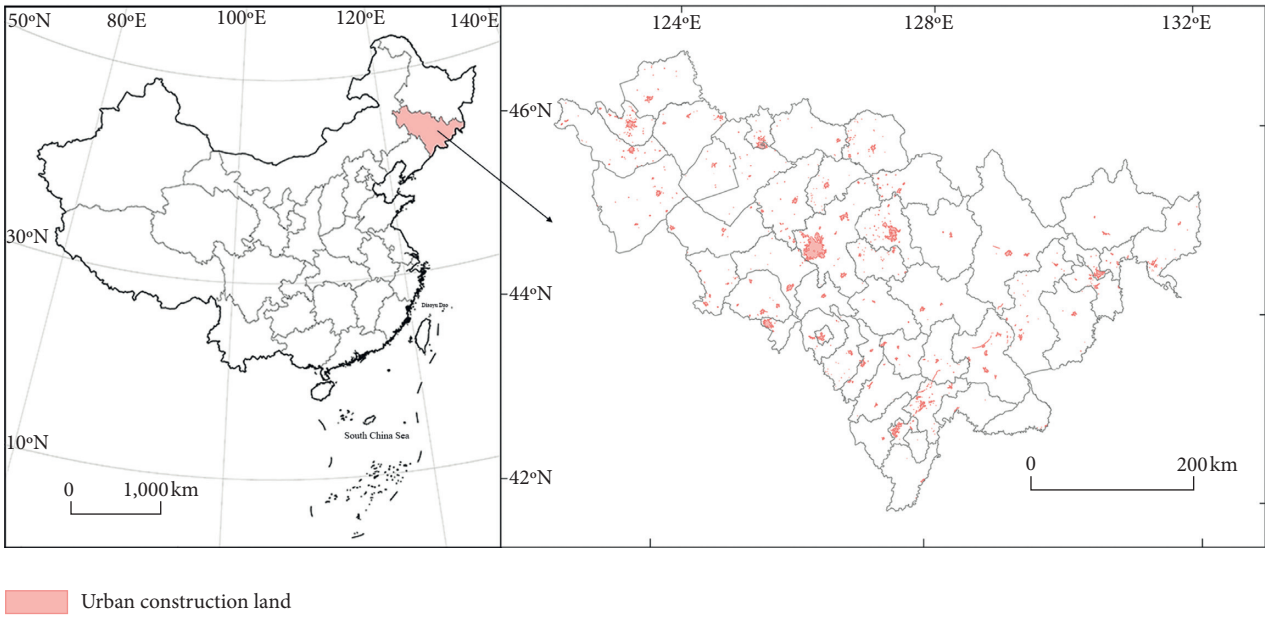

Figure 1: Location of the study area (Jilin, China).

calculated and converted with the above data. See Table 1 for specific data sources and descriptions.

2.1. Unexpected Output Super-SBM. SBM model is a non-radial and nonparametric model based on relaxation variables, which allows input and output variables to change in different proportions and measures efficiency by improved average proportion. At the same time, in order to solve the problem that the highest efficiency value of multiple decision-making units is 1, a super-efficiency SBM model is proposed, and in order to reflect resource saving, pollution reduction, and economic growth, etc., based on the comprehensive realization degree of the goal, the pollution load index is introduced as the unexpected output to build the unexpected output super-SBM, which is more in line with the internal requirements of GUEUCL. Specific evaluation index is shown in Table 2. Pollution load index = 0.20 × ACOD × COD emissions/total regional annual precipitation + 0.20 × ANH_3 × ammonia nitrogen emissions/total regional annual precipitation + 0.20 × ASO_2 × SO_2 emissions/regional area + 0.10 × ASO_1 × solid waste disposal/regional area + 0.10 × AYFC × smoke (powder) dust emissions/regional area + 0.20 × ANO × nitrogen oxide emissions/regional area (according to the national environmental protection of the People's Republic of China Standard).

Suppose that there are n DMUs, and each DMU requires m inputs (x) to produce desirable outputs (y^d) and undesirable outputs (y^u). In this paper, they can be denoted by the vectors $x \in R^m$, $y^d \in R^{r1}$, and $y^u \in R^{r2}$; then, we can define the matrices X, Y^d, and Y^u as $X = [x_1, \ldots, x_2]$, $Y^d = y_1^d, \ldots, y_n^d \in R^{r1xn}$, and $Y^u = y_1^u, \ldots, y_n^u \in R^{r2xn}$, and SBM (SSBM) can be expressed as follows [30]:

$$\begin{aligned}
\min \rho &= \frac{1 - (1/m)\sum_{i=1}^{m}(w_i^-/x_{ik})}{1 + 1/(r_1 + r_2)\sum_{s=1}^{r1} w_s^d/y_{sk}^d \sum_{q=1}^{r2} w_q^u/y_{qk}^u} \\
\text{s.t. } x_{ik} &= \sum_{j=1}^{n} x_{ij}\lambda_j + w_i^-, \quad i = 1, \ldots, m, \\
y_{sk}^d &= \sum_{j=1}^{n} y_{sj}^d \lambda_j + w_s^d, \quad i = 1, \ldots, r_1, \\
y_{qk}^u &= \sum_{j=1}^{n} y_{qj}^u \lambda j + w_s^u, \quad i = 1, \ldots, r_2, \\
\lambda_j &> 0, \quad j = 1, \ldots, n, \\
w_i^- &\geq 0, \quad i = 1, \ldots, m, \\
w_s^d &\geq 0, \quad s = 1, \ldots, r_1, \\
w_q^u &\geq 0, \quad q = 1, \ldots, r_2.
\end{aligned} \tag{1}$$

When $\rho = 1$, in other words, $w^- = 0$, $w^d = 0$, and $w^u = 0$, the DMU_k is efficient. In this paper, we can define that the

Table 1: Data sources and descriptions.

Data	Date	Resolution (m)	Source
Landsat 8 OLI_TIRS	2011	30	Geospatial Data Cloud
	2015	30	Geospatial Data Cloud
DEM environmental pollution	2011/2015	30	Geospatial Data Cloud State Environmental Protection Administration
Social economy	2011/2015		Jilin Statistical Yearbook

Table 2: Evaluation index of green utilization efficiency of urban construction land.

Standard layer	Index
Input	Urban construction land Employees of the unit Investment in fixed assets
Expected output	Output value of the second and third industries
Unexpected output	Pollution load index (PLI)

DMU_k is efficient. The construction of a super-efficient SBM model with undesirable outputs is as follows [30, 35]:

$$\begin{aligned}
&\min \varphi = \frac{1-(1/m)\sum_{i=1}^{m}\left(w_i^{-}/x_{ik}\right)}{1+1/(r_1+r_2)\sum_{s=1}^{r1}\overline{y^d}/y_{sk}^d+\sum_{q=1}^{r2}\overline{y^u}/y_{qk}^u}\\
&\text{s.t. } \overline{x} \geq \sum_{j=1,\neq k}^{n} x_{ij}\lambda_j, \quad i=1,\ldots,m,\\
&\overline{y_d} \leq \sum_{j=1,\neq k}^{n} y_{sj}^d\lambda_j, \quad s=1,\ldots,r_1,\\
&\overline{y_d} = \sum_{j=1}^{n} y_{qj}^u\lambda j + w_s^u, \quad i=1,\ldots,r_2,\\
&\lambda_j > 0, \quad j=1,\ldots,n,\\
&\overline{x} \geq x_k, \quad i=1,\ldots,m,\\
&\overline{y\,d} \leq y_k^d, \quad s=1,\ldots,r_1,\\
&\overline{yu} \leq y_k^u, \quad q=1,\ldots,r_2.
\end{aligned} \tag{2}$$

2.2. Spatial Autocorrelation. According to Tobler's first law of geography, the closer the space distance is, the greater the correlation between the attribute values is, that is, the stronger the spatial dependence. In order to quantitatively measure the spatial dependence of GUEUCL, this paper chooses global spatial autocorrelation Moran's I. Moran's I is a widely used global spatial autocorrelation statistic, and its calculation formula is as follows [36]:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}\left(x_i,-\overline{x}\right)\left(x_j,-\overline{x}\right)}{\sum_{i=1}^{n}\sum_{j\neq i}^{n} w_{ij}\sum_{i=1}^{n}\left(x_i,-\overline{x}\right)^2}, \tag{3}$$

where x is the mean of the observations at all n positions (areas); W_{ij} is the spatial weight matrix; x_i and x_j are the observations at the spatial positions i and j. The range of Moran's I index is [−1, 1]. A value less than 0 indicates negative correlation, a value equal to 0 indicates no correlation, and a value greater than 0 indicates positive correlation.

2.3. Spatial Variogram. The spatial variability function is introduced to analyze the GUEUCL spatial variability. Spatial variability function, also known as semivariogram, is a basic means to describe the randomness and structure of regional variables and is an effective tool for the analysis of spatial variability and structure. The calculation formula is given by [37]

$$\gamma(h) = \frac{\sum_{i=1}^{N(h)}\left[Z\left(x_i\right)-Z\left(x_i+h\right)\right]^2}{2N(h)}, \tag{4}$$

where $Z(x_i)$ and $Z(x_i+h)$ are the GUEUCL ($i=1, 2, 3, \ldots, N(h)$) of $Z(x)$ on the space units x_i and x_i+h, respectively, and (h) is the sample size of the segmentation distance h.

Fractal dimension is another important parameter to characterize the variation function, and its value is determined by the relationship between the variation function $\gamma(h)$ and distance h [38]:

$$2\gamma(h) = h^{(4-2D)}, \tag{5}$$

where the fractal dimension D is the slope in the logarithmic linear regression equation and represents the curvature of the variogram. The larger the value, the higher the spatial heterogeneity caused by the spatial autocorrelation part; the closer the value is to 2, the more balanced the spatial distribution.

2.4. Support Vector Machine Regression Model. Support vector machine is a method of machine learning based on statistical theory. It integrates multiple technologies such as maximum interval plane, Mercer kernel, convex quadratic programming, and relaxation variables. The practical problems in the classification of small samples, nonlinearity, high digits, and local minimum points are well solved. The basic idea of regression is to map the data x to the high-dimensional feature space F through a nonlinear mapping Φ and perform linear regression in this space. The calculation formula is as follows [39–43]:

$$\begin{aligned}
&f(x) = (\omega\Phi(x)) + b,\\
&\Phi\cdot R^n \longrightarrow F, \quad \omega\in F,
\end{aligned} \tag{6}$$

where b is the threshold and the high-dimensional feature space corresponds to the nonlinear regression of the low-dimensional input space, which eliminates the dot product

calculations in high-dimensional spaces ω and $\Phi(x)$. Since Φ is fixed, the sum of the empirical risks R_{emp} affecting ω and $\|\omega\|^2$ makes it flat in the high space. Then, the calculation formula is as follows [39–43]:

$$R(\omega) = R_{\text{emp}} + \lambda\left\|\omega^2\right\| = \sum_{i=1}^{l} e\left(f\left(x_i\right) - y_i\right) + \lambda\|\omega\|^2, \quad (7)$$

where l represents the number of samples, e is a loss function, and λ is an adjusted constant. Minimize $R(\omega)$ to get ω expressed as data points:

$$\omega = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^*\right)\Phi\left(x_i\right), \quad (8)$$

where α and α^* are solutions that minimize $R(\omega)$. Considering equations (6) and (8), $f(x)$ can be expressed as follows [39–43]:

$$f(x) = \sum_{i=1}^{l}\left(\alpha - \alpha_i^*\right)\left(\Phi\left(x_i\right)\Phi(x)\right) + b = \sum_{i=1}^{l}\left(\alpha - \alpha_i^*\right)k\left(x_i, x\right) + b, \quad (9)$$

where $k(x_i, x) = \Phi(x_i)\Phi(x)$ is called the kernel function. It is the dot product of any symmetric kernel function that satisfies the Mercer condition corresponding to the feature space.

In order to better illuminate the models and algorithms used in the research and the purpose of each research part, the method flowchart is drawn (Figure 2).

3. Results

3.1. Spatial and Temporal Characteristics of Green Utilization Efficiency of Urban Construction Land. In order to analyze the distribution characteristics of GUEUCL units more clearly, according to the results of unexpected output super-SBM model evaluated, the spatial pattern scale of GUEUCL is divided into three categories: high, medium, and low by the method of natural interruption. The spatial scale distribution of GUEUCL in two time periods in Jilin Province is shown in Figure 3. The GUEUCL of counties and urban areas in Jilin Province is relatively low, mainly distributed in small and medium scale. In 2011, high-efficiency units accounted for about 8.51%, medium efficiency units for about 25.53%, and low-efficiency areas for about 65.96%; in 2015, high-efficiency units accounted for about 17.02%, medium efficiency units for about 34.04%, and low-efficiency areas for about 48.94%. The average level of GUEUCL in 2011 and 2015 was 0.36 and 0.43, respectively, it has an overall growth trend, but the spatial scale distribution is still showing a significant imbalance.

3.2. Spatial Autocorrelation of Green Use Efficiency of Urban Construction Land. In order to explore the temporal and spatial characteristics of GUEUCL, the spatial autocorrelation analysis method is used to analyze its spatial dependence. As can be seen from Figure 4, Moran's I of GUEUCL in 2011 and 2015 is 0.23 and 0.19, respectively, with P value less than 0.05, indicating that it has significant positive spatial correlation, but has been at a low value, that is, the degree of spatial agglomeration is not large.

In order to further reveal the local spatial autocorrelation change characteristics of GUEUCL, the LISA value of green use efficiency of urban construction land in two years is calculated (Figure 5). It can be seen from the figure that the spatial distribution pattern of GUEUCL in the two years is basically stable. L-L (low-low) cluster area is mainly distributed in the eastern part of Jilin Province, including Dunhua, Antu County, and Helong. The spatial distribution of H-H (high-high) cluster area is relatively scattered, and there is no cluster scale.

3.3. Spatial Heterogeneity of Green Use Efficiency of Urban Construction Land. According to Table 3, from 2011 to 2015, the nugget coefficient decreased, but all of them are small values, and the determination coefficient is relatively large, which shows that the theoretical and practical situations fit well, which can reflect the interaction and linkage effect of the high and low GUEUCL, which is basically consistent with the results of spatial autocorrelation analysis. From 2011 to 2015, the step length of GUEUCL in Jilin Province remained unchanged, but the range of variation increased, indicating that the spatial influence range of GUEUCL increased. This kind of spatial heterogeneity is influenced by both structural and random components. The degree of spatial variation caused by random components (such as policy and regulation elements and human factors) is less than that of structural components (such as social elements, economic elements, and resource and environment elements) [44], which also lays a foundation for the analysis of influencing factors below.

According to Table 4, from 2011 to 2015, the quantile is far away from 2 in all directions, indicating that the spatial heterogeneity of GUEUCL is relatively large and tends to be relatively balanced with the time change, but the spatial heterogeneity is still large, which is basically consistent with the results of spatial scale distribution. From the quantiles of all directions, from 2011 to 2015, the east-west dimension value is the smallest, and the fitting degree is the best, which shows that the spatial heterogeneity of GUEUCL in east-west direction in Jilin Province is the largest from 2011 to 2015, but the spatial heterogeneity is slightly reduced. It can be seen from Kriging interpolation 3D fitting chart that, from 2011 to 2015 (Figure 6), the peak value increased, mainly distributed in the northwest, and in the east, the structure distribution is mostly flat. In general, the characteristics of spatial heterogeneity and spatial scale distribution are basically the same.

3.4. Decomposition of Structural Factors of Green Utilization Efficiency of Urban Construction Land. The green utilization efficiency of urban construction land is the expression of comprehensive efficiency. Pure technical efficiency is the technical efficiency after eliminating the influence of the organizational scale of the decision-making unit. Scale efficiency is a measure of whether the decision-making unit is producing at the optimal scale. Pure technical efficiency and

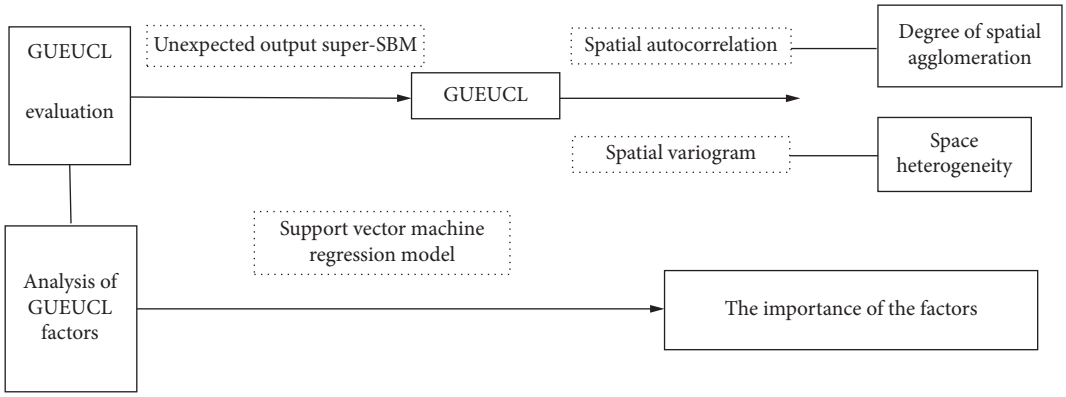

Figure 2: Method flowchart.

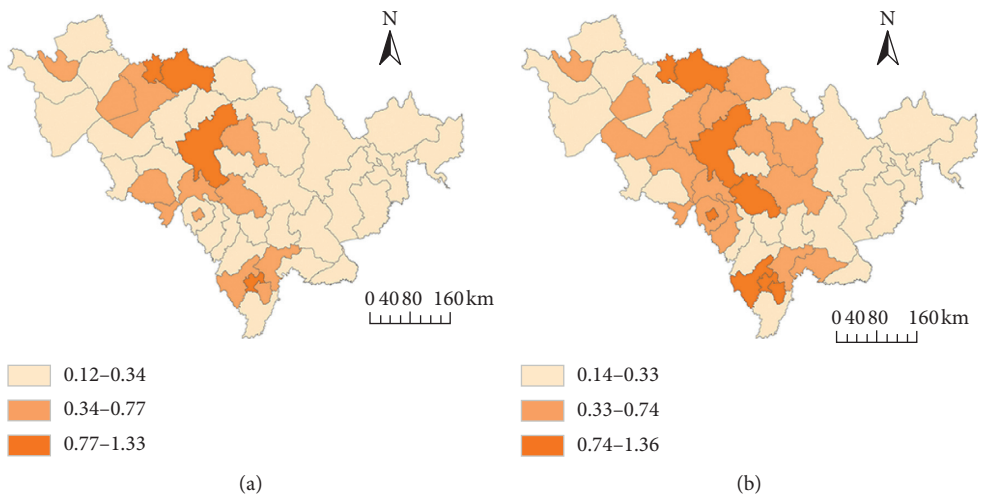

Figure 3: Spatial-temporal pattern of green utilization efficiency of urban construction land in different time periods: (a) 2011 and (b) 2015.

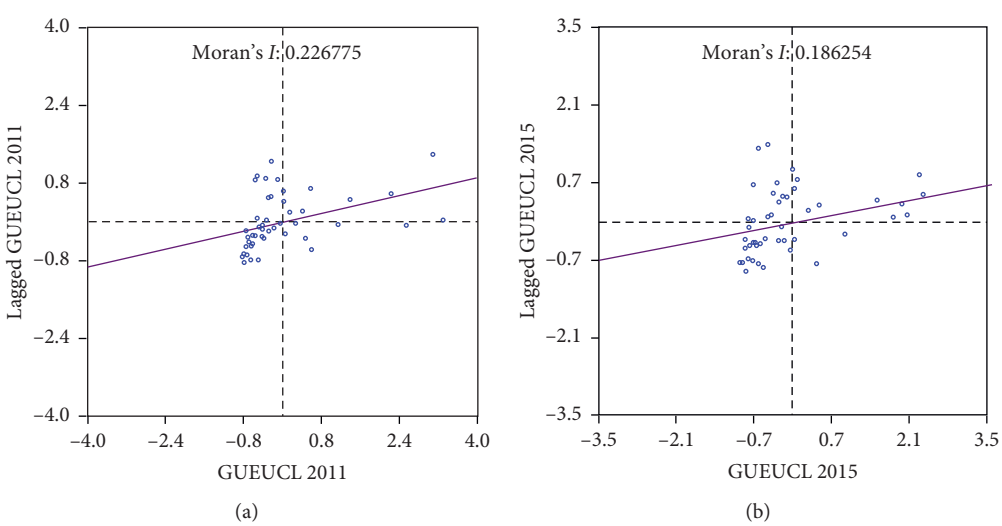

Figure 4: Moran scatter plot of green utilization efficiency of urban construction land at different time intervals.

scale efficiency are also calculated by the unexpected output super-SBM model. In order to reflect the contribution of pure technical efficiency and scale efficiency to comprehensive efficiency, a scatter plot (Figure 7) of the relationship between comprehensive efficiency and its decomposition efficiency can be drawn based on the DEA

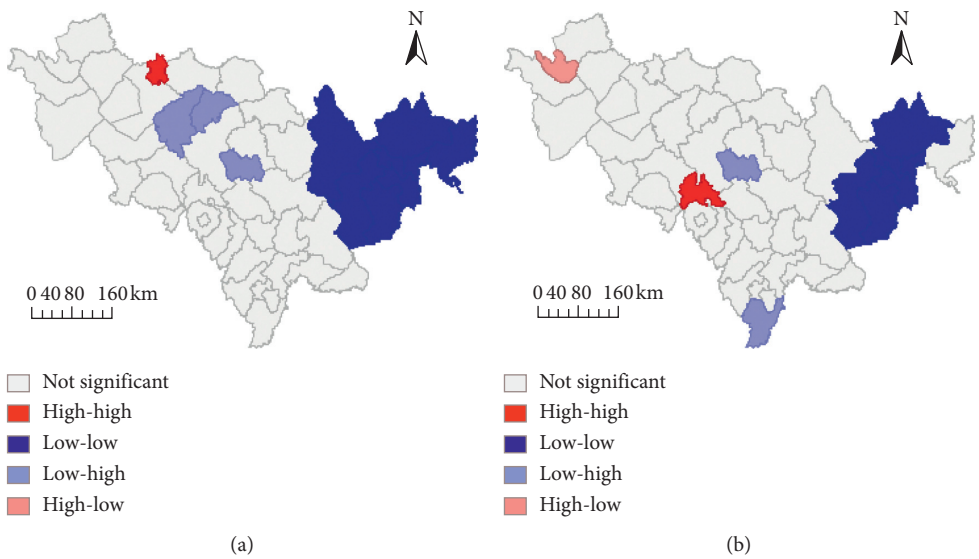

Figure 5: LISA spatial agglomeration of green utilization efficiency of urban construction land at different time periods: (a) 2011 and (b) 2015.

Table 3: Variability function fitting parameters of green utilization efficiency pattern of urban construction land.

Index	Parameter	2011	2015
Range	a	291900	818000
Nugget value	C_0	0.2340	0.2330
Abutment value	$C_0 + C$	0.6150	0.9320
Abutment value nugget coefficient	$C_0/C_0 + C$	0.3804	0.2500
Fitting the model	Model	Gaussian	Spherical
Decisive factor	R^2	0.701	0.600

results. The scatter points in the figure cannot be well matched with the 45-degree diagonal, indicating that the comprehensive efficiency is simultaneously affected by the two kinds of decomposition efficiency. Because only a few cities have reached the effective state of comprehensive efficiency, compared with pure technical efficiency, more scale efficiency has reached effective state, and the scale efficiency is generally greater than pure technology efficiency, so there are more dispersions determined by scale efficiency and comprehensive efficiency. The points are located at the top and upper part of the scatter plot, which makes these scatter dots deviate from the 45-degree diagonal more than the deviation of pure technical efficiency, and the points in the scatter plot constructed by the comprehensive efficiency and pure technical efficiency are closer to the 45-degree diagonal. The results show that in the decomposition of the comprehensive efficiency of urban construction land green utilization, the pure technical efficiency has a greater impact on the comprehensive efficiency, the restriction on production capacity is greater than the scale efficiency, and factors such as management and technology have a greater impact on the comprehensive efficiency. The results show that, in the decomposition of the comprehensive efficiency of urban construction land green utilization, the pure technical efficiency has a greater impact on the comprehensive efficiency, the restriction on production capacity is greater than the scale efficiency, and factors such as management and technology have a greater impact on the comprehensive efficiency.

3.5. Driving Factors of Green Utilization Efficiency of Urban Construction Land. In order to alleviate the contradiction between man and earth, we must understand the relationship between human activities and GUEUCL. According to the existing literature and research, this paper studies the driving factors of spatial differentiation of green use efficiency of urban construction land in Jilin Province from three aspects: social economic factors, natural science and technology factors, and urban development factors [24–33].

Before the establishment of SVM regression model, firstly preprocess the data, and use the feature selection model to remove the indicators that have little correlation with the comprehensive efficiency. In order to accurately classify the test data, we need to search for the best parameters, divide the training sample data into two, take 70% of them as the training set and 30% as the test set, and continue cross-validation until the classification effect is the best, then select the RBF kernel function, and establish the SVM regression model. The results (Table 5) show the relative importance of all independent variables in the form of percentages. The sum of the relative importance of all these variables is 100%. The contribution rate of social and economic factors in 2011 is 0.57, which is greater than that of urban development factors (0.31) and natural science and technology factors (0.12). The contribution rate of social and economic factors in 2015 is 0.47, which is greater than that of urban development factors (0.31) and that of natural science and technology factors (0.12) and elements of natural science and technology (0.21). Therefore, socioeconomic factors have the greatest impact on the comprehensive efficiency. With the change of time, the relative importance ranking of

Table 4: Variation dimension of green utilization efficiency pattern of urban construction land.

Years	All-round		S-N (0°)		Ne-Sw (45°)		E-W (90°)		Se-Nw (135°)	
	D	R^2	D	R^2	D	R^2	D	R^2	D	R^2
2011	1.844	0.677	1.846	0.146	1.983	0.002	1.589	0.821	1.878	0.406
2015	1.900	0.406	1.942	0.026	1.861	0.242	1.614	0.703	1.978	0.026

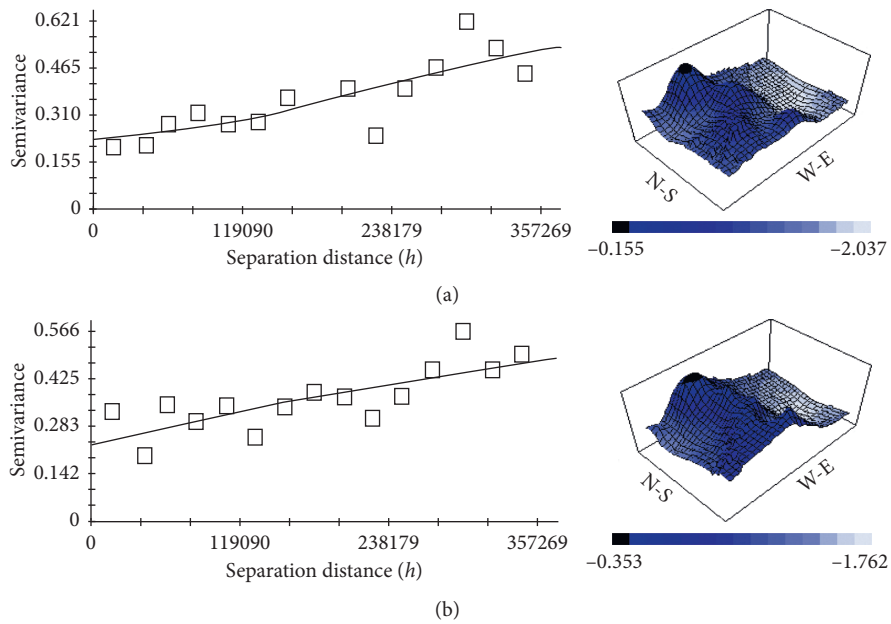

Figure 6: Evolutionary graph of variation function of green utilization efficiency of urban construction land: (a) 2011 and (b) 2015.

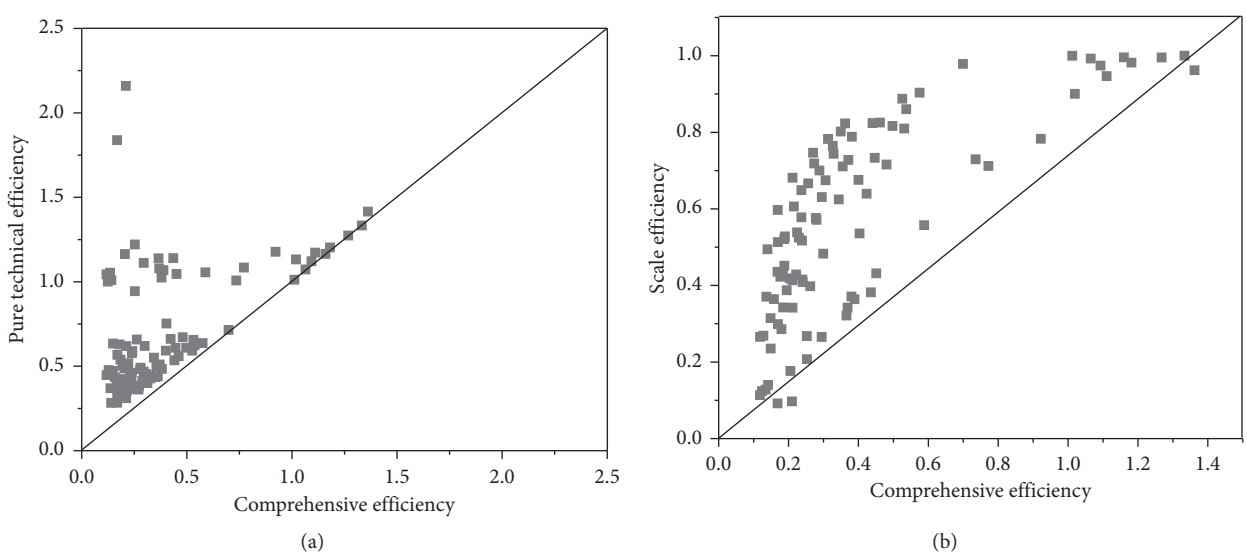

Figure 7: Analysis of the contribution of decomposition efficiency to total efficiency. (a) Comprehensive efficiency-pure technical efficiency. (b) Comprehensive efficiency-scale efficiency.

factors has not changed. The main reason for the distribution of factor proportions is that population density and land development intensity are relatively influential. The relative importance of socioeconomic factors has decreased, and the reason may be that the implementation effect of the "Overview of Jilin Province Ecological Province Construction Master Plan" has appeared. In addition, under the background of the new economic normal, more attention has been paid to the quality of economic development, which has slowed down the speed of social and economic development in the short term, thereby reducing the impact on GUEUCL; the relative importance of natural science and

Table 5: Relative importance of each variable.

Element	Factor layer	Index	2011			2015		
Socioeconomic factors	Foundation of social development	Population density	0.57	0.44	0.38	0.47	0.27	0.20
		Public facility			0.06			0.07
	Economic development level	Real GDP per capita		0.13	0.09		0.20	0.07
		Wages of employees			0.04			0.13
Elements of natural science and technology	Natural environment support	Slope	0.12	0	0	0.21	0.08	0
		Land stress index			0			0.08
	Technological innovation ability	Professional skill worker		0.12	0.06		0.13	0.07
		Patent number			0.06			0.06
Elements of urban development	Scale of urban construction	Urbanization rate	0.31	0.08	0	0.31	0.06	0
		City size			0.08			0.06
	Degree of urban development	Land development intensity		0.23	0.23		0.25	0.25
		Industrial output structure			0			0

technology factors has increased, and the main reason is that the land quality has suffered from increased stress, and soil erosion and land desertification are becoming more and more serious. The relative importance of each index has changed significantly, which needs specific analysis.

3.5.1. Analysis of the Role of Socioeconomic Factors. Social development is the basis of land use, and land use is a spatial expression of human activity needs. Population density reflects the uniform distribution of regional spatial population, the increase of population density, and the bearing of more population per unit of urban construction land, and the development of space utilization mode is more compact and refined, which promotes the growth of GUEUCL. The relative importance of population density and public service facilities in 2011 were 0.38 and 0.06, the concentration degree of population distribution is the most important factor influencing GUEUCL. Even though the relative importance of population density dropped to 0.20 in 2015, it is still the second only indicator of land development intensity, and the relative impact of public service facilities has increased slightly. As more people gather in urban space, the impact of the compact development model on GUEUCL has begun to decline.

The quality of economic development is the connotation reflection of land use efficiency, and the quality of economic development is particularly important in the process of land use. GDP per capita is an important indicator for measuring the level of economic development and the quality of people's lives. Under the same technical conditions, the growth of GDP per capita means that each unit of labor produces more wealth and increases land output. The increase in the wages of employees in the unit means the increase in people's remuneration for labor, which indirectly increases the enthusiasm and efficiency of labor production. The relative importance of per capita GDP in 2011 and 2015 was 0.09 and 0.07, and the relative importance of unit employee wages was 0.04 and 0.13, respectively.

3.5.2. Analysis of the Role of Natural Science and Technology Elements. The natural construction environment is the precondition of land use, which determines the appropriate way and suitability of land use. A good natural environment can reduce the cost of construction project investment and later maintenance. The slope is the steepness of the surface unit. Generally, the slope of urban construction land should not be greater than 25 degrees. The greater the slope, the higher the cost of construction and maintenance, and the risk of natural disasters and soil erosion. Therefore, the slope will directly affect GUEUCL. The land stress index is an evaluation of the extent to which land quality is subject to stress. The decline in land quality will definitely affect the ability of land use and land output and stress the efficiency of urban construction land use. The relative importance of the land stress index in 2015 was 0.08, indicating that the impact of land quality and land output stress began to appear in 2015, but the impact was not significant.

Science and technology are the primary productive forces. The ability of scientific and technological innovation drives productivity to increase, changes the combination of factors, and reduces environmental pollution. Professional and technical personnel can be regarded as the accumulation of human capital and the key indicator of technological progress. Human capital can create new technology or enhance the ability of existing technology and promote the growth of productivity. The number of patents is an important indicator of innovation ability, which optimizes the use of land resources through the research and development of new technologies, upgrading of production equipment, improvement of organizational models, and management methods. From 2011 to 2015, the relative importance of professional and technical personnel was 0.06 and 0.07, and the relative importance of the number of patents was 0.06. Science and technology and innovation ability are important impact indicators.

3.5.3. Analysis of the Role of Urban Development Factors. The larger a city is, the more it is able to attract, own elements and markets, and more effectively create value. Different sizes of cities have different attractive forces when attracting external factors. Decentralization will also promote the growth of urban construction land by promoting

competition between local governments and ensuring fiscal revenue. From 2011 to 2015, the relative importance of the city scale was 0.08 and 0.06, respectively. The different levels of cities and governments have certain effects on attracting investment capacity and guiding land development and utilization.

Reasonable urban development intensity can promote rational external communication and provide space for carrying investment. The intensity of land development is a process of continuous development of urban construction land, population, and economy. Reasonable intensity of land development is conducive to the effective allocation of resources and intensive use of land resources. From 2011 to 2015, the relative importance of land development intensity was 0.23 and 0.25, respectively. With the increase of land use and the density of bearing materials, the rational growth of urban space development became more important to GUEUCL.

4. Discussion

4.1. GUEUCL Model Evaluation. Urban construction land is a space carrier for resource allocation. Since urban space is a complex socioeconomic-natural ecosystem, this process will produce environmental pollution while generating economic benefits. In the past, most of the studies used the construction land including rural residential areas and urban built-up area in the statistical yearbook as urban construction land. As the area of urban built-up areas generally does not include high-value construction land such as factories and mines, large-scale industrial areas, oil fields, salt fields, and quarries; the construction land including rural residential areas cannot express the output value of the secondary and tertiary industries well [8–10]. Therefore, it is very important that the urban construction land interpreted by remote sensing is the basis for the scientific evaluation of GUEUCL. Secondly, most scholars only evaluate GUEUCL from a single land pollution indicator as the undesired output, which is not enough to comprehensively express the undesired output of urban construction land to scientifically evaluate GUEUCL [22,25]. Therefore, this article comprehensively considers the wastewater, chemical requirements, ammonia nitrogen, sulfur dioxide, nitrogen oxides, soot, and other pollutants in the land pollution as the pollution load index to express the unintended output of urban construction land, and more scientifically and accurately evaluates GUEUCL. The evaluation results are of great value to the construction of ecological pilot and ecological environmental protection economic system in Jilin Province.

4.2. Analysis of Influencing Factors. Machine learning-based urban and sustainable development research is rapidly emerging. In the study of the influencing factors of urban resource allocation, we try to use the machine learning method to analyze the more abundant driving factors of GUEUCL, which is more difficult and deeper than the case of the impact analysis of urban land use efficiency under normal circumstances. This study only has 47 counties and districts, because of the multidimensionality and complexity of urban systems and the heterogeneity and timing of GUEUCL; machine learning can find unknown relationships hidden in complex data and explore deeper problems than traditional statistical models. Support vector machine is a method of machine learning, which has many unique advantages in solving small sample, nonlinear, and insensitive sample dimension. Therefore, it is more scientific and accurate to explore the causes of the spatial and temporal pattern characteristics of GUEUCL by using support vector machine [36–40]. Population agglomeration, economic level, land quality, city scale, and land development intensity are the specific driving indicators affecting GUEUCL. It has been generally believed that excessive pursuit of development intensity and scale will lead to the decline of land use efficiency because the dual effects of population agglomeration and scale economy are ignored. In this paper, the impact of population agglomeration and development intensity is the largest among the specific driving indicators of GUEUCL, and under the "ceiling" of construction land, the growth of urban construction land is inevitable, which reasonably controls the disorderly spread of urban space; what is needed is a compact urban spatial structure, and smart and rational growth planning means redeveloping inefficient and idle land; subjective value changes from incremental planning to stock and reduction planning and agglomeration of urban population. It is an effective way for the green use of urban construction land in Jilin Province to continue to implement the policies and measures to attract population growth and agglomeration in Changchun, Jilin big cities, and the central urban agglomeration of Jilin Province and promote the common development of scale economy and population agglomeration by dual means, which is also a reference experience and practical value for the improvement period of ecological construction in 2016–2030.

5. Conclusions

In this study, 47 counties and urban areas of Jilin Province are taken as the research units. Unexpected output super-SBM, spatial analysis method, and support vector machine regression model are used to evaluate GUEUCL and analyze the characteristics of spatial-temporal pattern and influencing factors:

(1) From 2011 to 2015, the research area's GUEUCL value is relatively low, mainly in small- and medium-sized distribution, with an overall growth trend. However, the spatial scale distribution still shows obvious nonequilibrium, with significant positive spatial correlation, but the degree of spatial agglomeration is small. The LL agglomeration area is mainly distributed in the eastern region, with different spatial structure characteristics and greater spatial heterogeneity in the two periods.

(2) The internal factor decomposition shows that pure technical efficiency has an impact on overall efficiency and its ability to restrict it is greater than scale

efficiency. Management and technology factors have a greater impact on overall efficiency; the relative importance of external factors has been ranked as socioeconomic factors, urban development factors, and natural science and technology factors, but the relative importance of socioeconomic factors has declined, and the relative importance of natural science and technology factors has increased.

(3) The specific performance of the impact is as follows: population density is an important indicator of impact, but the impact of urban spatial population agglomeration on GUEUCL began to decline; the economic conditions giving people better material conditions can increasingly affect GUEUCL by increasing labor enthusiasm; the government's ability to attract investment to guide land development and utilization has certain effects; the rational growth of urban space development has become increasingly important to GUEUCL and has become the most important impact indicator.

In view of the research results, improving GUEUCL can be started from several aspects: ① continue to play the role of government policy regulation, adhere to the concept of green development, put forward compact city and smart growth policy recommendations, and shift planning to the value of stocks and reductions; ② according to the functional positioning of different cities, divide the development goals of different GUEUCL, adjust and optimize the spatial pattern of GUEUCL in Jilin Province, pay special attention to the low-lying cities around high-efficiency cities, and strictly prevent them from becoming refuges for the extensive use of low-lying land in policies; ③ continue to develop the management and guidance role of "Outline of Jilin Province Ecological Province Construction Master Plan" and implement the economic growth model of urban clusters in central Jilin, in-depth thoughts, and measures for the construction of green transformation and development zone in eastern Jilin.

There are two main contributions of this study. Firstly, the concept of GUEUCL is proposed, and the pollution load index is introduced as the unexpected output of urban construction land, which is a new method to evaluate and measure GUEUCL. Secondly, based on the support vector machine regression model, the index system of influencing factors is designed, combined with the results of the model, this paper explores the causes of the spatial-temporal pattern of green use of urban construction land in Jilin Province, and it is conducive to improving the green utilization level of urban construction land in Jilin Province, alleviating the contradiction between human and land relations, providing an academic basis for the land sector to formulate green development policies, and providing reference for other similar regions around the world.

Of course, the study also has certain limitations. It only explores the impact of structural components on GUEUCL, and it lacks randomness (policy and other factors) quantitative research. At the same time, the support vector machine regression model was used to analyze the influencing factors. Due to the limitation of data acquisition, the analysis was performed only for a single time period, and the difference in influence over a long time period was not compared. Therefore, the analysis of random components and temporal differences, combined with panel data to explore the influencing factors, is the focus of subsequent research.

Data Availability

The data used to support the findings of this study are available from the first author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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