Hindawi
Advances in Mathematical Physics
Volume 2022, Article ID 1113693, 10 pages
https://doi.org/10.1155/2022/1113693

Research Article

Evaluation and Analysis of Land Input-Output Comprehensive Benefit Based on Fuzzy Mathematics and Analytic Hierarchy Process

Xincheng Zhu,[1] Yan Zhang,[2] Yunzhi Hou,[1] and Minda Jiang[3]

[1]*Anglo Chinese School International 61 Jln Hitam Manis, Singapore 278475*
[2]*School of Management, Guangzhou College of Technology and Business, Guangdong 510850, China*
[3]*Australian International School 1 Lor Chuan, Singapore 556818*

Correspondence should be addressed to Yan Zhang; yanzhanggz@outlook.com

Received 5 June 2022; Accepted 18 July 2022; Published 5 September 2022

Academic Editor: S. E. Najafi

Land use and comprehensive land evaluation are essential. Based on fuzzy mathematics theory and biological heuristic algorithm, the land input-output benefits are evaluated comprehensively. This paper firstly selects six indicators from six aspects of land resource input, capital input, and economic output, and so on. Based on land input and output, this paper constructs the evaluation indicator system of comprehensive benefit for land use. Then, based on the theory of fuzzy mathematics, the improved particle swarm optimization (PSO) algorithm is used to identify the fuzzy density value of the evaluation index. Combined with the analytic hierarchy process (AHP), comprehensive evaluation method, through the combination of subjective and objective methods, is comprehensively evaluating land benefits. Finally, the Tobit model is constructed to further analyze the influencing factors of total factor productivity of urban land use and explore the influencing mechanism of government regulation, land opening, and other factors and land development. The research results of this paper can provide reference for future urban planning, land structure adjustment, land resource utilization and protection, food security, ecological security, economic security, and so on.

1. Research Background

Since the birth of the earth, land resources have been born from it. It is the first natural substance that human beings have been exposed to since its birth, an abstract reflection in the human brain. Its connotation has constantly been changing as human beings have deepened their use and understanding. It is both a natural material form of existence and great material wealth of human society. With the development of human beings, the land has been continuously developed and utilized, which has broadened the space for human activities and improved the quality of human life. The relationship between man and land is constantly evolving, and the contradiction between man and land is also constantly prominent. People began to understand and study the relationship between man and land, the law of change, and development of man and land and looked forward to better playing the function of every inch of land.

In the 19th century, Germany was the first country to study land use. The famous agricultural geographer Duneng (Johann Heinrich-von Thun-en 1783-1850), who selected a piece of land 50 miles away from the city as a research object, analyzed the distribution of farming operations dominated by the level of land rent prices. In 1832, he published the publication of the book "The Relationship of Isolated Countries with Agriculture and The National Economy" which also heralded the birth of the theory of agricultural location. Over the next period, land-use research developed rapidly. In the 1920s, the Americans Thor and Jones proposed the concept of land use, and the British Bona made a rough estimate of the country's land resources. In 1930, the famous geographer Sample studied the quality of land in Britain and compiled a British land use map. After that, large-scale land investigation and research in Europe and the United States, represented by Britain and the United States, and

Japan in Asia, continued to advance. In the later development process, Brazil and Mexico in Latin America also carried out land surveys. By the beginning of this century, all countries have compiled their land use status maps. With the advent of new technologies, especially the widespread use of remote sensing (RS), GIS, and GPS, the rapid development of land survey data collection has been promoted. At the same time, as land resources become increasingly scarce, people are beginning to realize the importance of rational planning of existing land and evaluating the benefits of the original land use. Food and Agriculture Organization of the United Nations published the Outline of Land Valuation to guide land-use master planning. In 1993 published, the Guide to Land-Use Planning set out three goals of sustainability, equity, and acceptability.

By the 1990s, the focus shifted to the impact of land use on the global environment, focusing on land use and cover change (LUCC). In this area, the processes of biological and human social activities intersect most closely. With solid support from the International Union of Sciences and the International Federation of Social Sciences, the focus of research work shifted to how land use affects the regional and global environment, focusing on the integrated evaluation of the drivers of land use and regional and global models. The LUCC research plan, adopted internationally in 1996, is guided by five framework issues: first, how human activity has changed land cover over the past three centuries; second, the causes of the leading human factors that have changed in human land use; third, how land-use change will change land cover over the next 50-100 years.

Moreover, fourth, how humans and biophysics have directly driven sustainable land-use development and the specific types of impacts it has. Fifth is the interplay between land use and cover change, global climate change, and biogeochemical change. In the subsequent research process, the impact of land use on the ecological environment, including the study of environmental problems caused by the process of land reclamation in tropical rainforest areas of South America and the Caribbean, was strengthened. Land development on the island of Madagascar is responsible for nearly 50% of the destruction of forest land, and the adverse consequences are evaluated and predicted. It also includes the ecologically fragile areas of Africa, Sumatra, the Philippine Archipelago, the Indochina Peninsula, and other parts of the world where the contradictions are more serious. In the twenty-first century, LUCC's research focus is still on the relationship between global land cover change and the environment, and the C cycle is one of the research hotspots, which mainly explores the distribution, flow, conversion, storage, loss, and the total amount of C in natural and human activities, which is not only closely related to the biological world but also communicates the atmosphere, hydrosphere, lithosphere, and human activities. Humans are trying to unravel the carbon cycle between organisms and the atmosphere, the exchange of carbon dioxide between the atmosphere and the ocean, and the formation and decomposition of carbonaceous rocks.

At the same time, the emergence of remote sensing, computer mapping, global positioning systems, geographic information systems, various mathematical calculation methods, and new technologies has been of great help to the continuous evolution of land evaluation tools, means, and methods, improve the scope and accuracy of data collection, and the accuracy of evaluation. In these areas, foreign scholars have achieved many research results, such as Stark's analysis of GIS technology in German farm planning, land management, and significant projects for land demand analysis; Canada's M. C Roberts and India's J. C Randolph and J.R. Chiesa, who jointly studied the Monroe lake transport in southern India and applied GIS to analyze spatial properties and their combinations; Moisten Ahmadinejad, Yoshihisa Maruyama, Fungi Yamasaki costudied the Zaja region of Iran, and jointly studied the impact of human factors on the land surface cover in the region through multitemporal satellite imagery and GIS technology; Ademola Braimoh and Paul L.G. Vlek costudied rural land cover change in northern Ghana, showing that human activities also have a more significant impact on rural land use; L. M Paden and K. Venkataramaiah applied satellite imagery to study land use in the Indian state of Boulanger District of Orissa in 1983 [1–4]. E.R. Alexander, Faludi, through a large number of empirical studies, proposed the PPIP evaluation model; the most important research results are that in addition to land use research, it also includes land planning research. At present, the more famous ones are the Canadian Institute of Planners (CIP) and the American Institute of Planners (APA).

2. Related Types of Research

The land is one of the essential factors of production, and improving its total factor productivity (TFP) has also become an important research topic. Foreign scholars' research on TFP began with the economic growth accounting method established by Solow [5]. It mainly analyzes the effects of technological progress and institutions on economic growth [6]. Later, Hansen and Prescott [7] considered the land factor and believed that land, capital, and labor are all critical factors in promoting economic growth. Although different scholars have different research emphases, it has become a consensus in the academic world that land, capital, and labor are regarded as the primary factors affecting the total factor productivity of urban land use. Presently, domestic scholars have conducted in-depth studies on urban land use efficiency, and the research results can be summarized into three aspects: the first is the research on the role of urban land use in economic growth. For example, Du and Cai [8] incorporated land resources as input factors into the analysis framework of economic growth and quantitatively analyzed the role of construction land and other factors in economic growth, providing a possibility for in-depth analysis of the role of land resources in economic growth. The second is the evaluation of urban land use extent. Early scholars mainly used the envelope analysis method [9] and the stochastic frontier method [10] to measure urban land use extent in different regions. With the development of econometrics, improving the extent of urban land evaluation methods, study methods tend to be diversified; SBM [11] and the superefficiency model [12] were gradually applied to the related research of the assessment of urban land. The third is the study on the influencing factors and regional differences

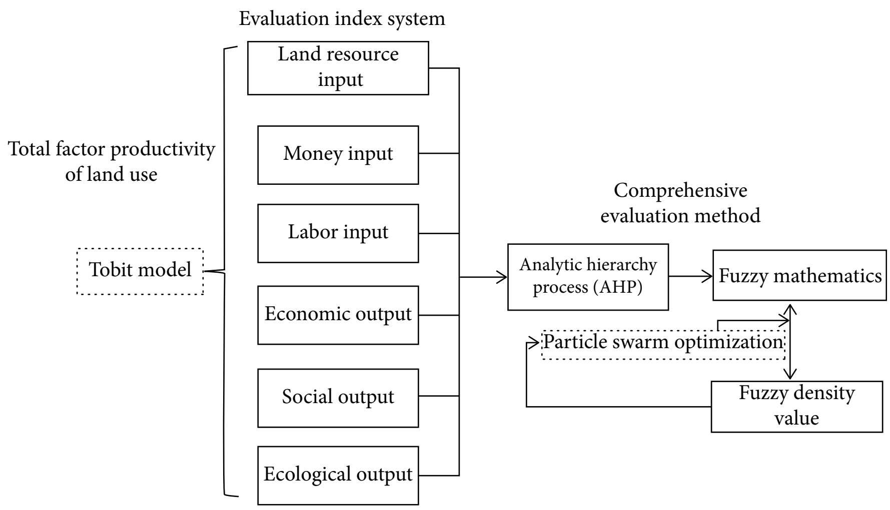

Figure 1: The technology roadmap in this study.

in urban land use extent. In this aspect, the influencing factors and regional differences in urban land use efficiency are analyzed by taking the whole country [13], different regions [14], and different urban agglomerations [15] as case areas [16].

The comprehensive evaluation method uses a more systematic and standardized method to evaluate multiple indexes and units simultaneously. It is an important means to deeply understand and objectively know the evaluated object. It is the decision base for sorting and optimizing the evaluation objects. The evaluation of employees, the finalization of the company's planning scheme, and the rectification of construction projects are inseparable from the comprehensive evaluation method. Therefore, the comprehensive evaluation method is essential for the development of human society. Many comprehensive evaluation models are currently commonly employed in management, economy, society, and education.

The analytic hierarchy process [17] belongs to the system engineering method, entropy value method [18] from the information theory method, and rough sets theory [19] border areas from the fuzzy mathematics thought; fuzzy comprehensive evaluation model is by the method of fuzzy mathematics [20] of evolution; the matter-element analysis method [21] is based on extension set theory; the grey clustering analysis [22] is derived from the gray system theory; TOPSIS model method [23] and cosine decision method [24] are both multiattribute decision methods. In contrast, the catastrophe series method [25] is a mathematical theory derived from topology. The grey-fuzzy safety evaluation method for the antifloating anchor system is established using the grey theory and the relevant theory of fuzzy mathematics [26]. The researcher uses the multilevel fuzzy comprehensive evaluation method to evaluate the human resource performance of enterprises [27]. Researchers construct a method based on data and the model of the analytic hierarchy (AHP) process [28], by using the fuzzy comprehensive evaluation method for water evaluation [29]. Evaluation methods developed rapidly from the 1950s to the 1980s, and various disciplines gradually integrated into evaluation research during this period. AHP, fuzzy comprehensive evaluation method, entropy method, and catastrophe progression method are all produced in this stage. Therefore, with the development of evaluation methods, the application of comprehensive evaluation is increasing. After the evaluation methods are gradually enriched, many scholars also turn their research focus to the evaluation of evaluation methods. The matter-element analysis method, grey clustering analysis method, Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) model method, rough set multiattribute decision theory, and cosine decision method are developed innovatively based on the formation of essential theories of evaluation methods in the early stage.

With the development of evaluation methods, some combinatorial evaluation methods based on fuzzy mathematics are applied more successfully [30–32]. This paper intends to combine the analytic hierarchy process, particle swarm optimization algorithm, and fuzzy mathematics comprehensive evaluation method, through the subjective and objective mutual combination of methods, a comprehensive evaluation of the comprehensive benefits of the land. In addition, this paper further analyzes the influencing factors of total factor productivity of urban land use by constructing the Tobit model and discusses the influencing mechanism of government regulation, land openness, and other factors and land development. The Tobit model is first proposed by Amemiya [33]. Figure 1 shows the technology roadmap in this study. Fuzzy measure and fuzzy integral are introduced in Section 3, Section 4 introduces the land economic benefit evaluation method based on fuzzy integral, Malmquist index is constructed in Section 5, and Tobit model and APH processing are introduced in Sections 6 and 7.

3. Model Building: Fuzzy Measure and Fuzzy Integral

In 1974, the Japanese scholar Sugeno first defined fuzzy measures and defined the integration of measurable functions concerning fuzzy measures [34]. The fuzzy measure is the scale of subjective measurement of faint objects, the principle of which is to convert the probability theory generally based on the measurement of things into a possible theory and consider the correlation between evaluation indicators. Generally, when fuzzy measures are applied to decision-making problems, the candidate sets represent evaluation items, and the fuzzy measure is the weight value of the evaluation items [35]. Thus, fuzzy measure refers to the degree to which the object to be measured is sure to belong to the candidate set.

Definition: Let g be a mapping from $P(X)$ (power set of X) to [0,1]; if g satisfies:

Bounded: $g(\varnothing) = 0$, $g(x) = 1$;

Monotonicity: $A, B \in P(X)$, if $A \subseteq B$, so $g(A) \le g(B)$;

Continuity: if $A_i \in P(X)$ and $\{A_i\}_{i=1}^{\infty}$ are monotonous, that is, $A_1 \subseteq A_2 \subseteq \cdots \subseteq A_n \subseteq \cdots$ or $A_1 \supseteq A_2 \supseteq \cdots \supseteq A_n \supseteq \cdots$, then there is $\lim_{i\longrightarrow\infty} g(A_i) = g(\lim_{i\longrightarrow\infty} A_i)$, then g is said to be a fuzzy measure on $P(X)$.

Three common measures are as follows:

Probabilistic measure: if $A, B \in P(X)$ and $A \cap B = \varnothing$, then $g(A \cup B) = g(A) + g(B)$;

F additive measure: if $A, B \in P(X)$, then $g(A \cup B) = \max \{g(A), g(B)\}$;

(1) λ measure: if $A, B \in P(X)$ and $A \cap B = \varnothing$, then $g(A \cup B) = g(A) + g(B) + \lambda g(A) g(B)$, where $\lambda \in (-1,\infty)$, records as g_λ, When $\lambda = 0$, the g_λ measure is a probabilistic measure

If $X = \{x_1,\cdots,x_n\}$ is a finite set, and each variable x_i corresponds to the fuzzy function g_i, then g_λ can be written as

$$g_\lambda\{x_1,\cdots,x_n\} = \sum_{i=1}^{n} g_i + \lambda \sum_{i_1=1}^{n-1} \sum_{i_2=i_1+1}^{n} g_{i_1} g_{i_2} + \cdots + \lambda^{n-1} g_1 g_2 \cdots g_n = \frac{1}{\lambda} \left| \prod_{i=1}^{n} (1 + \lambda g_i) - 1 \right|, \lambda \in (-1,\infty). \tag{1}$$

When $g(X) = 1$, λ can be calculated as

$$\lambda + 1 = \prod_{i=1}^{n} (1 + \lambda g_i). \tag{2}$$

When calculating the λ fuzzy measure using the above method, the initial fuzzy measure needs to be given by an expert first. If you require a g_λ fuzzy measure of set $A \subseteq X$, you only need to know the fuzzy density g_i of each metric, then find the value of λ from Equation (2), and then get its fuzzy measure according to Equation (1).

Fuzzy integral is a nonlinear function defined based on fuzzy measures. It is not necessary to assume that the evaluation indicators are independent of each other in the comprehensive evaluation. Therefore, it can be applied to situations where there is a correlation between evaluation indicators and is particularly suitable for dealing with the evaluation of subjective values. There are many ways to fuzzy integration, the most commonly used such as Sugeno integrals and Choquet integrals. Choquet integrals describe the degree of interaction between evaluation indicators with fuzzy measures, considering the respective importance of evaluation indicators. Assuming that the question does not lose its generality, $f(x_1^k) \ge \cdots \ge f(x_i) \ge \cdots \ge f(x_n^k)$, $f(x_i)$ represents the normalized evaluation value of the ith evaluation index to evaluate the kth protocol. The fuzzy measure $g(\bullet)$ of $f(\bullet)$ has a Choquet integral on X as [36–38]:

$$\int f dg = f\left(x_n^k\right) g(X_n) + \left[f\left(x_{n-1}^k\right) - f\left(x_n^k\right)\right] g(X_{n-1}) + \cdots + \left[f\left(x_1^k\right) - f\left(x_2^k\right)\right] g(X_1), \tag{3}$$

where $g(X_1) = g(\{x_1\})$, $g(X_2) = g(\{x_1, x_2\})$, $\cdots$, $g(X_n) = g(\{x_1, x_2, \cdots x_n\})$ represents the fuzzy measure of each indicator set. $f = (c) \int f dg$ is the total evaluation value after the fuzzy integral is calculated.

4. Model Building: Land Economic Benefit Evaluation Method Based on Fuzzy Integral

Before evaluating the land economic benefits of the development zone, the fuzzy measure of the evaluation indicators is determined by scoring the importance of each evaluation index and the set of indicators by experts. Suppose the fuzzy measure value given by an expert or determined by other methods does not satisfy the mathematical nature of the λ measure. In that case, it is tough to calculate the λ value from Equation (2). Therefore, the following optimization calculations can be used to go from the fuzzy measure given by the experts to the fuzz measure that meets the requirements of the definition. $\widehat{g}_\lambda(A), A \in P(X)$ represents the λ fuzzy measure given by the expert, and $\widehat{g}_\lambda^i$ represents the fuzzy density value given by the expert. When the set of solutions is a univariate, the optimization equation is as follows:

$$\min_{\lambda} \sum_{A \in P(X)} \left| \widehat{g}_{\lambda}(A) - \frac{1}{\lambda} \left[\prod_{x_i \in A} \left(1 + \lambda \widehat{g}_{\lambda}^{i} \right) - 1 \right] \right|, \quad \text{s.t.} -1 < \lambda < \infty. \tag{4}$$

When the set of solutions is $(g_{\lambda}^{1}, g_{\lambda}^{2}, \cdots, g_{\lambda}^{n}, \lambda)$, the optimization equation is as follows:

$$\min \sum_{A \in P(X)} \left| \widehat{g}_{\lambda}(A) - \frac{1}{\lambda} \left[\prod_{x_i \in A} \left(1 + \lambda g_{\lambda}^{i} \right) - 1 \right] \right|, \quad \text{s.t.} -1 < \lambda < \infty. \tag{5}$$

In the actual data analysis, an improved PSO is used in this paper to identify the λ value and the fuzzy density value of the evaluation index.

5. Model Building: Malmquist Index

Mquist Productivity Index (from now on referred to as MI) is a unique index used to measure changes in total factor productivity. When the evaluated unit data is panel data containing observed values at multiple time points, the effect of productivity change, technical efficiency, and technological progress on productivity change can be analyzed. The formula is:

$$MI_{t,s} = \left[\frac{d^t(x^s, y^s)}{d^t(x^t, y^t)} \times \frac{d^s(x^s, y^s)}{d^s(x^t, y^t)} \right]^{1/2}, \tag{6}$$

where (x^t, y^t) and (x^s, y^s) are the input-output relationship of t and s phases, respectively; $d^t(x^t, \quad)$ is the distance function, representing the distance between the production configuration (x^t, y^t) and the system frontier at time t. The Malmquist index can be divided into the technological change index and technological efficiency change index under the condition of constant return to scale. After the constraint of constant return to scale is removed, the change index of technical efficiency can be further decomposed into a change of pure technical efficiency and change of scale efficiency.

6. Model Building: Tobit Model

James Tobin first proposed the regression problem that explained variables have an upper limit, lower limit, or extreme value. Then, scholars will be limited in the value of explained variables. There is a choice behavior model called the Tobit model. Because of the urban land measured TFP and decomposition efficiency have been cut and the characteristics of the truncated, traditional least squares estimation method, there is a significant deviation, so using truncation method Tobit regression model analyzes the influencing factors, and the model is:

$$Y_i = \alpha + \beta_i X_i + \varepsilon, \tag{7}$$

where Y_i is the dependent variable; X_i is the independent variable; α is the intercept vector; β_i is the parameter vector; ε is a random vector.

7. Model Building: Weighting by Principal Component Analysis

This article will introduce standardization of evaluation indicators, determination of dataset, and weight hierarchical model building. Hierarchical single ordering and hierarchy total ranking, and its consistency test also will be introduced in detail.

7.1. Standardization of Evaluation Indicators. The data itself should have corresponding units and orders of magnitude differences in the various types of data collected. In order to eliminate the impact of data units on data analysis in the statistical analysis process, it is necessary to standardize the data processing (undimensionization processing, normalization processing). Usually, there are several standardized treatment methods: the power function, the standardized method, the maximum method, the coefficient of variation method, and so on. Therefore, this paper uses the power method in the process of data standardization, and its expression is as follows:

Positive indicators, that is, the bigger the value, the better the indicator, take their upper limit effect:

$$M_{ij} = \frac{(X_i - b_i)}{(a_i - b_i)}. \tag{8}$$

Negative indicators, that is, the smaller the value, the better the indicator, take their lower limit effect:

$$M_{ij} = \frac{(a_i - X_i)}{(a_i - b_i)}, \tag{9}$$

where M_{ij} is the value of the jth indicator in the ith year; a_i and b_i are the dataset's upper and lower limits, respectively; X_i is the data that needs to be standardized.

In practical application, the upper and lower limits of the dataset can be determined according to the relevant policies, statistical standards, and the actual situation of socioeconomic development. For this article, the maximum value of the data is used as the upper bound and the minimum value as the lower limit.

7.2. Model Building: Determination of Dataset Weights. Being able to accurately, reasonably, and effectively determine the weight of each indicator is a crucial step in the overall land efficiency evaluation. The weighting process emphasizes the final effect or contribution of some phenomenon (or dataset) to some aspect. The subjective empowerment method is based on the experience of experts and subjective judgments, such as the analytic hierarchy method (AHP) and Delphi method; these methods were used earlier and have been widely used in economics, management, mathematics, and statistics, more mature. Of course, this method will be affected by subjective factors, but if a large amount of data is collected, the bias caused by subjective factors can be reduced as much as possible. The objective empowerment method analyzes the data processing process mainly according to the situation of the original data itself and does not rely on people's subjective judgment, for example, coefficient of variation method, entropy method, factor analysis method, and complex correlation coefficient. In this paper, the analytic hierarchy (AHP) method is used to determine the weights according to the actual situation of the data.

The analytic hierarchy method, also known as AHP, was first proposed by Professor T. L SARRTY, who teaches at the University of Pittsburgh. He can analyze and process some uncertain indicators through a combination of qualitative and quantitative methods through mathematical models. This method can use people's subjective judgment to link the elements within the system mathematically and list them layer by layer according to the corresponding hierarchical level by sorting their importance and comparing them with each other (must pass the consistency test), from which to find a way to solve the problem.

7.2.1. Build a Hierarchical Model. First, after data collection, the necessary analysis of the interrelationship between the elements within the data is required to determine their internal correlation. Select the correlation factor as the target layer A, criterion layer B, and factor layer C. Maintain the independence of each factor to form a hierarchical relationship, and finally, establish an evaluation system.

7.2.2. Constructing a Judgment Matrix. In the AHP method, to achieve a comparison between the two pairs of data and to determine the importance relative to each other and their clear level, it is necessary to construct a judgment matrix. This is shown in Table 1.

Table 1: The judgment matrix.

Factor layer	C1	C2	⋯	C1n
C1	A11	A12	⋯	A1n
C2	A21	A22	⋯	A2n
…	…	…	⋯	…
Cn	An1	An2	⋯	Ann

7.2.3. Method for Determining Matrix Elements A_{ij} Scale. Psychologists believe it is best not to exceed nine levels of comparative factors in comparing the elements. Therefore, the comparison is made on a scale of 1-9.

7.2.4. Hierarchical Single Ordering and Its Consistency Test. According to the results of the expert scoring the importance of each indicator, the judgment matrix is constructed, and the characteristic vector λ max of the most prominent feature root of the corresponding judgment matrix is calculated. Then, the W value is calculated by the corresponding standardized method. W is the weight of the next level in the hierarchy relative to the previous level, and we call this the single hierarchical order.

Once the W weight value is derived, it cannot be used immediately, and it needs to be tested for consistency so that its value falls within the allowable value. Otherwise, the matrix is readjusted until it passes the test. The test can be performed according to the following: theorem 1, the only nonzero feature root of the nth order uniform array is n; the maximum Eigen root of the nth-order positive and negative array A is $\lambda \geq n$, if and only if $\lambda = nA$ is a uniform array.

However, in practical applications, the degree of consistency of A can be measured by the size of the $\lambda - n$ numeric value. Its consistency formula is as follows:

Table 2: Stochastic consistency indicator RI.

n	1	2	3	4	5	6	7	8	9
RI	0	0	0.46	0.87	0.98	1.13	1.45	1.61	1.65

$$\mathrm{CI} = \frac{(\lambda - n)}{(n-1)}. \tag{10}$$

If CI = 0 indicates that the matrix has a firm consistency, which is extremely unlikely; CI is close to 0, it has a satisfactory consistency in most cases; CI is huge, it does not have consistency, and it cannot pass the test. The next step is to find the consistency ratio and define it as CR = CI/RI; when $\mathrm{CR} < 0.1$, if the inconsistency of A is within the allowable range, through the consistency test, it can be normalized as a weight vector. Instead, the judgment matrix needs to be reconstructed to adjust the elements. Table 2 shows the stochastic consistency indicator RI.

7.2.5. Hierarchy Total Ranking and Its Consistency Test. Total hierarchy refers to calculating the weight of the relative importance of all factors at a certain level to the highest level (target layer). It is from the highest layer A to the B layer until the end of the lowest level indicator layer C. The hierarchy is tested for consistency (consistency ratio) by calculating the total hierarchy order:

$$\mathrm{CR} = \frac{\sum w_j \mathrm{CI}_j}{\sum w_j \mathrm{RI}_j}, \quad (j = 1, 2, 3, \cdots, n). \tag{11}$$

When the $\mathrm{CR} < 0.1$, it passes the real hierarchy consistency test. Instead, we need to adjust the values of the CR elements so that the overall hierarchical system passes the test. The weights of each level are derived sequentially, along with their single weight W.

8. Data Using

8.1. Data Description. The data in this paper are mainly from The Statistical Yearbook of Chinese Cities from 2012 to 2021, the Statistical Yearbook of China's Land and Resources, and the Statistical Yearbook of Corresponding Provinces. To ensure comparability, using the CPI will involve revised economic data up to 2012. The indexes selected in this paper are all from the level of municipal districts.

Table 3: Variable descriptive.

Rule layer	Type of indicator	Indicator layer	Unit
Input indicators	Land resource input	Built-up area	Km^2
	Money input	Fixed asset investment	Ten thousand yuan
	Labor input	Workers in the secondary industry	Ten thousand people
		Workers in the tertiary industry	Ten thousand people
Output indicators	Economic output	The added value of the secondary industry	Ten thousand yuan
		The added value of tertiary industry	Ten thousand yuan
	Social output	Per capita disposable income of urban residents	Yuan
	Ecological output	The afforestation coverage area of built-up area	Km^2
Influencing factors	Land relationship	The population density	$People/Km^2$
	The openness of the city to the outside world	Amount of foreign investment	Ten thousand yuan
	Government regulation	The ratio of fiscal expenditure to GDP	%
	Spatial structure of urban land use	The ratio of built-up area to the municipal area	%
	Land marketization level	"Recruit auction listings" account for the total land offered	%
	The industrial structure	The output value of the tertiary industry accounts for the regional GDP	%

The output value of tertiary industry and gross regional product.

8.2. Variable Description

8.2.1. Evaluation Indicators. Based on reference to previous studies and based on the theory of C-D production function, the investment index is selected from land, capital, and labor. That is, the built-up area (km^2) of the use area represents the investment of urban land resources. Investment in urban fixed assets (ten thousand yuan) represents a capital investment. In contrast, the number of employees in the secondary and tertiary industries (ten thousand people) represents the level of labor investment. Urban land use efficiency is based on urban land use. Urban land output includes three aspects: economy, society, and ecology. Urban land is mainly used to meet the needs of production, living activities, and urban ecological protection. Therefore, the economic output is selected as the added value of the second and third industries (ten thousand yuan) that can directly reflect the output level of urban land use. Social output is expressed as per capita disposable income of urban residents (yuan); the ecological output is expressed by the green coverage area (km^2) of the built-up area.

8.2.2. Influencing Factor Indicators. Man-land relationship: using population density to represent the man-land relationship, good population density can promote urban land use efficiency. Otherwise, the too high or too low population density will lead to overloading or idle urban infrastructure, urban disease, or lack of economic development power, which will reduce urban land use efficiency.

City openness: when the technical efficiency reaches a certain level, the substitution rate between capital and land is high, the scarcity of urban land is insufficient to restrict economic development, and the efficiency of urban land use is improved. On the contrary, the less open we are to the outside world, the more constrained the efficiency of urban land use is.

Government regulation: the ratio of local financial general budget expenditure to GDP represents the level of government regulation. Because the market has blindness and other defects, the government must adjust, and the government increase in financial expenditure can correct the market failure and improve the efficiency of urban land use to a certain extent. However, excessive government regulation and interference with the market will backfire.

Spatial factors of urban land: according to the proportion of built-up area in the area of administrative divisions of municipal districts, generally speaking, under the constraints of urban planning, the higher the proportion of the built-up area is, the less possible it is to strive for a land use index for economic development through urban land expansion, and the more it can force the improvement of existing urban land use efficiency. The lower the proportion of the built-up area is, the lower the cost of land acquisition may be in the process of urban economic development, which reduces the pressure of intensive and economical use of urban land, and, thus is less conducive to improving the efficiency of urban land use.

Marketization level of the land: the ratio of the total area of land transfer with "recruitment, auction, and listing" is expressed. The higher the level of land marketization is, the higher the degree of participation in the market competition is, and the higher the efficiency of urban land use is.

Table 4: Mean value of Malmquist indexes and its decomposing results on urban land use in the land economic zone.

Period	Technical efficiency (TEC = PTEC ∗ SEC)	Technological advancements (TC)	Purely technical efficiency (PE)	Scale efficiency (SE)	TFP (TFP = TEC ∗ TC)
2013	1.111	1.237	0.899	0.962	1.093543
2014	1.166	1.109	0.953	0.963	1.021637
2015	1.113	1.116	0.92	0.943	0.996
2016	1.121	1.158	0.92	0.951	1.038
2017	1.12	1.17	0.913	0.957	1.04265
2018	1.124	1.083	0.935	0.939	0.977445
2019	1.121	1.052	0.919	0.952	0.931068
2020	1.119	1.128	0.915	0.954	1.00296
2021	1.129	1.167	0.928	0.951	1.055376

Table 5: Tobit regression analysis results.

Explanatory variable	TFP		TEC		TC	
	Coefficient	Z-value	Coefficient	Z-value	Coefficient	Z-value
Man-land relationship	0.024	0.560	0.06	2.45^{**}	0.015	0.412
City openness	-0.027	-3.14^{**}	0.006	0.99	-0.02	-2.14^{**}
Government regulation	-0.140	-0.96	-0.031	-0.24	-0.18	-1.012
Spatial factors of urban land	-0.41	-1.13	-0.39	-2.13^{**}	-0.502	-1.542^{**}
Marketization level of land	0.112	1.45 ∗	0.078	0.291	0.069	1.125^{*}
Industrial structure	0.000	0.15	0.002	0.111	0.000	0.113
Constant	1.41	3.8	0.456	2.12	1.24	3.93

Note: "∗∗∗" means passing 1% significance test, "∗∗" means passing 5% significance test, and "∗" means passing 10% significance test.

Table 6: Evaluation accuracy of different optimization algorithms on the test set.

Test sets/total datasets = 0.2		Test sets/total datasets = 0.3	
Accuracy (PSO)	Accuracy (GA)	Accuracy (PSO)	Accuracy (GA)
76.54%	73.56%	75.67%	74.65%

Industrial structure: the proportion of output value of the tertiary industry to GDP is used to represent the status of the urban industrial structure. Under the current situation of high-speed urbanization, the proportion of the output value of the tertiary industry in the GDP of municipal districts can better distinguish the characteristics of urban industrial structures. The descriptive variables are shown in Table 3.

9. Evaluation Analysis Empirical Test

9.1. Spatio-Temporal Analysis of TFP of Urban Land Use. Based on the Malmquist index, the TFP of urban land use in 18 prefecture-level cities in the land Economic Zone was measured with an annual cycle. The results (Table 4) show that from 2013 to 2021, the average TFP of each city fluctuated between [0.993, 1.09].

9.2. Analysis of Influencing Factors of Total Factor Productivity of Urban Land Use. Tobit model was constructed to analyze further the influencing factors of TFP of urban land use. The results (Table 5) show that the influence coefficients of urban land use spatial factors on TFP and decomposition efficiency were negative, and this index's influence on technological progress and efficiency passed the significance test of 5%. The possible explanation is that in the process of urban land expansion, the increase of urban land area alone cannot effectively improve the effectual output and efficiency of urban land use. The land marketization level passes the significance test for the TFP and technological progress of urban land use at the 10% level. The improvement of land marketization management level can promote urban technological progress and thus promote the TFP of urban land use. The influence coefficients of industrial structure on the TFP and decomposition efficiency of urban land use were positive. However, the influence coefficients were minor and did not pass the significance level test, indicating that the proportion of tertiary industry should be increased. The advantages of technology, capital, and information should be utilized to improve the effectual output of urban land use, and there is still plenty of room for improvement.

9.3. Comprehensive Evaluation Results. Table 6 shows the evaluation accuracy of different optimization algorithms on

Table 7: Comprehensive land use benefits of 18 selected regions.

	2013	2014	2015	2016	2017	2018	2019	2020	2021
C1	0.002	0.018	0.022	0.0645	0.0634	0.0591	0.0624	0.0667	0.0829
C2	0.0628	0.0676	0.0662	0.0642	0.059	0.0462	0.0268	0.0175	0.0098
C3	0.0026	0.002	0.0071	0.0038	0.0029	0.0129	0.0055	0.0101	0.0143
C4	0.0687	0.002	0.096	0.0417	0.0675	0.0704	0.0827	0.1168	0.1472
C5	0.002	0.0023	0.0117	0.0105	0.0153	0.0252	0.0459	0.0585	0.0718
C6	0.0046	0.002	0.0053	0.0087	0.0158	0.0162	0.0164	0.0158	0.0158
C7	0.0341	0.055	0.0264	0.031	0.0223	0.0239	0.0228	0.0139	0.0059
C8	0.0032	0.002	0.0031	0.0047	0.0054	0.006	0.006	0.0083	0.0098
C9	0.002	0.0052	0.0079	0.0127	0.0166	0.0209	0.0264	0.0346	0.0463
C10	0.0307	0.002	0.0143	0.0267	0.0297	0.03	0.0297	0.0248	0.0236
C11	0.0278	0.002	0.0125	0.0177	0.0243	0.025	0.0258	0.0222	0.0222
C12	0.002	0.0036	0.0043	0.0046	0.0048	0.0048	0.005	0.005	0.0056
C13	0.002	0.0039	0.0068	0.0097	0.0134	0.0183	0.0241	0.0299	0.039
C14	0.0253	0.0282	0.0253	0.0192	0.0142	0.0078	0.002	0.0049	0.0115
C15	0.0052	0.002	0.0024	0.0159	0.019	0.0277	0.0277	0.0333	0.0325
C16	0.0024	0.0061	0.002	0.0234	0.0234	0.0354	0.0368	0.0378	0.0396
C17	0.003	0.0032	0.002	0.006	0.0145	0.0259	0.0266	0.0291	0.0291
C18	0.0132	0.01322	0.0127	0.0121	0.0111	0.01	0.0089	0.0057	0.002
Comprehensive benefit	0.2936	0.22032	0.328	0.3771	0.4226	0.4657	0.4815	0.5349	0.6089

the test set; as seen from Table 6, the optimization efficiency of the proposed algorithm for the comprehensive evaluation model is higher than that of the benchmark model GA.

Table 7 shows the total benefit evaluation values of land input and output in 18 selected regions from 2010 to 2021 (based on the fuzzy mathematical model optimized by particle swarm optimization). It can be seen from the table that the overall comprehensive evaluation value of land keeps increasing, which indicates that the comprehensive benefit of land keeps expanding.

10. Ending

In this paper, first of all, we select 6 indicators from 6 levels, including land resource input, capital input, and economic output, and build the evaluation index system of land use comprehensive benefit based on land input and output. Then, based on the fuzzy mathematics theory, this paper adopts the improved particle swarm optimization algorithm to identify the fuzzy density value of the evaluation index. This paper, combined with the AHP comprehensive evaluation method, carries out a comprehensive evaluation of the comprehensive benefit of land through the combination of subjective and objective methods. Finally, this paper further analyzes the influencing factors of total factor productivity of urban land use by constructing the Tobit model. It discusses the influencing mechanism of government regulation, land openness, and other factors and land development. The research results of this paper can provide a reference for future urban planning, adjustment of land structure, utilization and protection of land resources, food, and ecological security, and economic security.

Data Availability

The data can be obtained by the corresponding author.

Conflicts of Interest

The authors of this article have no conflicts of interest of any kind.

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