land

Article

A Multi-Attribute Approach for Low-Carbon and Intensive Land Use of Jinan, China

Qingling Yu [1], Jing Li [1,*], Xinhai Lu [1] and Liyu Wang [2]

[1] College of Public Administration, Huazhong University of Science and Technology, Wuhan 430074, China; bright_qingling@sina.com (Q.Y.); xinhailu@163.com (X.L.)
[2] Jinan City Planning and Design Institute, Jinan 250013, China; wang_louis@163.com
* Correspondence: lijing.99@mail.hust.edu.cn

Abstract: This paper establishes an evaluation system based on the low-carbon intensive land use in Jinan city from 2010 to 2017 and uses a multi-attribute approach named grey fuzzy integral to build the evaluation model. In this model, based on the Mobius transformation coefficient of subjective and objective weights of index factors and the interaction degree between index factors, 2-additive fuzzy measures can be obtained; therefore, evaluation of low-carbon and intensive land use in Jinan city is processed by combining the grey correlation degree and Choquet fuzzy integral. The results show that in the study period, land input intensity, land use degree, land output benefit and land sustainability in Jinan city all show a good upward trend, but the low-carbon land use level of has been in a declining state. Although there is a good development trend of low-carbon and intensive land use in Jinan, the state is not stable. A Low-carbon and intensive land use pattern will not be achieved completely overnight, and it is bound to be a dynamic game process.

Keywords: the grey fuzzy integral; low-carbon; intensity; land use

check for updates

Citation: Yu, Q.; Li, J.; Lu, X.; Wang, L. A Multi-Attribute Approach for Low-Carbon and Intensive Land Use of Jinan, China. *Land* **2023**, *12*, 1197. https://doi.org/10.3390/land12061197

Academic Editor: Hossein Azadi

Received: 23 March 2023
Revised: 22 May 2023
Accepted: 30 May 2023
Published: 8 June 2023

1. Introduction

Science has allowed us to find new sources of energy, new raw materials, better machinery and new methods of production. Nanotechnology, genetic engineering and artificial intelligence can redefine “production” and resource shortages may be overcome, but the real enemy of the modern economy is ecological collapse. Ecological collapse would lead to economic collapse, political instability and a decline in living standards that could threaten the very existence of human civilization [1]. One of the causes for ecological collapse is greenhouse gas emission, especially carbon emission, which causes global warming. Most scholars and a growing number of politicians have begun to realize the reality and extent of the danger of global warming. There is extensive discussion about global warming, but when it comes to reality, humans are unwilling to make real economic, social or political sacrifices to stop the scourge. Instead of reducing greenhouse gas emissions from 2000 to 2010, it grew at an annual rate of 2.2%, whereas, during 1970–2000, its annual growth rate was only 1.3% [2]. The Kyoto Protocol, a 1997 agreement to reduce greenhouse gases, aims only to slow rather than stop global warming, but the US, the world’s largest polluter, refuses to sign up and makes no attempt to significantly reduce greenhouse gas emissions for fear of hindering its economic growth [3,4]. The Paris Agreement on global climate governance, which entered into force on 4 November 2016 and had been signed by 195 countries and ratified by 190 countries on January 2021, is no less than a binding and universal agreement. This agreement is designed to limit greenhouse gas emissions to levels that would prevent global temperatures from increasing more than 2 °C (3.6 °F) above the temperature benchmark, which is set before the beginning of the Industrial Revolution, but the measures necessary to achieve this goal have been put off until 2030, or even the second half of the 21st century [5]. So far, neither comments nor related seminars, summits nor agreements on global warming have been able to curb global emissions of greenhouse gases. The Emission Database for Global Atmospheric Research (EDGAR) [6] shows that emissions fell only during periods of economic crisis and stagnation. The small and obvious decline in greenhouse gas emissions between 2008 and 2009 was caused by the global financial crisis and not the Copenhagen Accord, which was proclaimed in December, 2019. A viewpoint is that the only sure way to stop global warming is to stop economic growth; however, no government would want to do that at the expense of people's material well-being [1]. Therefore, finding ways to sustain economic growth and at the same time mitigating greenhouse gas emissions is particularly important and rewarding.

Since human behaviors on land and the maintenance and transformation of land use are the main sources of terrestrial carbon emissions [7], and regional land use change has a great impact on the carbon emissions from land use [8,9], analyzing the change of carbon emissions caused by land use from the perspectives of "low carbon" and "intensity" is conducive to optimizing the allocation of land resources and controlling regional carbon emissions to a certain extent. Additionally, there has been a growing consensus in the literature that climate change mitigation efforts should be location-based, especially in the midst of urbanization since there are no universal strategies that are guaranteed to be effective in all settings as local geography, demography, resources, cultural values, etc. [10,11]. At the same time, feedbacks among the aspects of sustainability, for example, the Sustainable Development Goals (SDGs), adopted by the United Nations as part of its 2030 Agenda, have to be considered in policymaking and implementation [12–14].

As for the researches on mitigating carbon emission, there are several aspects, such as investments and stocks, carbon strategy, carbon trade, low-carbon transition, low-carbon land usage and other aspects.

From the aspect of investments and stocks, Choi D, Gao Z and Jiang W [15] proposed that in financial markets, stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Monasterolo I and De Angelis L [16] indicated that stock market investors have started to consider low-carbon assets as an appealing investment opportunity after the Paris Agreement but have not yet penalized carbon-intensive assets. Schoenmaker D [17] found that a low carbon allocation can be done without undue interference to the transmission mechanism of a monetary policy. Liu P and Qiao H [18] studied carbon asset stranding risks under climate policy. Benz L, Paulus S, Scherer J, et al. [19] examined the exposure to and management of carbon risks of different investor types. Cheng S and Qi S [20] assessed the potential of carbon-intensive sectors and non-carbon-intensive sectors in attracting China's Foreign Direct Investment to identify the major determinants of investment, as well as to inform China's investment policy, and render positive contributions to the Green Belt and Road Initiative based on location and sector information. Sun X, Fang W, Gao X, et al. [21] indicated that the carbon market is an important mechanism to promote carbon reduction, and the document announcing the formal launch of China's carbon trading system prompted the dominant market of their causality shifting from carbon market to stock markets.

Some researchers discuss low-carbon from the perspective of companies' behaviors on carbon strategy and voluntary carbon disclosure (VCD). Moussa T, Allam A, Elbanna S, et al. [22] provided evidence of the mediating effect of carbon strategy on the relationship between board environmental orientation (BEO) and carbon performance. Abd Rahman NR, Rasid SZA, and Basiruddin R [23] investigated the quality of VCD in the annual report of publicly listed Malaysian companies operating in carbon-intensive industries and suggested that VCD practices of these public listed companies are more symbolic rather than, and to have carbon disclosure regulated and independently assured is necessary. Lu W, Zhu N and Zhang J [24] investigated the impact of carbon disclosure on financial performance and put forward policy recommendations for the construction of China's carbon disclosure system.

Some research has been conducted on the aspect of carbon trade. Hotak S, Islam M, Kakinaka M, et al. [25] addressed how carbon trade balances relate to carbon emissions under a globalized world with fragmented production. Sun C, Chen L, and Zhang F [26] explored the embodied CO_2 emission effect by measuring the marginal net trading embodied CO_2 emissions and decomposing the exporting embodied CO_2 emissions from the international division perspective. Ji C-J, Hu Y-J, Tang B-J, et al. [27] discussed the price drivers in Chinese carbon emissions trading scheme pilots and provided policy implications for the development of pilots and the national carbon market. Ma N, Yin G, Li H et al. [28] investigated the economic and environmental effects of four possible industrial carbon tax rate models under carbon intensity constraints from 2021 to 2030 by a dynamic input–output optimization model to calculate the optimal industrial carbon tax for China, which is subject to certain constraints.

Progress in and methods of low-carbon energy transition and energy technology innovation are still discussed popularly. Wang J, Hu M, Tukker A, et al. [29] aimed to investigate the potential contribution of regional convergence in energy-intensive industries to CO_2 emissions reduction and to meeting China's emissions goals. Du W and Li M [30] analyzed the influences of environmental regulation on the low-carbon transformation of China' foreign trade from the perspective of export enterprises' dual margin and pointed out that government departments in China should improve and develop environmental policies and further strengthen environmental monitoring capabilities to achieve the structural adjustment and low-carbon transformation of China's foreign trade. Rosenloom D and Rinscheid A [31] structured the fragmented strands of research engaging with the purposive decline of carbon-intensive systems and their components (e.g., technologies and practices), interrogating the role it may play in decarburization. Considering that energy-intensive industries are the primary sectors of energy and resources consumption and carbon emissions, and exploring the temporospatial pattern and influencing factors of carbon emission efficiency (CEE) of energy-intensive industries helps discover the contribution of energy-intensive industries to regional carbon emissions and formulate different regional low-carbon industry development strategies, Zhu R, Zhao R, Sun J et al. [32] estimated the CEE of the energy-intensive industries of China from the provincial level using a three-stage data envelopment analysis (DEA) model and analyzed the temporospatial distribution and influencing factors of CEE by spatial autocorrelation analysis and Tobit model. Dong K, Ren X, and Zhao J [33] found that low-carbon energy transition shows significant bidirectional causality with energy poverty alleviation and provided an important reference for the government to formulate relevant policies that promote the alleviation of energy poverty. In the context of achieving carbon neutrality, Zhao D and Zhou H [34] quantitatively explored the relationships among livelihoods, technological property constraints, and the selection of low-carbon technologies by farmers to promote agricultural modernization and carbon neutrality in the agricultural sector of China. Wang X, Liang S, Wang H et al. [35] analyzed the impact of fossil fuel price distortions on low-carbon transitions. The level of price distortions in coal, gasoline and diesel was evaluated based on which of the CO_2 mitigation potentials in China's Energy intensive industries (EIIs) were estimated and revealed that there is still much room for improvement in China's fossil fuel market reform. Through constructing the embodied carbon emission networks through industrial linkages and identifying the key nodes and paths of carbon risk transmission under low-carbon transition, Han M, Liu W, and Yang M [36] provided practical quantified supports and policy implications for the sustainable low-carbon transition and potential risk prediction related to China's energy-intensive industries. Xin L, Sun H, Xia X, et al. [37] examined the mechanism, spatial spillover effects, regional boundaries, and industry heterogeneity of renewable energy technology innovation (RETI) on manufacturing carbon intensity (MCI) using the spatial Durbin model and the findings provide empirical evidence for formulating targeted and differentiated policy in manufacturing low-carbon development.

Some researchers focus on the low-carbon land usage. Since the development of low-carbon agriculture is promising for mitigating climate change, Wang Z-b, Zhang J-z, Zhang L-f [38] used adjustments to the planting structure in Zhangbei County, China, as an example to evaluate whether the carbon footprint per unit of economic benefit is a suitable indicator of low-carbon agriculture and to determine if low-carbon agriculture is not necessarily low-input non-intensive agriculture. Wang J, Xue D, Ma B and Song Y [39] investigated and analyzed the intensive and agricultural carbon emission levels and their coupling coordinated development types of five provinces in Northwestern China by setting up the index system of intensive use of arable land and the agricultural carbon emission, and using the coupling coordination model and ArcGIS spatial analysis method.

Carbon neutrality is such popular an issue that a wide range of relevant aspects are discussed. For instance, since the decarbonization of energy-intensive systems (e.g., heat and power generation, iron, and steel production, petrochemical processes, cement production, etc.) is an important task for the development of a low-carbon economy, Cormos A-M, Dragan S, Petrescu L et al. [40] calculated, compared, and discussed the most significant technoeconomic and environmental performance indicators of various fossil-based industrial applications that have been decarbonized by two reactive gas–liquid (chemical scrubbing) and gas–solid CO_2 capture systems. Nurdiawati A and Urban F [41] analyzed various technological trajectories and key policies for decarbonizing energy-intensive industries and concluded that it may be technically feasible to strongly decarbonize energy-intensive industries by 2045, given financial and political support. At the same time, carbon storage by plants is explored, for example, Roman M, de los Santos CB, Roman S et al. [42] researched sea grass carbon stocks and influence factors.

In conclusion, research on mitigating carbon emission is prosperous, and the research on land use is otherwise relatively absent internationally. Therefore, the research on evaluating land use pattern and providing some recommendations for low-carbon land usage could contribute to the endeavors of mitigating carbon emission and, at the same time, enriching the relevant research area.

Since China, as a populous country, has been undergoing a rapid and extensive urbanization process, which is in parallel with economic growth and rising material living standards, how to use the valuable land resources in a way that could mitigate carbon emissions is now an urgent issue. Since the intensive land use could attribute to carbon emission mitigation, this research picks out the intensity of land use as a parallel dimension together with the dimension of low-carbon. This paper uses Jinan city in Shandong Province as a case study to provide empirical evidence of land use on the two dimensions of low-carbon and intensity to forecast the healthy land use prospects and possibilities of mitigating carbon emission.

In the multi-attribute comprehensive evaluation area, the grey comprehensive evaluation method is one of the conventional approaches, which integrates grey correlation numbers by using linear weighted average operator. Its advantages are that the analytical logic is clear, the loss caused by data asymmetry can be reduced to a large extent, and the requirements for sample data and distributions are low, therefore, this approach can greatly reduce the workload, whereas it assumes that the attributes of the object to be evaluated are independent from each other, which is difficult to exist in real life.

However, in the fuzzy integral based on fuzzy measures, the Choquet integral of the nonlinear integration operator can fully consider the interaction between attributes; therefore, the grey comprehensive evaluation method, fuzzy measure and fuzzy integral are organically combined in this research to establish a complete, scientific and reasonable evaluation system, named the grey fuzzy integral evaluation model, to apply to multi-attribute decision-making.

This multi-attribute approach is adopted to build the low-carbon and intensive land use evaluation model. This approach of combining advantages of grey relational degree and fuzzy integral, provides a new method of evaluation with a tolerance for the inconsistency of indicators. The results show that although there is a good development trend of low-carbon and intensive land use in Jinan, the state is still dynamic. The transformation of land use pattern from the extensive “high consumption and high emissions” one to the intensive “low consumption, low emission, high benefit” one would not be accomplished completely overnight, and it is bound to be a dynamic game process.

On the basis of the results of the study, this article puts forward the corresponding policy recommendations for low-carbon and intensive land utilization of Jinan. Since global society gradually adopts a new perspective of quality of life and sufficiency standards of service under a number of complex social, climate, disaster and unpredictable risks [43], this theoretical approach can be used by other cities, regions or nations for reference.

2. Materials and Methods

2.1. Study Area

Jinan is located in the mid-west of Shandong Province, bordering Mount Tai in the south and the Yellow River in the north. Since the Ming Dynasty in China's history, Jinan has always been the capital of Shandong Province, which is a big economic province in the east coast of China. After the founding of the People's Republic of China, besides being the capital of Shandong Province, Jinan has also become one of the 15 subprovincial cities of China; the central city in the south of Bohai Rim region; the political, economic, cultural, educational, transportation and science and technology center of the province; and the core city of the Shandong Peninsula city group and Jinan metropolitan circle. Besides being a provincial capital city with political status and so on, Jinan is also a historical and cultural city with a splendid civilization. It is one of the famous historical and cultural cities in China, with its beautiful natural scenery and numerous scenic spots. According to historians, there have been traces of human activity since as early as 45 centuries BC, and the city is also the birthplace of prehistoric Longshan culture. Even more distinct about Jinan is its unique geological structure, which makes it a spring enrichment zone with the most famous Spouting Spring group; therefore, Jinan is also known as the Spring City. Since the ancient city of Jinan is built on the spring group, spring water is not only used for living, but also for city defense and other functions. The moat surrounding the old city of Jinan is the only river formed by the confluence of spring water in China. In addition to the unique rich spring group, there are three major water systems: Yellow River and Xiao Qing River together with the famous Da Ming Lake. Besides water resources, Jinan is also rich in mineral, forest, planting and breeding resources, which has laid a solid material foundation for Jinan's economic development and urban and rural construction [44].

At the same time, Jinan is also one of the important cities for the emergence and development of modern industries in China. It occupies a pivotal position in the whole country and has a very rich industrial heritage. It is also required by the planning and layout of traditional industry to be classified as an industrial zone [45].

As a city with the mixed statuses of politics, economies, historical culture, natural landscape, transportation, etc., the land use of Jinan confronts the complex conflicts of different expectations; therefore, it is a typical example for the research in the urbanization process of China.

Figure 1 illustrates the geographical location of Jinan in Shandong Province together with the rough land use categories. Unlike the previous statistical caliber, since 2010, the relative standards of classification for statistics of land use in Jinan have been divided into eight categories, including cultivated land, garden, forest, grass, urban village and industrial and mining land, transportation land, land for water and facilities as well as other land, which is roughly consistent with the first-level standard of Land Use Classification [46] edited by Ministry of Land and Resources and jointly issued by General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China and Standardization Administration in 2007; therefore, to ensure the uniformity of data, the starting year of this study was set as 2010.

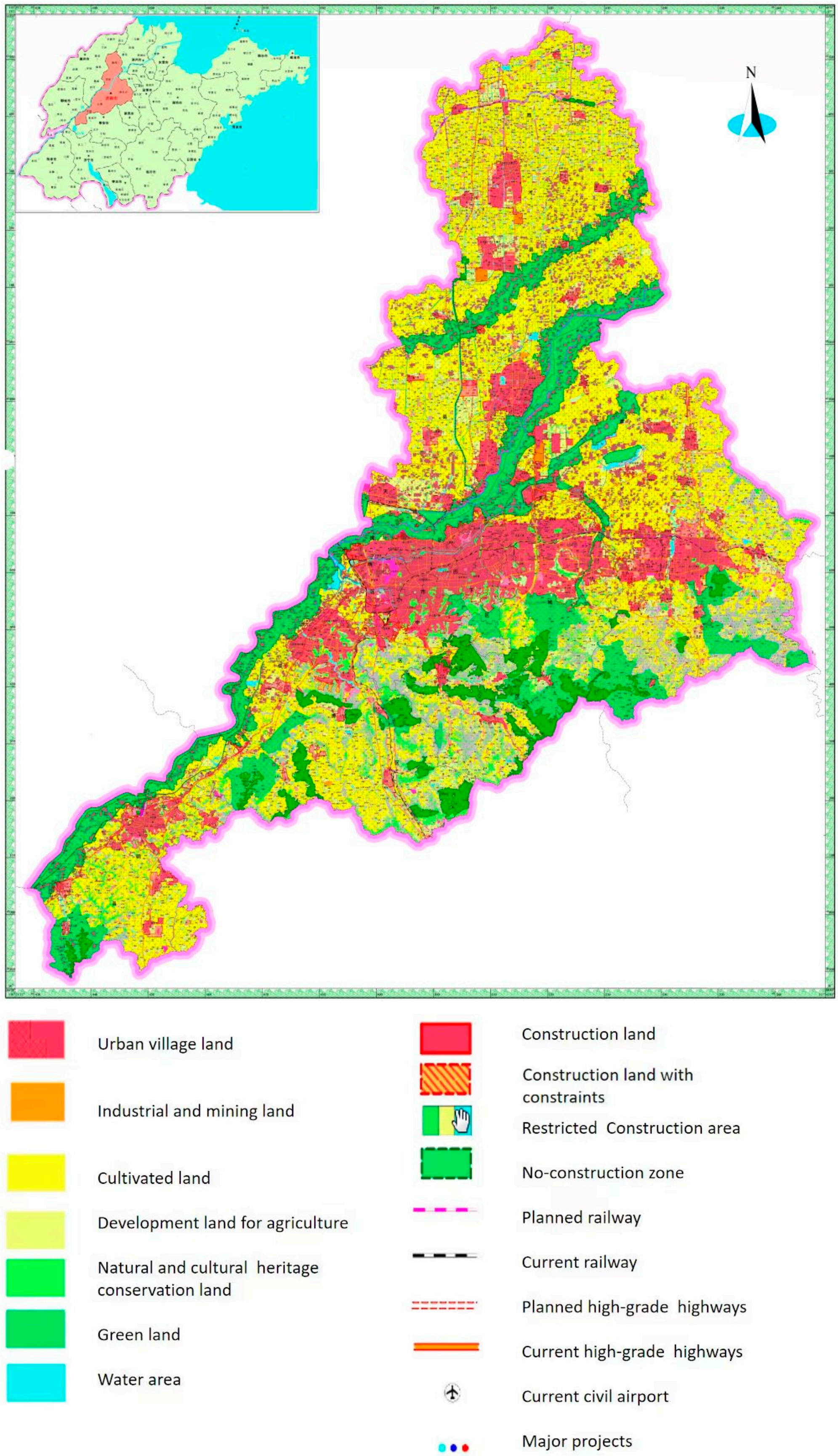

Figure 1. Land use plan of Jinan (2006–2020) by Jinan Urban Design Institute.

In 2017, the Shandong provincial government issued the Development Plan for Shandong Peninsula Urban Agglomeration (2016–2030), which clearly aims to make the Jinan metropolitan circle and Qingdao metropolitan circle better and stronger, supports Jinan and Qingdao in building national central cities, and includes Laiwu city into the Jinan metropolitan circle [47]. After that, on 26 December 2018, the state council approved the adjustment of Laiwu's administrative division in Shandong Province, abolishing Laiwu city and putting the area under the jurisdiction of Jinan city [48]; therefore, the relevant introduction of the study area in this paper is limited to the area before the zoning adjustment of Jinan city, and the termination year is set as 2017; the data is up to the statistical results in the 2018 edition of relevant yearbooks.

2.2. Data Sources and Processing

2.2.1. Changing Trend of Land Use Categories in Jinan

The socio-economic data of this study are mainly from the China Statistical Yearbook (2011–2018), Shandong Statistical Yearbook (2011–2018) and Jinan Statistical Yearbook (2011–2018). The relevant data are calculated according to the definition of index factors. Additionally, the weights and measures used in the yearbook are all international standard units of measurement, and the statistical caliber includes Jinan urban area, Pingyin County, Jiyang County and Shanghe County.

The data of land use type area change from 2010 to 2017 were collected from the Jinan Statistical Yearbook from 2011 to 2018. After analyzing the data obtained (Table 1), it can be seen that from 2010 to 2017, the value of cultivated land area in Jinan City showed a downward trend on the whole and only picked up a little in 2013; however, it returned to a continuous decline in 2014, with the largest decline in 2014–2015. From 2015 to 2016, the total area of cultivated land continued to decline, but slightly slowed down. During 2016–2017, the decline increased again. In addition, the area of garden land, forest land and grassland also showed a sharp downward trend year by year, especially during 2012–2013. After the growth period of 2010–2011, the land area of water and water conservancy facilities also entered a state of decline year by year. At the same time, the overall area of urban and village land, industrial and mining land, and transportation land showed an increasing trend year by year. The area of urban, village, industrial and mining land was the inflection point in 2014, and there was a trend of slowing growth before 2014. After 2014, there was a significant increase, especially during 2014–2015 and 2016–2017. Transportation land also only changed during 2012–2013 and recovered with a large increase after a relatively small reduction. After a sharp decrease year by year, the area of other land gradually rose in 2013 as the inflection point and the sharpest rising happened during 2013–2014, then the rise slowed down. After that, there was an inflection point in 2016, and a decreased trend happened significantly again during 2016–2017.

Table 1. Area change of land use categories in Jinan 2010–2017 (Unit: Hectare).

Year \ Category	Cultivation	Garden	Forest	Grass	UIM	Transportation	Water and Its Facilities	Others
2010	362,303	26,790	86,663	58,894	135,194	28,190	51,195	50,612
2011	361,251	26,632	86,070	58,404	137,306	28,459	51,324	50,395
2012	360,279	26,485	85,682	58,193	139,087	28,742	51,246	50,127
2013	361,012	26,233	85,100	57,520	140,218	28,740	51,155	49,863
2014	360,241	26,180	84,963	57,430	140,772	29,068	51,039	50,150
2015	358,568	26,054	84,676	57,250	142,969	29,135	50,962	50,227
2016	357,601	25,957	84,484	57,151	144,219	29,319	50,875	50,236
2017	355,659	25,801	84,175	57,018	146,819	29,617	50,696	50,055

Note: UIM—Urban village, Industrial and Mining land as one category. Transportation land refers to land used for the purpose of transportation, including roads and railways.

There are many reasons for these changes, mainly due to the acceleration of urbanization and industrialization in Jinan under the general trend of national urbanization. Although the cultivated land increased a little in 2013 through ways of land reclamation and other measures, the general trend is that a large number of cultivated land, garden land, forest land and grassland are transformed into urban and village land, industrial and mining land or transportation land to meet the needs of economic construction.

2.2.2. Energy Consumption Situation in Jinan

The energy consumption data used in this paper are from the Jinan Statistical Yearbook (2011–2018). Since energy consumption mainly comes from the industrial sector, the data of energy consumption of industries above a designated size in Jinan City was selected as the energy consumption index. According to the availability of data and the actual situation of energy consumption in Jinan City, six energy sources, including coal, gasoline, kerosene, diesel, fuel oil and electricity, were selected for carbon emission calculation. Data of land use change from 2010 to 2017 were also taken from the Jinan Statistical Yearbook from 2011 to 2018.

Carbon dioxide emissions from fossil fuel consumption are calculated using the following formula, based on the baseline methodology provided by the Department of Energy Section of the IPCC Guidelines for National Greenhouse Gas Inventories 2006 [7]:

$$\text{Carbon dioxide emissions} = \text{fossil fuel consumption} \times \text{carbon dioxide emission coefficient}$$

$$\text{Carbon dioxide emission coefficient} = \text{low calorific value} \times \text{carbon emission factor} \times \text{carbon oxidation rate} \times \text{carbon conversion coefficient}$$

As the above coefficients refer to the empirical values of foreign countries, they are not necessarily consistent with the actual conditions of China; therefore, the Department of Resource Conservation and Environmental Protection of the National Development and Reform Commission and the first Industrial Standard of the Standardization Administration have put forward the new General Principles for Calculation of Total Production Energy Consumption (GB/T2589-2008) [49]. This standard specifies the definition and calculation method of comprehensive energy consumption, which is applicable to the calculation and management of the indicators of energy consumption per unit of energy use. It provides the average low calorific value of fossil fuels and the conversion coefficient of standard coal [49].

To further strengthen the capacity of provincial greenhouse gas inventories, the Department of Climate Change of the National Development and Reform Commission organized experts from the Institute of Energy Research of the National Development and Reform Commission, Tsinghua University, Institute of Atmospheric Sciences of the Chinese Academy of Sciences, Institute of Environmental Protection and Development of the Chinese Academy of Agricultural Sciences, Institute of Environmental Protection and Environmental Protection of the Chinese Academy of Forestry, Climate Center of the Chinese Academy of Environmental Protection and other units to compile the Guide for the Compilation of Provincial Greenhouse Gas Inventories (Trial) with the support of national key basic research and development programs.

The guidelines specify CO_2 emission coefficients for major fossil fuels: raw coal, 1.9003 kg-CO_2/kg; fuel oil, 3.1705 kg-CO_2/kg; gasoline, 2.9251 kg-CO_2/kg; kerosene, 3.0179 kg-CO_2/kg; diesel oil, 3.0959 kg-CO_2/kg; etc. This also includes the average carbon dioxide emission coefficient of power supply per unit of Chinese regional power grid [50].

To sum up, the calculation formula of carbon emissions of energy consumption is as follows:

$$C = \sum C_i = \sum M_i E_i \tag{1}$$

where C is the total carbon emission, C_i is the total carbon emission of the i-th energy consumption, M_i is the i-th energy consumption, and E_i is the carbon emission coefficient of the i-th energy.

Although carbon emissions related to living consumption of Chinese residents show an increasing trend year by year [51], the proportion is still relatively small, and energy consumption mainly comes from the industrial sector, so the energy consumption data of Jinan industrial subsectors are selected as the energy consumption index. According to the availability of data and the actual situation of energy consumption in Jinan City, six kinds of energy sources, including coal, gasoline, kerosene, diesel, fuel oil and electricity were selected for carbon emission calculation. Although heat consumption was included in the original data, it was not included in the calculation because carbon emissions of heat mainly came from fossil energy, such as raw coal. According to Formula (1) and relevant data, the total carbon emission, carbon emission intensity and carbon emission per capita of Jinan City can be obtained, where carbon emission intensity is the carbon emission per unit of GDP, as shown in Table 2.

Table 2. Total carbon emission, carbon emission intensity and per capita carbon emission in Jinan 2010–2017.

EC / Year	Total Carbon Emission	Carbon Intensity	Carbon Emissions per Capita
2010	39,246,241,462.00	10,036,041.52	64,968,615.85
2011	41,981,465,515.00	9,527,621.99	69,203,259.78
2012	37,081,527,865.00	7,719,416.17	60,868,219.28
2013	35,144,037,816.00	6,719,457.19	57,307,848.05
2014	37,308,803,330.00	6,465,324.81	60,019,631.81
2015	36,184,060,122.00	5,931,589.48	57,826,954.31
2016	37,004,399,194.00	5,661,523.84	58,474,470.54
2017	33,924,190,968.00	4,710,410.91	52,708,416.41

Notes: EC—energy consumption; carbon emissions per capita—kg/10 thousand people. Unit of total carbon emission—kg; unit of carbon intensity—kg/100 million yuan.

2.3. Methodology

At present, there are many methods for analyzing and synthesizing various linear and nonlinear systems, but the methods for systems that are too complex to be analyzed accurately are still quite lacking. Such complex systems, pervasive in philosophy, economics, psychology, and the social sciences, preclude the possibility of classical mathematical analysis. The main reason why classical mathematical methods are difficult to deal with complex system problems is that they cannot describe fuzzy things effectively. By fuzzy, we mean uncertainty arising not from randomness but from lack of clarity from one member to another. The concept of fuzzy sets was proposed by Zadeh L.A. in 1965 [52]. Fuzzy set theory and research has formed a complete system since its concept was proposed, and fuzzy technology has been deeply applied in pattern recognition, image processing, decision support, automatic control and other fields. As a branch of fuzzy set theory, fuzzy measure and fuzzy integral were first formed in the 1970s, focusing on the non-additive case, which is the extension of classical measure and integral. This branch of research enriches nonlinear mathematical theory because measure additivity is only an ideal state and practical problems are usually non-additivity. Thus, it is widely used to describe non-additive and nonlinear systems, such as decision analysis and subjective evaluation, in the mathematical model [53–58]. Japanese scholar M. Sugeno proposed the concept of fuzzy measure for the first time in 1974, and defined the integral of measurable function with respect to fuzzy measure accordingly [59]. Its most classical characteristic is non-additivity, so fuzzy measure is usually called non-additivity measure [60]. In the multi-attribute evaluation, the candidate set represents the evaluation item, and the fuzzy measure is not only the weight value of the evaluation item but also the degree to which the object to be tested belongs to the candidate set [56].

In multi-attribute evaluation, different attributes not only have different importance but also have interactions with other attributes. For an evaluation index system, the relationship between the two groups of attributes can be divided into three situations: repeated or negative cooperation; complementary or active cooperation; or independence. In general, the three situations in an attribute set often exist simultaneously, and the 2-additive fuzzy measure can describe them at the same time [61].

The grey comprehensive evaluation method is a comprehensive evaluation method based on expert evaluation and guided by grey relational analysis theory. It uses the known information to generate and develop the unknown information of the system. Yet, the traditional comprehensive evaluation method is based on the assumption that index factors are independent of each other, but in practical application, there is usually a certain degree of interaction between index factors. In order to solve this problem, combining the respective advantages of grey relational degree and fuzzy integral, this paper designs a grey fuzzy integral multi-attribute evaluation model for data analysis. In the designed model, the Mobius transformation coefficient is determined based on the subjective and objective weights of index factors and the degree of interaction between index factors, and the 2-additive fuzzy measure was obtained by calculation. Then, the grey correlation degree and Choquet fuzzy integral are combined to evaluate the low-carbon intensive use of land. The specific steps of grey fuzzy integral multi-attribute evaluation method are as follows.

2.3.1. Establishment of Index System

Assuming that there are m evaluated objects, a systematic, scientific and practical evaluation index system is established by taking the characteristics of the evaluated objects and the purpose preference of decision-makers as the reference basis. The evaluation system is divided into b levels, and the evaluation of each level can be subdivided under some secondary indexes, with each independently belonging to the same index level, and at the same time, there is only one kind of relationship between every two secondary indexes under the same level, which could be repeatable, complementary, or independent. In addition, the degrees of interaction between indexes are obtained by expert scoring.

2.3.2. Indicator System Description

The evaluation system of intensive land use based on low-carbon goal needs to integrate the three characteristics of intensive, low carbon and ecological, as well as the natural, economic, social, energy and environmental aspects in an orderly manner. In order to guarantee the relative objectivity and rationality of the evaluation process and results, this study follows the principles of systematicity, scientificity, consistency, flexibility and practicability with reference to the Procedures for Evaluating the Potential of Intensive Use of Urban Land (Trial) [62] and the literature on low-carbon intensive land use and low-carbon economy research during the process of index system construction. Based on the status quo of land resources, the regional environment and the social and economic development of Jinan and fully considered the availability of data and expert advice, index factors are selected from five aspects: Land input intensity, Land use degree, Land output efficiency, Land low-carbon level and Land sustainability. On this basis, an evaluation index system of low-carbon intensive land use is established as shown in Table 3, including target layer, criterion layer and index factor layer, and the index layer contains 21 factors. The margin of index definition or calculation formula indicates that the data are directly from the statistical data.

Table 3. Evaluation index system of low-carbon intensive land use.

Target	Critierion	Index Factor	Index Definition or Calculation Formula	Unit of Measurement
Evaluation index system of low-carbon intensive land use	B_1 Land input density	C_{11} Fixed asset investment per hectare	Fixed assets investment/Total land area	10,000 yuan/ha
		C_{12} Average employment	Total number of employees/Total land area	10,000 people/km_2
		C_{13} Energy consumption per unit GDP	Energy consumption/GDP	Ton of standard coal/100 million yuan
		C_{14} Transportation land area per 10,000 people	Transportation land area/Total population	ha/10,000 people
	B_2 Land use degree	C_{21} Urban population density		People/km^2
		C_{22} Construction land area per 10,000 people	Construction land area/Total population	km^2/10,000 people
		C23 Percentage of urban, village, industrial and mining land area	Urban, village, industrial and mining land area/Total population	%
	B_3 Land output efficiency	C_{31} GDP per hectare	GDP/Total population	100 million yuan/ha
		C_{32} Retail sales of social consumer goods per capita	Retail sales of social consumer goods/Total population	100 million yuan/ha
		C_{33} Fiscal revenue per hectare	Financial revenue/Total population	10 thousand yuan/ha
		C_{34} Wastewater discharge amount per hectare	Wastewater discharge amount/ Total population	10 thousand ton/ha
	B_4 Land low-carbon level	C_{41} Carbon emissions per hectare	Total carbon emissions/Total population	ton/ha
		C_{42} Energy consumption elasticity coefficient		
		C_{43} Percentage of greenbelt coverage	Greenbelt area/Total population	%
		C_{44} Fertilizer and pesticide usage per unit cultivated area		kg/ha
		C_{45} Operating vehicles per 10,000 people	Total operating vehicles/ Total population	vehicles/10,000 people
		C_{46} PM10 annual mean concentration		kg/ha
	B_5 Land sustainability	C_{51} Percentage of water and its conservancy facilities area	Water and its conservancy facilities area/Total population	%
		C_{52} Cultivated land area per capita		mu
		C_{53} Green coverage rate of built district		%
		C_{54} Centralized sewage treatment rate	Sewage treatment quantity/Sewage quantity to be treated	%

(1) Land input density. The ideal state of land intensive use is that the marginal cost of land use input is equal to the marginal revenue, and the land use benefit reaches the maximum ideal value, while the land input density reflects the input level of land-use-related factors. In the index factors of land input density, Fixed asset investment per hectare, Average Employment, Energy consumption per unit GDP and Transportation land area per 10,000 people correspond to the capital input, the human labor input, the energy input and the infrastructure input, respectively. In the existing studies, the factor of land average energy consumption is mostly adopted to correspond to the environmental input index since the factor of land average energy consumption reflects the energy input in the land use process and mainly reflects the development degree of the city, while the amount of land average energy consumption in developed areas is higher than that in areas with a low degree of development. The calculation method of the factor is the ratio of the total energy consumption of various industries in a region to the total regional area, which can reflect the degree of carbon emission in the process of land input, The energy consumption per unit GDP can reflect not only the energy input in the land use process but also help to reflect the connotation of low-carbon intensive land utilization as a result of its nature itself that is associated with the gross national product, which strengthens the constraint of the factor in low carbon [63]. The calculation method of the factor is the ratio of energy consumption in the region to the GDP.

(2) Land use degree. The degree of land use can reflect the current situation of land use. Generally, the greater the population density is within the land area, the higher the intensity of land use becomes. Construction land area per 10,000 people reflects the reasonable degree on a regional scale. In the existing land use structure, urban, village, industrial and mining land and other carbon-source land are the inevitable results of economic and social development, which can reflect the degree of effective land use to a certain extent and have an important impact on the intensity of urban land use.

(3) Land output efficiency. The total benefit of land use is reflected by the land output efficiency, which mainly involves the economic efficiency, the social efficiency and the ecological efficiency in the process of land use. GDP per hectare, Retail sales of social consumer goods per capita and Fiscal revenue per hectare correspond to the economic and social efficiency in the process of land use, among which Fiscal revenue per hectare of local finance is an important indicator to measure the disposable financial resources of a local government; the fiscal revenue adopts the amount of general public budget income. The ecological benefit index chooses to consider the discharge of the industrial "three wastes", which are the main pollution sources: the discharge of local waste gas, local waste water and local solid waste; however, the statistical data show that the solid waste is treated completely after the processes of comprehensive utilization, storage or disposal, and finally achieves zero emission; therefore, it is not included in the index system. Due to the variation of statistical caliber and statistical types during the study period, the indicator of waste gas emission on the average ground level was abandoned since the data is hard to be unified. In view of the continuity and availability of data, this study adopted Wastewater discharge amount per hectare as an ecological efficiency indicator.

(4) Land low-carbon level. The low-carbon level of land is mainly evaluated from the perspective of low carbon by means of two indexes, i.e., Carbon emissions per hectare and Percentage of greenbelt coverage which is the proportion of forest, grassland and garden plots, as well as Energy consumption elasticity coefficient, Fertilizer and pesticide usage per unit cultivated area, Operating vehicles per 10,000 people and PM10 annual mean concentration in terms of carbon sources. The calculation formula of Energy consumption elasticity coefficient is: Energy consumption elasticity coefficient = Δ Total energy consumption/ΔGDP. The operating vehicles include buses, trolleybuses and taxis. The use of chemical fertilizers and pesticides is not only easy to cause environmental pollution but also deteriorates the physical properties of the soil, disperses the soil colloids, destroys the soil structure and causes land consolidation, which not only affects the yield and quality of crops, but also destroys the carbon storage capacity of the soil and releases the carbon in

the soil into the atmosphere. In addition, a significant amount of nitrogen fertilizer either evaporates directly from the soil surface or is converted by microorganisms into nitrogen and nitrogen oxides and enters the atmosphere. In consideration of the above causes, the fertilizer and pesticide usage per unit of cultivated land area is included in the criterion layer of land low-carbon level.

(5) Land sustainability. The impact of urban land use structure layout on natural resources and ecological environment is mainly reflected by land sustainability. Because the cultivated land, water area and land for water conservancy facilities play a certain role in alleviating the traffic congestion, ground hardening and crowds gathering in order to mitigate the pollution of the environment, the two index factors, Percentage of water and its conservancy facilities area and Cultivated land area per capita, together with Green coverage rate of built district are incorporated into the system to reflect the sustainability of land use from the aspect of carbon mitigation. Centralized sewage treatment rate reflects the sewage treatment capacity and efficiency of the study area, and also reflects the environmental protection effort and environmental sustainability of the study area to a certain extent. The above four index factors reflect the requirements of utilization of natural resources and ecological environment protection in the land use process.

2.3.3. The calculation Process

(1) Acquisition of Initial Evaluation Data

In this paper, the index data of the criterion layer are all quantitative indexes, and the scoring of quantitative indexes can be obtained by statistical means. The socio-economic data in this paper are mainly from the China Statistical Yearbook (2011–2018), Shandong Statistical Yearbook (2011–2018) and Jinan Statistical Yearbook (2011–2018).

The sample data come from 10 experts in related research fields in Jinan, Qingdao, Wuhan, Chongqing and other places. By means of questionnaire survey, experts were invited to score the index factors screened out in the indicator system and determine the values of the interaction degree of index factors. In this part, consistency of scoring is not necessary due to the characteristics of this approach, because some fuzzy measures between evaluation indexes are super additive, and some are sub-additive, or even zero additive. By using the weight score set by experts as fuzzy measures, we can better use the fuzzy measures to deal with the correlation among indexes, and enhance the correctness and acceptability of the comprehensive evaluation result of fuzzy integrals.

(2) Determine the single weight of index factors

Calculate the subjective weight of each indicator. The subjective weight value of each indicator can be obtained by expert scoring method. At first, the relevant experts give the weight value of each indicator after comprehensively considering the actual situation and the goal preference of decision-makers, among other factors, and then take the average value of the weight values given by each expert. After that, add the weight values of each indicator to get the sum of the weights, and finally, the ratio of the weight values of each indicator to the sum of the weights is the final weight value of the indicator. The scoring criteria for subjective weight of index factors are shown in Table 4.

Table 4. Scoring criteria of index factors' subjective weight.

Degree of Importance	Very Unimportant	Less Important	Unimportant	Important	More Important	Very Important
Scoring standard	0	0.20	0.40	0.60	0.80	1

Calculate the objective weight of each indicator. The decision matrix A1 is obtained by reordering the index factors according to their importance of attributes from large to small. Calculate the mean value and standard deviation of each column of sample matrix

A1 and obtain the normalized matrix S. Matrix V is obtained by Schmidt orthogonal to the normalized matrix S. Then, normalize matrix V to obtain the Mahalanobis distance matrix D. The SNR (signal noise ratio) is calculated according to the Mahalanobis distance matrix D, and the objective weight of an indicator, which belongs to a single attribute index, is obtained.

The comprehensive weight of a single attribute index is obtained by integrating the subjective and objective weights.

(3) Determine the interaction degree between index factors

The existing multi-attribute decision making methods assume that there is no interaction between various influencing factors or index factors, and grey comprehensive evaluation method is no exception; however, this assumption does not exist in real life, so the interaction relationship and interaction degree between attributes should be taken into account. According to the experience of experts, problems about whether there is an interactive relationship between two index factors in the evaluation level and the degree of interaction between them can be determined. If two index factors have no interaction relationship and are completely independent of each other, then the interaction degree of the two index factors is 0. If there is a certain degree of complementarity between the two index factors and a more accurate evaluation can be obtained by the combination of the two index factors, then the interaction degree of the two index factors is greater than 0, and the larger the value of the interaction degree, the stronger the complementarity between the two index factors. If repeatability exists between two index factors, the interaction degree is less than 0, and the smaller the value of the interaction degree, the stronger the repeatability between the two index factors. The scoring criteria for the interaction degree between two index factors are shown in Table 5 [64].

(4) Calculate Mobius transformation coefficients of index factors

To calculate the grey fuzzy integral relational degree, the fuzzy measure should be determined firstly, and the 2-additive fuzzy measures can be calculated by defining the Mobius transformation coefficients m_n and m_{nj}. Suppose $b_1 = \{b_{11}, b_{12}, \ldots, b_{1i}\}$ is the attribute set under the evaluation level of b_1; the weight sets of b_1 can be expressed as $W_1 = \{w_{11}, w_{12}, \ldots, w_{1i}\}$, then the Mobius transformation coefficients of the single attributes $b_{1n}(n \leq i)$ and two-attributes $\{b_{1n}, b_{ij}\}(n, j \leq i, n \neq j)$ are shown as follows, respectively:

$$m_n = \frac{w_{1n}}{P} \tag{2}$$

$$m_{nj} = \frac{\xi_{nj} w_{1n} w_{1j}}{P} \tag{3}$$

The interaction degree between b_{1n} and b_{1j} is ξ_{nj}, the value range is [–1, 1]; P is the sum of importance of all the single attributes $b_{1n}(n \leq i)$ and the two-attributes $\{b_{1n}, b_{ij}\}(n, j \leq i, n \neq j)$, and it is expressed as $P = \sum\limits_{n \in b_1} w_{1n} + \sum\limits_{n,j \subset b_1} \xi_{nj} w_{1n} w_{1j}$.

(5) Calculation 2-additive fuzzy measures

The 2-additive fuzzy measure can solve the contradiction between precision and complexity because their parameter values can measure the interaction factors and importance factors in the interaction. The 2-additive fuzzy measure is further defined by the k-additive fuzzy measure based on the pseudo Boolean function and the Mobius transformation, so by using the Mobius transform coefficients of the single attributes m_n and the two-attributes m_{nj} and according to Formula (3), the 2-additive fuzzy measure of the attribute can be calculated:

$$g(K) = \sum_{n \in K} m_n + \sum_{\{n,j\} \in K} m_{nj}, \forall K \subseteq X \tag{4}$$

Table 5. Scoring criteria for the interaction degree between two index factors.

Interaction Degree	Extremely Repetitive	Very Repetitive	Repetitive	Slightly Repetitive	Independent	Slightly Complementary	Complementary	Very Complementary	Extremely Complementary
Scoring standard	−0.90	−0.70	−0.50	−0.30	0	0.30	0.50	0.70	0.90

In the formula, m_n is the Mobius transform coefficient of the single attribute x_n, and m_{nj} is the interaction degree between attributes x_n and x_j as well as the Mobius transform coefficient of the two-attribute $\{x_n, x_j\}$.

(6) Calculate grey correlation coefficients

The optimal index and grey correlation coefficient matrix are calculated as follows:

$$\xi_i(m) = \begin{bmatrix} \xi_1(1) & \xi_1(2) & \dots & \xi_1(m) \\ \xi_2(1) & \xi_2(2) & \dots & \xi_2(m) \\ \dots & \dots & \dots & \dots \\ \xi_i(1) & \xi_i(2) & \dots & \xi_i(m) \end{bmatrix} \quad (5)$$

$\xi_i(m)$ is the grey correlation coefficient of indicator i in scheme m.

(7) Grey fuzzy integral correlation degree of each decision scheme

Based on the theory of fuzzy measure, Choquet fuzzy integral represents a nonlinear function. To define the grey fuzzy integral correlation degree on the basis of Choquet fuzzy integral could make the grey relational degree be used for decision making, and at the same time, the interaction between attributes can be fully considered.

Suppose that a row of vector expression of evaluation matrix C is $C_i = \{C_i(m)\}$, which is called the comparison sequence of system referring to the evaluation vector of indicator i, which is on the evaluation level b_1 of object m, and $C_0 = \{C_0(m)\}$ is the reference sequence, then the grey fuzzy integral correlation degree of C_n and C_0 could be given by the formula:

$$\int \gamma(C_n, C_0)dg = \sum_{n=i}^{i} [\gamma_{0n}(x_{(m)}) - \gamma_{0n}(x_{(m-1)})]g(X_{(m)}) \quad (6)$$

In the formula, (m) is the subscript after sorting according to $\gamma_{0n}(x_{(1)}) \leq \gamma_{0n}(x_{(2)}) \leq \dots \leq \gamma_{0n}(x_{(i)})$, $X_{(m)} = \{x_{(m)}, x_{(m+1)}, \dots, x_{(i)}\}$, $\gamma_{0n}(x_{(0)}) = 0$. The final decision result can be determined by sorting the grey fuzzy integral correlation degree [65].

3. Empirical Results and Analyses

Due to the limitation of space, this paper gives merely the empirical results as shown in Tables 6 and 7, and the analyses.

Table 6. The 2-additive fuzzy integral comprehensive evaluation values (B_1–B_5) of 2010–2017.

Evaluation Value \ Year	2010	2011	2012	2013	2014	2015	2016	2017
Grey fuzzy Choquet integral evaluation value (B_1)	0.6078	0.5965	0.5758	0.4725	0.4729	0.4658	0.5069	0.6304
Grey fuzzy Choquet integral evaluation value (B_2)	0.3330	0.3554	0.3792	0.4350	0.4760	0.5316	0.7361	1.0000
Grey fuzzy Choquet integral evaluation value (B_3)	0.3333	0.3668	0.4247	0.5716	0.6485	0.7471	0.7166	0.9015
Grey fuzzy Choquet integral evaluation value (B_4)	0.6510	0.6977	0.5537	0.5625	0.5308	0.4963	0.4715	0.4601
Grey fuzzy Choquet integral evaluation value (B_5)	0.3333	0.3654	0.4273	0.5856	0.6601	0.7542	0.6849	0.8518

Table 7. Comprehensive evaluation values of Jinan low-carbon intensive land use of 2010–2017.

Evaluation Value \ Year	2010	2011	2012	2013	2014	2015	2016	2017
Grey fuzzy Choquet Integral evaluation value	0.5235	0.5877	0.4295	0.4105	0.4213	0.4461	0.4765	0.7991

Line B1 represents the change in the trend of land input intensity in the criterion layer; it experienced a slow decline and then a rising process during 2010–2017 was observed, which can be divided into two stages: The first is the decline stage from 2010 to 2015, in which the decline degree from 2012 to 2013 is the most obvious. The evaluation value from 2013 to 2015 is generally low, and the lowest value occurred in 2015. The second is the period of rapid improvement from 2015 to 2017. For the study period as a whole, the assessment value in 2017 was only 0.0226 higher than that in 2010, with an overall growth rate of about 3.72%; however, during the upgrading period from 2015 to 2017, the land input intensity increased by 35.34%, with an average annual growth rate of 17.67%, showing an obvious trend of rapid improvement. All in all, the results show that during the study period, the land input intensity in Jinan city gradually shows a relatively positive increase trend after the idle period of decline and slow increase.

Line B2 represents the change trend of the degree of land use in the criterion layer; it is in an overall rising stage from 2010 to 2017, and is divided into two stages with 2015 as the turning point: one is a slow rising stage from 2010 to 2015; the second is the period of rapid improvement from 2015 to 2017. In terms of the study period as a whole, the annual average growth rate of evaluation value in 2017 compared with 2010 is about 28.57%. The degree of land use can only reflect the degree of intensive urban land use during the upgrading period from 2015 to 2017, and the average annual growth rate of its assessed value is 44.06%, showing an obvious trend of rapid improvement, indicating that the degree of intensive land use in Jinan is getting higher and higher during the study period.

Line B3 represents the change trend of the land output efficiency in the criterion layer, and it is in an overall rising stage during 2010–2017, only slightly declining during 2015–2016, and rapidly rising after 2016 with a growth rate of 25.80%. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 24.35%. The results show that the overall situation of land output efficiency in Jinan is good during the study period.

Line B4 represents the low-carbon land level in the criterion layer, and it is in an overall decline stage during 2010–2017: after the increase in 2010–2011, it enters an obvious decline stage during 2011–2012. After the non-significant increase during 2012–2013, it enters the stage of gradual annual decline during 2013–2017. For the study period as a whole, the average annual decline in 2017 compared to 2010 is about 4.19%. Although the annual decline rate of low-carbon land assessment value is small, the overall trend of decline is very obvious. This shows that the situation of low-carbon land use in Jinan is still relatively grim.

Line B5 represents the land sustainability in the criterion layer; it is in an overall rising stage from 2010 to 2017 and only in a declining stage from 2015 to 2016. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 22.22%. Although the overall upward trend of land sustainability evaluation value is obvious, the fluctuation of the values between 2015 and 2017 is also obvious. Considering that the land low-carbon level of in criterion layer B_4 in Figure 2 has been declining significantly in recent studies and that the indexes of criterion layer B_4 and B_5 are repeatable, this indicates that the situation of land use sustainability in Jinan is not stable and still needs close attention.

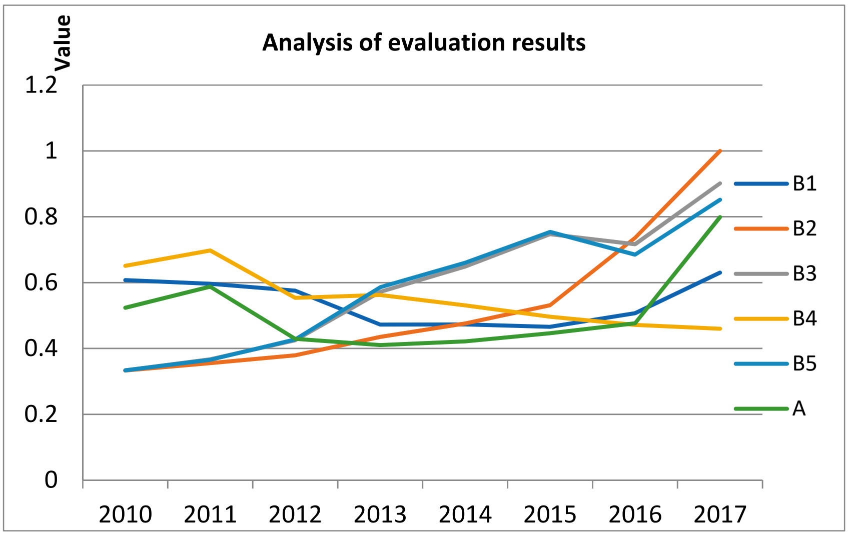

Figure 2. Change trend diagrams of criteria level and purpose level.

In conclusion, during the study period, the low-carbon land use level in Jinan has been declining, and the situation is severe. Although the change trends of land input intensity fluctuated slightly, the land input intensity, the land use degree, the land output efficiency and the land sustainability show a good upward trend on the whole.

Line A represents the change trend of comprehensive evaluation of low-carbon intensive land use. It can be seen from Figure 2 that the comprehensive evaluation results of low-carbon and intensive land use in Jinan fluctuate on the whole from 2010 to 2017. After the rise in 2010–2011, the evaluation value decreases sharply in 2011–2012, even lower than that in the beginning of the study. After the insignificant downward trend during 2012–2013, it enters the slow upward stage during 2013–2016 with 2013 as the turning point. At the end of the study period from 2016 to 2017, it shows a rapid upward trend. For the study period as a whole, the average annual growth rate in 2017 compared to 2010 is about 7.52%; however, the numerical fluctuation during the study period is very obvious, indicating that although the low-carbon intensive land use in Jinan has a good development trend, the state is not stable.

All in all, after a period of extensive development focused solely on economic benefits, China’s 12th Five Year Plan and 13th Five Year Plan have promised to limit carbon emissions, emphasized the in-depth implementation of the scientific outlook on development, and accelerated the construction of a “resource-conserving and environmentally friendly” society. In the process of rapid urbanization, Jinan has actively responded to the call of the central government and formulated the corresponding low-carbon industrial upgrading, low-carbon energy transformation and other supporting carbon-reduction systems and measures. The transformation from the “high consumption and high emission” extensive land use pattern to the of “low consumption, low emission and high benefit” low-carbon intensive land use pattern will not be accomplished overnight, and it must be a dynamic game process. This is also reflected in the evaluation results of each criterion level, and the whole index system of land low-carbon and intensive use. The low-carbon and intensive land use in Jinan still needs to be paid enough attention. This paper will put forward suggestions on the path and guarantee mechanism of low-carbon and intensive land use in Jinan in order to promote the sustainable and healthy development of land use.

4. Policy Recommendations

Based on the dynamic mechanism and the main factors affecting the evolution of urban space environment of modern urban development, this paper proposes the guaranteed mechanism of low-carbon and intensive land use in Jinan from five perspectives:

(1) Perspective of policy system. The land use control mode in China is a comprehensive land use control mode which is oriented by planning, and the direct guidance and basis function are land use planning and urban planning. On the basis of the evaluation results of low-carbon and intensive land use, Jinan city needs to formulate land use planning that integrates urban and rural regions to ensure the coordination and unity of urban planning and land use planning. Since land use planning and urban planning are important statutory plannings for local governments to implement land space management, the integration of the two regulations is conducive to unified management by the government.

(2) Perspective of science and technology. On the one hand, scientific and technological revolution and innovation can produce new technological industries and accelerate the upgrading of traditional industries, thus optimizing the industrial structure of the whole society and promote social development. On the other hand, speeding up the construction of carbon emission trading system will also rely on market-oriented means to promote enterprises to actively improve industrial technology level and accelerate scientific and technological innovation so as to make the enterprises achieve the goals of energy conservation and mitigation of carbon emission.

(3) Perspective of society and culture. Establishing the concept of "green and low-carbon development", changing the environmental protection mode of "pollution first, treatment later", correctly guiding people's consumption concept, advocating moderate consumption, eliminating luxury and waste phenomena, controlling the discharge of pollutants and reducing the use of pesticides and fertilizers, and promoting the use of green energy as well as forming a social and cultural atmosphere for sustainable development could guarantee and promote the low-carbon and intensive land use in Jinan to should be emphasized to a certain extent.

(4) Perspective of resources and environment. Under the guidance of sustainable development concept, the coexistence of natural resources development and protection, the pursuit of natural environment protection and other sustainable development modes are given priority from various aspects of concept, consciousness and measures, which will certainly help to provide a powerful guarantee for the low-carbon and intensive land use in Jinan.

(5) Perspective of regional integration. When Jinan meets the challenge of regional development, it should also find the following opportunities: firstly, it could take advantage of the status of the core city to strengthen the connection with the surrounding areas in economy, transportation, ecology and other aspects, and complement each other while realizing resource sharing. secondly, carrying out actively intensive, coordinated and group-developed urbanization within each region, together with scientific and technological innovation, optimizing the layout of land use structure, transforming enterprises with serious pollution and backward technology, and developing high-tech industries according to local conditions of the characteristics of cities at all levels in Shandong province should be focused. It not only closely links with the surrounding areas for the coordinated development, but also strengthens Jinan's driving ability both in Shandong and in relevant economic regions, such as Bohai Rim, and actively guides and implements the low-carbon and intensive land use in a wider geographical range.

5. Conclusions

This paper establishes an evaluation system based on the low-carbon intensive land use in Jinan city from 2010 to 2017, and uses the grey fuzzy integral multi-attribute evaluation model, which is the integration of respective advantages of grey relational degree, and fuzzy integral for data analysis in view of the large amount of interaction between index factors. In this model, based on the Mobius transformation coefficient of subjective and objective weights of index factors and the interaction degree between index factors, 2-additive fuzzy measures can be obtained; therefore, evaluation of low-carbon intensive land use in Jinan city is processed by combining the grey correlation degree and Choquet fuzzy integral. The results show that in the study period, land input intensity, land use degree, land output benefit and land sustainability in Jinan city all show a good upward trend, but the low-carbon land use level of has been in a declining state. Although there is a good development trend of low-carbon intensive land use of Jinan, the state is not stable, and the transformation of land use from the "high consumption and high emissions" extensive land use pattern to the "low consumption, low emission, high benefit" low-carbon and intensive land use pattern will not be accomplished overnight, and it is bound to be a dynamic game process; therefore, this paper puts forward the corresponding recommendations for low-carbon intensive land use in Jinan city.

With the adjustment of the zoning scope at the end of 2018 and the beginning of 2019, the relevant statistical data of Jinan city will inevitably change accordingly. The current research data and results are applicable before the adjustment of administrative division, which can provide a reference for future refinement and in-depth research; however, for data processing after the adjustment, the influence brought by it, needs to be considered. Although the research scopes or research objects, for instance, target city or target region, could be different, the research method is still worth being used for reference.

Although there could be a common goal of humankind or international treaties to mitigate the carbon emission to make the global environment suitable for the survival of humankind, there are always conflicts of interest between countries in political and economic aspects, and once the balance of various forces is broken, it is easy to cause friction; therefore, when conflicts or wars break out, all carbon mitigation targets and measures together with international collaborations would be abandoned. In conflicts, energy could also become a bargaining chip between countries. When the international environment for energy cooperation is damaged, the priority of the countries concerned is the survival and livelihood of their citizens, rather than the mitigation of carbon emissions. This would undoubtedly shift the global climatic environment, which has been greatly affected by the increase in carbon emissions, from bad to worse. It is more fundamental and significant to seek an international environment of peace, friendship, and common development and prosperity for humankind so as to adopt appropriate policies, measures and technological means to mitigate carbon emissions.

Author Contributions: Conceptualization: J.L. and X.L.; funding acquisition: J.L.; methodology: Q.Y.; data processing and analysis: Q.Y. and L.W.; questionnaire design: Q.Y.; writing—original draft preparation, Q.Y.; writing—review and editing, J.L. and X.L.; Visualization, L.W. All authors have read and agreed to the published version of the manuscript.

Funding: The authors gratefully acknowledge the funding support from Humanities and Social Science Foundation of the Ministry of Education, China (Grant number 17YJA790045).

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Harari, Y.N. *Homo Deus: A Brief History of Tomorrow*; Citic Publishing House: Beijing, China, 2017.
2. Intergovernmental Panel on Climate Change (IPCC). *Climate Change 2014: Mitigation of Climate Change—Summary for Policymakers*; Edenhofer, O.R., Pichs-Madruga, Y., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., et al., Eds.; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2014.
3. United Nations Environment Programme (UNFP). *The Emissions Gap Report 2012*; UNEP: Nairobi, Kenya, 2012.
4. International Energy Agency (IEA). *Energy Policies of IEA Countries: The United States*; IEA: Paris, France, 2008.
5. United Nations (UN). *Paris Agreement under the United Nations Framework Convention on Climate Change*; UN: Paris, France, 2015. Available online: https://www.britannica.com/topic/Paris-Agreement-2015 (accessed on 12 September 2021).
6. The European Economic Area. The Relative Change in Main Global Economic and Environmental Indicators from 1970 to 2018. *European Environment Agency.* 2021. Available online: https://www.eea.europa.eu/data-and-maps/figures/relative-change-in-main-global (accessed on 12 September 2021).
7. IPCC. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*; Prepared by the National Greenhouse Gas Inventories Programme; IGES: Tokyo, Japan, 2006.
8. Houghton, R.A.; Hackler, J.L.; Lawrence, K.T. The U.S. carbon budget: Contributions from land-use change. *Science* **1999**, *285*, 574–578. [PubMed]

9. Houghton, R.A.; Hackler, J.L. Emissions of carbon from forestry and land-use change in tropical Asia. *Glob. Chang. Biol.* **1999**, *5*, 481–492.
10. Hester, R.T., Jr. *Design for Ecological Democracy*; MIT Press: Cambridge, MA, USA, 2006.
11. Romero-Lankao, P.; Gurney, K.R.; Chester, M.; Duren, R.M.; Hughes, S.; Stokes, F. A critical knowledge pathway to low-carbon, sustainable futures: Integrated understanding of urbanization, urban areas, and carbon. *Earth's Future* **2014**, *2*, 515–532. [CrossRef]
12. United Nations (UN). *Transforming Our World: The 2030 Agenda for Sustainable Development*; UN: Paris, France, 2015. Available online: https://sustainabledevelopment.un.org/post2015/transformingourworld (accessed on 12 September 2021).
13. The World in 2050 (TWI2050). *Transformations to Achieve the Sustainable Development Goals*; Report Prepared by The World in 2050 Initiative; International Institute for Applied Systems Analysis (IIASA): Laxenburg, Austria, 2018. Available online: https://www.twl2050.org (accessed on 12 September 2021).
14. Sachs, J.D.; Schmidt-Traub, G.; Mazzucato, M.; Massner, D.; Nakicenovic, N.; Rockstroam, J. Six Transformations to Achieve the Sustainable Development Goals. *Nat. Sustain.* **2019**, *2*, 805–814.
15. Choi, D.; Gao, Z.; Jiang, W. Attention to Global Warming. *Rev. Financ. Stud.* **2020**, *33*, 1112–1145.
16. Monasterolo, I.; de Angelis, L. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecol. Econ.* **2020**, *170*, 106571.
17. Schoenmaker, D. Greening monetary policy. *Clim. Policy* **2021**, *21*, 581–592. [CrossRef]
18. Liu, P.; Qiao, H. How does China's decarbonization policy influence the value of carbon-intensive firms? *Financ. Res. Lett.* **2021**, *43*, 102141. [CrossRef]
19. Benz, L.; Paulus, S.; Scherer, J.; Syryca, J.; Truck, S. Investors' carbon risk exposure and their potential for shareholder engagement. *Bus. Strategy Environ.* **2021**, *30*, 282–301. [CrossRef]
20. Cheng, S.; Qi, S. The potential for China's outward foreign direct investment and its determinants: A comparative study of carbon-intensive and non-carbon-intensive sectors along the Belt and Road. *J. Environ. Manag.* **2021**, *282*, 111960.
21. Sun, X.; Fang, W.; Gao, X.; An, H.; Liu, S.; Wu, T. Complex causalities between the carbon market and the stock markets for energy intensive industries in China. *Int. Rev. Econ. Financ.* **2022**, *78*, 404–417.
22. Moussa, T.; Allam, A.; Elbanna, S.; Bani-Mustafa, A. Can board environmental orientation improve US firms' carbon performance? The mediating role of carbon strategy. *Bus. Strategy Environ.* **2020**, *29*, 72–86. [CrossRef]
23. Abd Rahman, N.R.; Rasid, S.Z.A.; Basiruddin, R. Hard and soft carbon disclosures: Malaysia's carbon intensive industries. In Proceedings of the 9th International Economics and Business Management Conference (IEBMC), Melaka, Malaysia, 2–3 November 2019.
24. Lu, W.; Zhu, N.; Zhang, J. The Impact of Carbon Disclosure on Financial Performance under Low Carbon Constraints. *Energies* **2021**, *14*, 4126. [CrossRef]
25. Hotak, S.; Islam, M.; Kakinaka, M.; Kotani, K. Carbon emissions and carbon trade balances: International evidence from panel ARDL analysis. *Environ. Sci. Pollut. Res.* **2020**, *27*, 24115–24128.
26. Sun, C.; Chen, L.; Zhang, F. Exploring the trading embodied CO_2 effect and low-carbon globalization from the international division perspective. *Environ. Impact Assess. Rev.* **2020**, *83*, 106414.
27. Ji, C.-J.; Hu, Y.-J.; Tang, B.-J.; Qu, S. Price drivers in the carbon emissions trading scheme: Evidence from Chinese emissions trading scheme pilots. *J. Clean. Prod.* **2021**, *278*, 123469.
28. Ma, N.; Yin, G.; Li, H.; Sun, W.; Wang, Z.; Liu, G.; Xie, D. The optimal industrial carbon tax for China under carbon intensity constraints: A dynamic input-output optimization model. *Environ. Sci. Pollut. Res.* **2022**, *29*, 53191–53211. [CrossRef]
29. Wang, J.; Hu, M.; Tukker, A.; Rodrigues, J.F.D. The impact of regional convergence in energy-intensive industries on China's CO_2 emissions and emission goals. *Energy Econ.* **2019**, *80*, 512–523.
30. Du, W.; Li, M. Influence of environmental regulation on promoting the low-carbon transformation of China's foreign trade: Based on the dual margin of export enterprise. *J. Clean. Prod.* **2020**, *244*, 118687. [CrossRef]
31. Rosenbloom, D.; Rinscheid, A. Deliberate decline: An emerging frontier for the study and practice of decarbonization. *WIREs Clim. Chang.* **2020**, *11*, e669. [CrossRef]
32. Zhu, R.; Zhao, R.; Sun, J.; Xiao, L.; Jiao, S.; Chuai, X.; Zhang, L.; Yang, Q. Temporospatial pattern of carbon emission efficiency of China's energy-intensive industries and its policy implications. *J. Clean. Prod.* **2021**, *286*, 125507. [CrossRef]
33. Dong, K.; Ren, X.; Zhao, J. How does low-carbon energy transition alleviate energy poverty in China? A nonparametric panel causality analysis. *Energy Econ.* **2021**, *103*, 105620. [CrossRef]
34. Zhao, D.; Zhou, H. Livelihoods, Technological Constraints, and Low-Carbon Agricultural Technology Preferences of Farmers: Analytical Frameworks of Technology Adoption and Farmer Livelihoods. *Int. J. Environ. Res. Public Health* **2021**, *18*, 13364. [CrossRef] [PubMed]
35. Wang, X.; Liang, S.; Wang, H.; Huang, S.; Liao, B. Do Fossil-Fuel Price Distortions Impact the Low-Carbon Transition in China's Energy Intensive Industries? *Front. Energy Res.* **2022**, *9*, 805224. [CrossRef]
36. Han, M.; Liu, W.; Yang, M. Carbon risk transmission of China's energy-intensive industries under low-carbon transition: From the embodied carbon network perspective. *Geogr. Res.* **2022**, *41*, 79–91.
37. Xin, L.; Sun, H.; Xia, X.; Wang, H.; Xiao, H.; Yan, X. How does renewable energy technology innovation affect manufacturing carbon intensity in China? *Environ. Sci. Pollut. Res.* **2022**, *29*, 59784–59801. [CrossRef]

38. Wang, Z.-B.; Zhang, J.-Z.; Zhang, L.-F. Reducing the carbon footprint per unit of economic benefit is a new method to accomplish low-carbon agriculture. A case study: Adjustment of the planting structure in Zhangbei County, China. *J. Sci. Food Agric.* **2019**, *99*, 4889–4897. [CrossRef]
39. Sun, Y.; Cheng, Y.; Zhang, H. Impact of urban industrial land intensive use on carbon emission efficiency—Take China's 15 sub-provincial cities as an example. *Resour. Environ. Yangtze Basin* **2020**, *29*, 1703–1712.
40. Cormos, A.-M.; Dragan, S.; Petrescu, L.; Sandu, V.; Cormos, C.-C. Techno-Economic and Environmental Evaluations of Decarbonized Fossil-Intensive Industrial Processes by Reactive Absorption & Adsorption CO_2 Capture Systems. *Energies* **2020**, *13*, 1268.
41. Nurdiawati, A.; Urban, F. Towards Deep Decarbonisation of Energy-Intensive Industries: A Review of Current Status, Technologies and Policies. *Energies* **2021**, *14*, 2408. [CrossRef]
42. Roman, M.; de los Santos, C.B.; Roman, S.; Santos, R.; Troncoso, J.S.; Vazquez, E.; Olabarria, C. Loss of surficial sedimentary carbon stocks in seagrass meadows subjected to intensive clam harvesting. *Mar. Environ. Res.* **2022**, *175*, 105570. [CrossRef] [PubMed]
43. The World in 2050 (TWI2050). *Innovations for Sustainability. Pathways to an Efficient and Post-Pandemic Future*; Report prepared by The World in 2050 Initiative; International Institute for Applied Systems Analysis (IIASA): Laxenburg, Austria, 2020.
44. Jinan Municipal Bureau of Statistics. *Jinan Statistical Yearbook 2017*; NBS Survey Office in Jinan, Ed.; China Statistics Press: Beijing, China, 2017.
45. Xun, Q. *History and Culture of Tianqiao District (Industry Volume)*; Jinan Publishing House: Jinan, China, 2012.
46. *GB/T21010-2007*; Land Use Classification. General Administration of Quality Supervision, Inspection and Quarantine of PRC, Standardization Administration: Beijing, China, 2007.
47. People's Government of Shandong Province. Development Plan for Shandong Peninsula Urban Agglomeration (2016–2030). Jinan. 2017. Available online: http://zwfw.sd.gov.cn/art/2017/2/3/art_1684_734.html (accessed on 12 September 2021).
48. Jinan Municipal Bureau of Statistics. *Jinan Statistical Yearbook 2021*; NBS Survey Office in Jinan, Ed.; China Statistics Press: Beijing, China, 2021.
49. *GB/T2589-2008*; General Principles for Calculation of Total Production Energy Consumption. Department of Resource Conservation and Environmental Protection of the National Development and Reform Commission, the first Industrial Standard of Standardization Administration: Beijing, China, 2008.
50. National Development and Reform Commission (NDRC). *Guide for the Compilation of Provincial Greenhouse Gas Inventories (Trial)*; NDRC: Beijing, China, 2011.
51. Wang, H.; Zhang, R.; Bi, J. Carbon emission accounting of Chinese cities: A case study of Wuxi City. *China Environ. Sci.* **2011**, *31*, 1029–1038.
52. Zadeh, L.A. Fuzzy sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
53. Dubios, D.; Prade, H.; Sabbadin, R. Qualitative Decision Theory with Sugeno Integrals. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 314–332.
54. Murofushi, T.; Sugeno, M. The Choquet Integral in Multiattribute Decision Making. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 333–347.
55. Grabisch, M.; Roubens, M. Application of the Choquet Integral in Multicriteria Decision Making. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 348–374.
56. Ishii, K.; Sugeno, M. A Model of Human Evaluation Process Using Fuzzy Measure. *Int. J. Man-Mach. Stud.* **1985**, *22*, 19–38. [CrossRef]
57. Tanaka, K.; Sugeno, M. A Study on Subjective Evaluation of Printed Color Images. *Int. J. Approx. Reason.* **1991**, *5*, 213–222. [CrossRef]
58. Kwon, S.H.; Sugeno, M. A Hierarchical Subjective Evaluation Model Using Non-Monotonic Fuzzy Measures and the Choquet Integral. In *Fuzzy Measures and Integrals: Theory and Application*; Grabisch, M., Murofushi, T., Sugeno, M., Eds.; Physica Verlag: New York, NY, USA, 2000; pp. 375–391.
59. Xie, J.; Li, Q.; Chen, S.; Huang, H. The fuzzy metric space based on fuzzy measure. *Open Math.* **2016**, *14*, 603–612. [CrossRef]
60. Sugeno, M. Theory of Fuzzy Integrals and Its Applications. Ph.D. Thesis, Tokyo Institute of Technology, Tokyo, Japan, 22 January 1974.
61. Grabisch, M. K-order Additive Discrete Fuzzy Measure. In Proceedings of the Sixth International Conference Information Processing and Management of Uncertainty in Knowledge-Based System, Granada, Spain, 1–5 July 1996; pp. 1345–1350.
62. Ministry of Land and Resources of the People's Republic of China. *Evaluating the Potential of Intensive Use of Urban Land (Trial)*; Ministry of Land and Resources of the People's Republic of China: Beijing, China, 2007.
63. Zeng, H.; Dong, L.-M. Evaluation of land intensive use in Wuhan city based on low carbon background. *Hubei Agric. Sci.* **2014**, *53*, 3456–3461.
64. Li, Y.; Gong, X.; Hui, H.; Tian, J. Construction of evaluation index system of government-civilian interaction degree under the condition of government microblog. *J. Chongqing Univ. (Soc. Sci. Ed.)* **2016**, *22*, 172–179.
65. Chang, Z.; Cheng, L. Grey fuzzy integral relational degree decision 5making model. *Chin. Manag. Sci.* **2015**, *23*, 105–111.