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Optimizing Land Use for Carbon Neutrality: Integrating Photovoltaic Development in Lingbao, Henan Province

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Abstract: This study aims to examine the impact of land use variations on carbon emissions by incorporating the development of photovoltaics as a scenario. To meet this end, we investigate the carbon emissions fluctuations resulting from different development scenarios: natural development, low-carbon strategies, and widespread adoption of photovoltaic technology. We identify important influencing factors related to these changes and utilize multi-objective optimization and the PLUS model to simulate land use patterns in Lingbao City projected for 2035, with a focus on achieving carbon neutrality. Through multiple scenarios, we analyze differences in carbon emissions, economic benefits, ecological impacts, and land use allocations. Our findings demonstrate that the photovoltaic scenario leads to a substantial 3500-ton reduction in carbon emissions and boosts overall benefits by RMB 85 million compared to the low-carbon scenario. This highlights the significant role of photovoltaic systems inefficient land utilization, meeting carbon emission targets, and generating economic gains. This research explores the relationship between land use alterations and carbon emissions, aiming to achieve ambitious carbon reduction objectives by integrating photovoltaic applications across diverse land types. It provides fresh perspectives for examining urban land utilization and strategies to reduce carbon emissions.

Keywords: land use optimization; carbon emission; photovoltaic; county-level cities; scenario simulation

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1. Introduction

Research Background

In recent years, global warming has triggered a series of extreme weather disasters that have severely impacted overall human survival. As the world's largest emitter of carbon dioxide, China's carbon neutrality goal has a profound impact on global ecosystem stability [1]. To cope with this worldwide challenge, many countries have made carbon-neutral commitments [2]. From the perspective of emission reduction, land use change affects atmospheric CO_2 concentration and is recognized as the second largest source of carbon emissions, right after fossil fuel combustion [3–5]. Moreover, changes in land type, intensity, and structure profoundly affect the carbon cycling process in the terrestrial ecosystem. It can be said that land use change is one of the key factors altering carbon emissions from terrestrial ecosystems. However, most of the existing studies have explored the relationship between carbon emissions and cities from an energy perspective while paying insufficient attention to the changes in carbon emissions due to land use. Therefore, studying and analyzing carbon emissions from the perspective of land use changes is of important significance for governing urban carbon emissions and achieving carbon neutrality goals.

Changes in land use are the result of multiple contributing factors. For example, the scale and location of urban power plants are examples of the impact of urban energy structures on urban land use change. According to statistics, the annual carbon dioxide emissions from the power sector in China account for about half of the national energy carbon emissions [6]. Transforming energy structures will be one of the most significant factors in helping Chinese cities achieve carbon neutrality at the land use level.

Studies have indicated that photovoltaic (PV) systems can effectively help the global energy sector achieve carbon reduction goals [7]. As of 2020, China's installed PV capacity reached 253 GW, while solar PV power generation accounted for only 3.42% of the total power generation (NEA, 2021). In order to further reduce carbon emissions and achieve energy structure transformation. China plans to have a total installed capacity of over 1.2 billion kilowatts of wind and solar energy by 2030. This will lead to a decrease of over 65% in carbon dioxide emissions per unit of China's gross domestic product compared to 2005, with non-fossil fuels accounting for about 25% of primary energy consumption and forest storage increasing by 6 billion cubic meters compared to 2005. Among PV systems, distributed photovoltaics are the preferred choice for implementing carbon reduction measures at the land use level in the future due to their wide applicability, relatively low peak demand, ease of implementation locally, fewer transmission issues, relatively independent and safe control methods, and ease of real-time monitoring [8]. However, previous studies have overlooked the impact of photovoltaic development on land use change and carbon emissions.

This study focuses on studying the impact of distributed photovoltaic systems on urban land use change and carbon emissions. By proposing new photovoltaic penetration scenarios, it may be found that the large-scale popularization of photovoltaics is beneficial for optimizing urban land use patterns and achieving carbon emission targets. This study aims to (1) analyze in depth the factors influencing carbon emissions from land use based on the land use data of Lingbao from 2000 to 2020. (2) take multiple factors of urban ecology, economy, and carbon emission demand into full consideration to obtain various land use demands under natural development (ND), low carbon emissions (CE), and PVP scenarios based on multi-objective optimization and visualize the scenarios by using patch-generating land use simulation (PLUS). Multi-objective optimization is mainly used to find the optimal solution of the objective function when influenced by multiple factors. The PLUS model is a cellular automaton (CA) model based on raster data that can be used for simulating patch-scale land use/land cover (LULC) changes. (3) compare the differences in economic benefits, carbon emissions, and ecological benefits under different scenarios and propose the optimal development scenario suitable for the future development of Lingbao. The objectives (1) and (2) of the article mainly focus on multi-objective optimization of methods and the PLUS model section. Goal (3) is presented in the Results and Discussion section of this article.

2. Literature Review

2.1. Impact of Land Use Changes on Spatiotemporal Patterns of Carbon Emissions

Land use change is an essential link between ecosystems and human activities and a significant factor in the escalation of urban carbon emissions. In recent years, more and more scholars have been considering changes in land use from the perspective of carbon emissions. Currently, studies in this field mainly focus on analyzing the impact of land use on the spatiotemporal patterns of carbon emissions [9], as shown in Table 1.

At the national level, Wan Yee calculated the increase in carbon emissions in each country due to changes in farmland areas based on statistics from 1885 countries [10]; Yang estimated the carbon emissions from historical land use changes based on China's 300-year historical land use/cover change (LUCC) dataset [11]. Tang quantified the impact of land use and landscape pattern changes on carbon emissions from a regional perspective [12]. At the provincial and city cluster levels, Chen and Gui analyzed the spatiotemporal evolution characteristics of carbon emissions in Guangdong Province and Northwest China, respectively [13,14]. Ye analyzed the evolution characteristics of land use carbon emissions (LUCEs) in Zhejiang Province from 2000 to 2020 and analyzed the impacts of various factors on LUCEs using Kaya identity and LMDI decomposition methods [15]. Cao proposed a water-energy-carbon spatial optimization strategy for land use in urban agglomerations based on cities in the middle reaches of the Yangtze River [16]. At the city level, Zhang analyzed the factors influencing land use changes [17]. Ke established a hybrid network framework and revealed the role of different types of land in the low-carbon development of megacities [18]. Moreover, many scholars have also conducted research on ecologically sensitive areas such as lake regions and watersheds. For example, Rong analyzed the spatiotemporal characteristics of carbon emissions at the watershed scale [19]. This indicates that under the system of research on the relationship between land use and carbon emissions, land use at the macro (national, provincial, and urban agglomeration) and meso levels (city and watershed) is relatively complete, while studies at the micro (county and village) levels are scarce.

Table 1. Research on the impact of land use changes on carbon emissions.

Research Scope	Research	Research Direction	Usage Method	Advantages and Disadvantages	Source
Macro	33 countries	Farmland changes, carbon emissions	PAS2050-1	Advantages: Demonstrated a consistent, globally applicable spatial approach to estimating land use changes and carbon emissions associated with crop production. Disadvantages: Temporary carbon sequestration is not considered for data reasons.	[10]
	United States	Agricultural production, carbon emissions, and land use changes	CARD model, dynamic nonlinear programming model, FASOM	Advantages: Expounded the impact of the carbon tax on U.S. agriculture and global commodity trade. Disadvantages: Issues such as rising costs due to climate change are not included in the scope of problems.	[20]
	China	Estimation of carbon emissions from land use	Estimation of carbon density based on vegetation in the historical LUCC dataset	Advantages: Re-estimated carbon balance in Chinese terrestrial ecosystems from 1700 to 1980 and updated the table function of carbon loss and gain. Disadvantages: The data cannot reflect the secondary fluctuations of LUCC in different years.	[11]
	Yangtze River Economic Belt, China	Land use, landscape pattern, and carbon emissions	Direct measurement method, material balance calculation method, and emission factor method	Advantages: Explored the impact of changes in land use and landscape patterns on carbon emissions from a regional perspective. Disadvantages: The spatial scale of the study focuses on the whole Yangtze River Economic Belt, while the heterogeneity of specific regions is insufficiently explored.	[12]
	Guangdong Province, China	Estimation of the land use carbon emission factor	Exploratory spatiotemporal data analysis (ESTDA)	Advantages: Estimated carbon emissions of 122 county-level administrative regions in Guangdong Province. Disadvantages: No feasible emission reduction path is proposed for the spatiotemporal evolution of carbon emissions.	[14]
	Zhejiang Province, China	Land use carbon emission estimation, carbon emissions, scenario simulation	The direct calculation method and the indirect proxy method for energy consumption	Advantages: Applied the multi-scenario analysis method to simulate future carbon emission changes. Disadvantages: The Random Forest algorithm itself is defective; The large span of the study area is not considered, leading to certain inaccuracies in carbon emission estimation.	[15]
	Yangtze River Delta, China	Optimization of land use allocation, carbon emissions	Multi-objective particle swarm optimization (MOPSO), TOPSIS	Advantages: Incorporate land use suitability into the multi-objective objective function to improve the scientific nature of the decision function. Disadvantages: GDP and carbon emissions were set as positively correlated in the study, simplifying the model but leading to errors.	[21]
	Northwest China	Land use changes, carbon emissions	NSGA-II, INVEST model, direct measurement method, energy consumption analysis method	Advantages: Proposed multiple scenarios for optimizing carbon emissions from land use. Disadvantages: The model references a gray prediction model, which may introduce errors in practical applications.	[13]

Table 1. *Cont.*

Research Scope	Research	Research Direction	Usage Method	Advantages and Disadvantages	Source
Meso levels	Cities of different tiers in Hubei Province, China	Land use changes	Descriptive statistical analysis, transition matrix analysis of land use/cover change, and OLS regression	Advantages: Analyzed the factors influencing land use changes in different urban systems. Disadvantages: The impact of economic and social factors on the expansion of urban construction land has been addressed in previous studies, but the differences between different tiers of cities have not been effectively identified.	[17]
	Shenzhen, China	Land use changes, carbon emissions	Hybrid network framework	Advantages: Constructed a hybrid network framework integrating carbon emission accounting, environmentally extended input-output tables, and land matrix data. Disadvantages: The division of land use across different sectors is insufficiently refined.	[18]
	Shanghai, China	Optimization of land use allocation, carbon emissions, and scenario simulation	Decomposition analysis of kaya identity drivers Multi-objective genetic algorithm (MOGA), decomposition analysis of kaya identity drivers	Advantages: Innovatively introduced the systematic research methodology of "carbon emission accounting–peak scenario analysis–objective optimization under carbon emission constraints–multi-objective land use optimization simulation". Disadvantages: The energy statistics of Pudong New Area are incomplete and need to be converted based on the land carbon emission intensity in Shanghai. The complexity of the planning content leads to the relative dispersion of the land layout output results.	[22]
	Bortala Mongol Autonomous Prefecture, China	Optimization of land use allocation and ecological footprint	Back propagation neural network (BPNN), multi-objective genetic algorithm (MOGA)	Advantages: Proposed an integrated framework combining ecological footprint, BPNN, MOGA, and PLUS models. Disadvantages: Factors, including social dimensions, are not incorporated into the optimization objectives.	[23]
	Yellow River Basin, China	Land use change and carbon emissions	Social network analysis, PLUS model	Advantages: Simulated and predicted future land-use patterns at the watershed scale in 2030. Disadvantages: The impact of policy factors is not considered.	[19]
Micro	Changxing, China	Optimization of land use allocation and carbon emissions	NSGA-II, LC-MLUA optimization model	Advantages: Proposed an improved algorithm, NSDE, based on NSGAS-II. Disadvantages: Study cases are insufficient.	[24]

2.2. Predicting Carbon Emission Scenarios

In the field of carbon emission scenario prediction, some scholars combine carbon emissions from land use with indicators from other fields [22], such as socio-economic [15,19], ecological [25,26], and energy [27,28] indicators. However, as a complex system, changes in urban land use are affected by a variety of factors, making it difficult to gain insight into the mechanisms and drivers of changes from a single aspect. In recent years, some scholars have begun to predict future land use patterns under different scenarios based on the coupling of multi-objective optimization and land use simulation models, as shown in Table 2. For example, Chen optimized the future land use structure of Northwest China in 2060 by proposing three objectives (ecological conservation, economic development, and carbon emissions) and setting four development scenarios, namely, natural development (ND), low carbon emission (CE), high carbon sequestration (CS), and carbon neutrality (CN) [13]. Zhang proposed a low-carbon development scenario by integrating multiple carbon emission identification models and combining them with an improved multi-objective genetic algorithm, and he gave layout suggestions for the optimization of land-use allocation in Pudong New Area, Shanghai [22]. Liu built a patch-based low-carbon multi-objective land use allocation (LC-MLUA) optimization model through the improved NSGA-II algorithm [24]. Fatemeh proposed six scenarios to optimize land use changes for the Ilam urban watershed in the northern part of Ilam province, western Iran, including food production (FP), water yield (WY), sediment retention (SR), recreational quality (RQ), aesthetic quality (AQ), and habitat quality (HQ), which provided new perspectives for land development in ecologically-oriented cities [29]. Wang proposed a LULC optimization scenario for the Bortala Mongol Autonomous Prefecture region in China by combining the ecological footprint, back propagation neural network (BPNN), multi-objective genetic algorithm (MOGA), and PLUS model. Compared with the ND scenario, this scenario can effectively improve the ecological carrying capacity of the local land in the future [23]. With the development of the new energy industry, PV systems have become one of the most critical factors for urban decarbonization. The appropriate location for PV installation is also closely related to land use changes in cities. Although existing studies have thoroughly analyzed the impact of land use changes on carbon emissions and comprehensively considered other factors influencing urban development based on the goal of urban carbon emissions, very few studies have included PV in the factors influencing land use changes.

Table 2. Research on carbon emissions scenario prediction.

Research Area	Research Topic	Research Method	Scenario Setting	Source
Northwest China	Multi-objective optimization, scenario simulation	Multi-objective genetic algorithm (NSGA-II)	Natural development scenario (ND), low carbon emission scenario (CE), high carbon sequestration scenario (HS), carbon neutral scenario	[13]
Shanghai, China	Multi-objective optimization, scenario simulation	Multi-objective genetic algorithm (MOGA)	Low carbon development scenario	[22]
Zhejiang Province, China	Scenario simulation	STIRPAT model, LMDI decomposition method	Natural development scenario, energy conservation and emission reduction scenario, energy structure adjustment scenario	[15]
Hainan Province, China	Scenario simulation	(LPM), Markov chain Linear programming model (LPM), Markov chain	Natural development scenario (ND), spatial planning (SP), low carbon emission (LE), and high carbon sequestration (HS)	[30]
Shenzhen, China	System dynamics, scenario simulation	System dynamics model (SD)	A business-as-unusual (BAU), carbon-neutral action (CNA)	[31]

In summary, existing studies have not adequately addressed the impact of PV system development on land use changes at the county scale. In this study, we hope to predict the changes in urban energy structure due to PV development and further assess its impact on urban land use, which may provide a new perspective for future research on urban and county-level land use reduction.

3. Data and Methods

3.1. Research Area

Lingbao City is located at the western edge of Henan Province, between latitude 34°07′10″–34°44′21″ N and longitude 110°21′18″–111°11′35″ E, with a total area of 3011 km^2 and a resident population of 653,800. There are many mountains and ravines in the city, with the small Qinling Mountain Range and Xiaoshan Mountain Range in the south, the Yellow River and valley plain in the north, and loess hills in the center. However, the national ecological and environmental protection policy of 2016 completely banned the development of gold mines in Lingbao territory, which led to a sharp drop in income and a serious loss of population in the city [32]. The terrain is high in the south and low in the north, and the ground elevation gradually rises to 2413.8 m from 308 m in the Yellow River in the north to the south, with a relative elevation difference of up to 2105.8 m and an average natural gradient of 34.4‰. The details of the research area are shown in Figure 1.

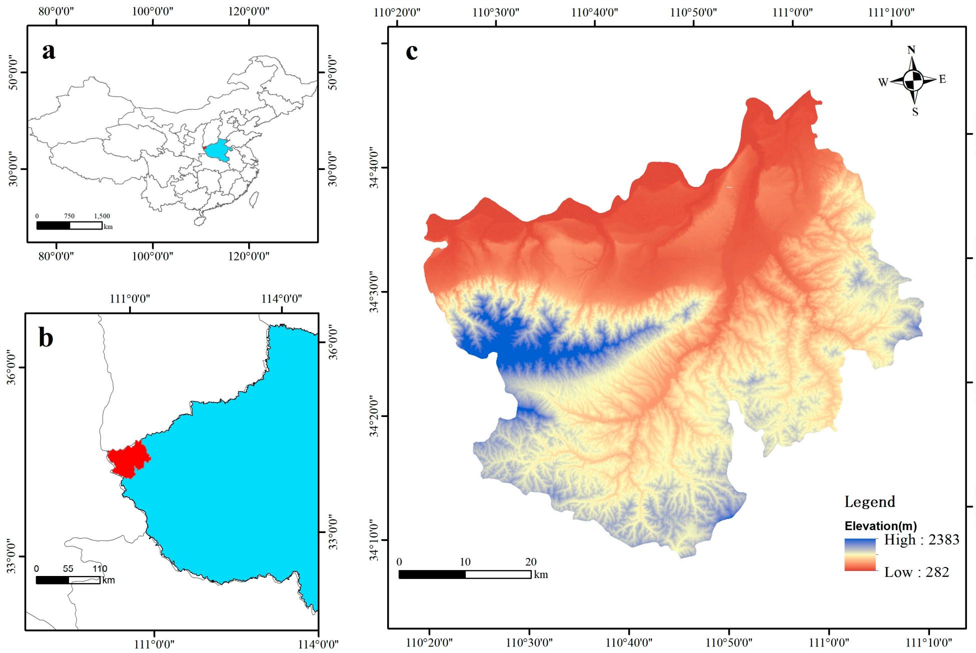

Figure 1. Location of the research area and digital elevation model (DEM), (**a**) Location of Henan Province, (**b**) Location of Lingbao in Henan Province, and (**c**) Digital elevation model (DEM) of Lingbao.

3.2. Data Sources

Based on the research method and content, the data involved in this study include three aspects: data required for PLUS model simulation, multi-objective optimization, and carbon emission factor correction.

Meteorological, soil type, and socio-economic data involved in the PLUS model simulation: Meteorological data came from the National Earth System Science Data Center (including yearly average rainfall and temperature data from 2000 to 2020) [33]. Soil-type data were from the FAO/UNESCO Soil Map of the World [34]. Socio-economic data, such as population, GDP, and public (railway) road distribution, was from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences (CAS) and the National Catalogue Service for Geographic Information [35,36]. All the data were parsed and processed by Arcgis10.8, and the coordinate system was uniformly converted to the CGCS2000 latitude and longitude coordinate system.

Multi-objective optimization requires the following data: Yearly output value of primary, secondary, and tertiary industries, as well as agriculture, forestry, fishery, and animal husbandry from 2000 to 2020 in Lingbao, was obtained from the Statistical Bulletin on the National Economy and Social Development in Lingbao [37] to calculate the economic benefit coefficient. Data on the sown area, yield per unit area, and price of grain crops in Lingbao from 2000 to 2020 was obtained from the Statistical Bulletin on the National Economy and Social Development in Lingbao and the National Agricultural Product Cost-Benefit Data Compilation [37,38] to calculate the ecological efficiency coefficient. Data on the energy structure of Lingbao from 1978 to 2007 was obtained from [39] to calculate the carbon emission factor. The carbon emission factor correction data are mainly related to PV systems, including building roof vector datasets [8].

3.3. Methods

In this study, based on the coupled NSGA-II and PLUS, future multi-scenario simulation and carbon reduction analysis were conducted for Lingbao, a county-level city in Henan Province, China. The framework of this paper mainly includes three parts (Figure 2). First, three objectives were set based on the ecological conservation, economic development, and carbon emissions of Lingbao. The multi-objective genetic algorithm NSGA-II was utilized to solve the land-use demand for each type of land use when the objective benefits were maximized. Second, given the impact of PV power generation on the urban energy structure, the area of land suitable for PV installation in Lingbao was first estimated, followed by solving the PV power generation capacity for the area and then converting the PV power generation capacity and correcting the carbon emission factor in the multi-objective optimization. Finally, the Markov model was used to predict the land use pattern of Lingbao in the natural state under the natural development scenario in 2035. At the same time, the land use demand obtained from multi-objective optimization before and after PV correction was inputted into the PLUS model to obtain the land use pattern under the energy conservation and emission reduction scenario and the PV development scenario, respectively.

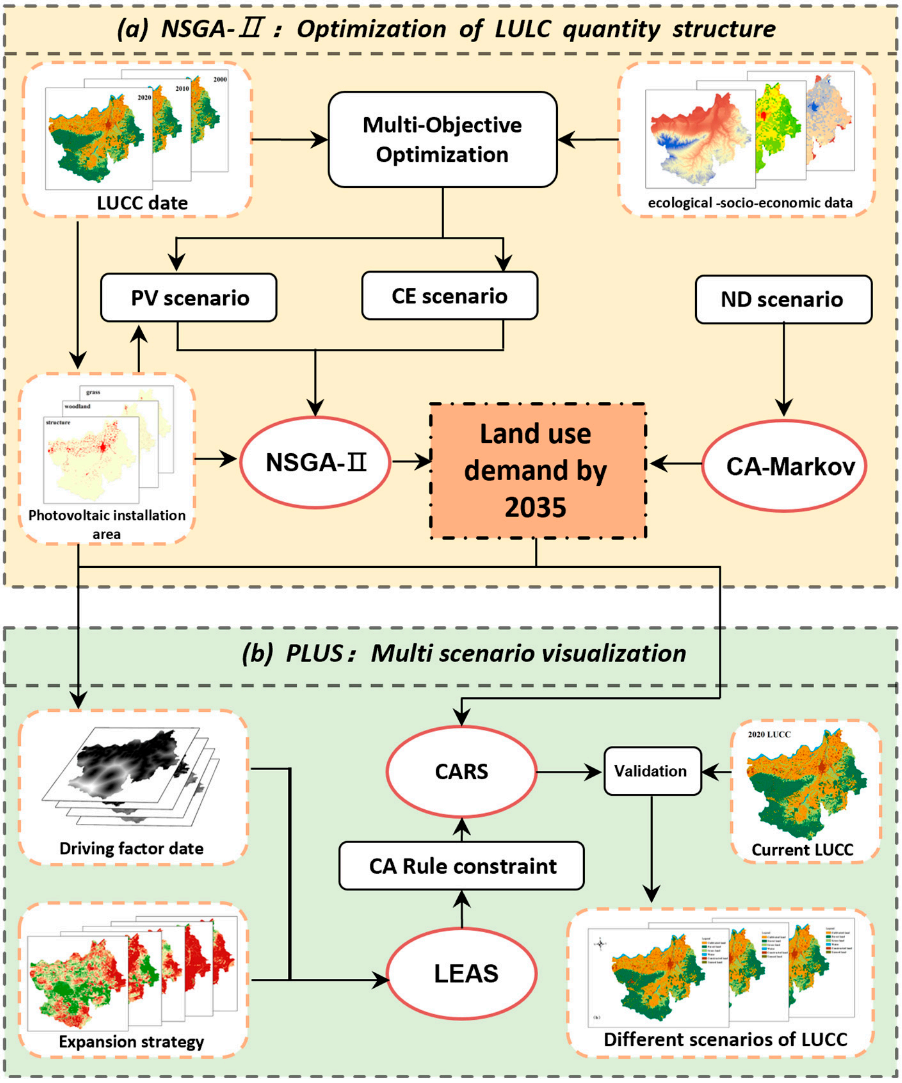

Figure 2. Research framework. (**a**) Optimization of LULC quantity structure. (**b**) Multi scenario visualization.

3.3.1. Predicting Land Use Demand

(1) Estimation method for carbon emissions

The estimation method for carbon emissions in this paper mainly refers to the Intergovernmental Panel on Climate Change's (IPCC) carbon inventory estimation method, which mainly categorizes carbon emissions into direct and indirect emissions [40]. Direct emissions can be directly calculated from the area and carbon density data on five types of land use [41], with the formula as follows:

$$E_a = \sum Cg\delta g \quad (1)$$

where E_a denotes the cumulative direct carbon emissions, Cg denotes the spatial extent of LULC type g, and δg denotes the carbon emission factor specific to LULC type g, which is derived with reference to the results of previous studies, as shown in Table 3.

Table 3. Carbon emission factors for different LULC types.

Land Use Type	Farmland	Woodland	Grassland	Waters	Unused Land
Carbon emission factor	0.36	−11.02	−5.76	−7.71	−3.87

Indirect carbon emissions, mainly from construction land, are calculated based on the energy structure data of construction land [39], with the formula as follows:

$$E_b = \sum_{i=1}^{n} m_i \times q_i \times \varphi_i \times 44/12 \quad (2)$$

where E_b denotes the total carbon emissions from the consumption of various types of fossil energy; i is the type of energy; m_i is the consumption of energy i, and its determination method is mainly based on [39]; and q is the standard coal equivalent coefficient for energy i; φ_i is the carbon emission factor, which is equal to the product of three indicators (average low heating value, carbon content, and oxidation rate) of various energy sources; 44/12 indicates the ratio of CO_2 to the molecular weight of carbon. The calculation of the carbon emission factor and standard coal equivalent coefficient for each energy type refers to the IPCC Guidelines for National Greenhouse Gas Inventories and China Energy Statistics Yearbook [42,43], as shown in Table 4.

Table 4. Energy carbon emission factor and standard coal equivalent coefficient.

Energy Name	Raw Coal	Coke	Crude Oil	Gasoline	Diesel	Fuel Oil	Liquefied Petroleum Gas (LPG)	Natural Gas	Electricity
Carbon emission factor (t/t)	0.5183	0.7801	0.8237	0.7978	0.8443	0.8647	0.8458	0.5897	0.928
Standard coal equivalent coefficient (kg standard coal/kg)	0.7143	0.9714	1.4286	1.4714	1.4571	1.4286	1.7143	1.33	0.1229

Total carbon emission is denoted by E_c, including direct and indirect carbon emissions, with the calculation formula as follows:

$$E_c = E_a + E_b \quad (3)$$

(2) Estimation method for economic benefits

Based on the economic output data per unit area of each land type from 2000 to 2020, the economic benefit coefficients of each land use in 2035 were calculated based on the gray prediction model GM (1, 1). The principle of the gray prediction model is a prediction method that establishes a mathematical model and makes predictions based on a small amount of incomplete information [44,45]. Among them, farmland, woodland, grassland, waters, and artificial surfaces are expressed as agricultural output value, forestry output value, pasture output value, fishery output value, and secondary and tertiary industry output value, respectively; wetland and unused land are not calculated as they do not directly produce economic value [46]. The calculation results are shown in Table 5.

Table 5. Economic benefit equivalent.

Land Use Type	Farmland	Woodland	Grassland	Waters	Construction Land
Equivalent factor (10,000 yuan/ha)	38.12	0.18	5.59	1.53	1351.20

(3) Estimation method for ecological benefits

Different from economic benefits, ecological benefits focus on the valuation of the goods and services provided by different ecosystems, directly or indirectly, that satisfy human needs. Their value is usually quantified in the form of economic terms based on their prices in the market or the prices of alternative goods and services [47,48]. In this study, the ecological benefits per unit area of each land type were calculated using the economic value of the annual natural grain yield of farmland with the national average yield per hectare as one standard equivalent [49]. The gray prediction model GM (1, 1) was used to obtain the ecological benefit coefficient of each land use scenario in 2035 based on the data from previous years. The calculation results are shown in Table 6.

Table 6. Ecosystem service value equivalent per unit area in Lingbao.

LULC Type	Farmland	Woodland	Grassland	Wetland	Waters	Construction Land	Unused Land
Equivalent factor (10,000 yuan/ha)	0.52	2.63	1.61	52.02	11.84	0.00	0.09

Gray prediction model, GM (1, 1)

Gray system theory (GST) is used to describe, predict, decide, and control incomplete information systems [44], and the GM (1, 1) formula is shown as follows [45]:

$$z^{(1)}(k) = \sum_{l=1}^{k} x^{(0)}(l) \tag{4}$$

$$\frac{dz^{(1)}}{dt} + \alpha z^{(1)} = \mu \tag{5}$$

$$z^{(1)}(k+1) = \left[z^{(0)}(1) - \frac{\mu}{\alpha}\right]e^{-\alpha k} + \frac{\mu}{\alpha} \tag{6}$$

$$z^{(0)}(k+1) = z^{(1)}(k+1) - z^{(1)}(k) \tag{7}$$

Assuming the amount of raw data on carbon emissions is v, the raw data on carbon emissions is $z^{(0)}$ = {z(0)(i), l = 1, 2, . . . , n}, the new sequence $z^{(1)}$ = {z(1)(k), k = 1, 2, . . . , n} is obtained by accumulation according to Equation (4). x represents a new set of sequences. $x^{(0)}$ be raw series, $x^{(1)}$ is said to be the one order accumulated generating operation series of $x^{(0)}$. Then, from the $z^{(1)}$ sequence, the time response sequence of differential Equation (6) is derived after least squares estimation of the values for parameters α and μ. Subsequently, the generated sequence is accumulated and recovered to determine the prediction formula for the recovered sequence, as shown in Equation (7). The final calculated factors for each type of land use are shown in Table 7.

Table 7. Carbon emissions per unit area, economic and ecological benefits in 2035 for each land type.

Factor	Farmland	Woodland	Grassland	Wetland	Water Bodies	Land Used for Construction	Unused Land
Economic benefits/10,000 yuan	38.1272	0.1856	5.5989	1	1.5301	1351.203	1
Ecological benefits/10,000 yuan	0.5186	2.6259	1.6082	23.45	11.8403	0	0.0867
Carbon emissions (CE scenario)/t	0.3570	−11.0179	−5.7549	0	−7.7113	74,095.4050	−3.8359
Carbon emissions (PV scenario)/t	0.3570	−11.0181	−5.7554	0	−7.7113	74,095.3964	−3.8675

Function construction

The NSGA-II algorithm generates a series of Pareto-optimal solutions based on fast sorting and elite strategies. It can achieve a balance between multiple optimization objectives and, therefore, has outstanding performance in solving multi-objective land use and land cover optimization problems [50]. In this study, the NSGA-II algorithm was used to solve the demand for each type of land that is most suitable for the development of Lingbao in 2035 based on a full consideration of the factors influencing urban development. Given the context of national PV development and the socio-economic development and ecological conservation requirements of Lingbao, this study proposes three prospective LULC development scenarios with the primary goal of achieving carbon neutrality.

ND scenario: The quantity structure of LULC for various types of land use in Lingbao in 2035 is predicted by the CA-Markov module in the PLUS model. This is an inertia scenario based on past land use data without considering any policy conditions.

CE scenario: The socio-economic development and ecological conservation objectives of Lingbao are taken into consideration while minimizing carbon emissions. The objective function is expressed as follows:

$$F_1(X) = Max\sum_{j=1}^{7} A_g X_g \tag{8}$$

$$F_2(X) = Min\sum_{j=1}^{7} B_g X_g \tag{9}$$

$$F_3(X) = Max\sum_{j=1}^{7} C_g X_g \tag{10}$$

$$F_4(X) = MaxF_1(X) - MinF_2(X) + MaxF_3(X) \tag{11}$$

where $F_1(X)$, $F_2(X)$, $F_3(X)$ denote the economic value factor (yuan·hm^{-2}), the carbon emission factor (t·hm^{-2}), and the ecological value factor (yuan·hm^{-2}). The variable Xg denotes the area of a particular land use type (hm^{-2}). The variable j represents different types of land use, where j_1 to j_7 represent cultivated land, forest land, grassland, wetland, water area, construction land, and unused land, respectively.

PV scenario: Given the impact of new energy development on the urban energy structure, it is assumed that Lingbao will be fully covered with PV on all lands suitable for PV installation in 2035. The objective function of this scenario is obtained by estimating the power generation capacity of PV systems on various land use types and correcting the carbon emission factor of the CE scenario. First, the areas of farmland, woodland, grassland, water, and unused land for PV installation should be determined. In general, locations with slopes greater than 5° are not suitable for solar panels, and areas with solar radiation below 5400 MJ/m^2 are also considered unsuitable [51]. Moreover, the land use policy restrictions in China are considered, i.e., permanent basic farmland and high-cover woodland and grassland are not allowed for PV project development. Water and unused land are not calculated as they are quite small in relation to the total shared area and scattered. Low-cover woodland, grassland, and roof land for construction are mainly selected as PV installation lands in this study. Among them, the PV installation area of woodland and grassland is obtained in Arcgis10.8 based on the overlay analysis of annual average rainfall, year-by-year solar radiation, and DEM data. The roof area of land for construction in Lingbao in 2035 is calculated with reference to [8]. The formula for estimating the power generation capability of a PV system is as follows [52]:

$$Sp = G\left[\frac{\text{kWh}}{\text{m}^2 y}\right] * Area\left[\text{m}^2\right] * eff[\%] * PR[\%] \tag{12}$$

where G denotes the average value of solar radiation over the surface area, area denotes the area of the façade or roof (m^2), eff denotes the efficiency (%) of the PV module, and PR denotes the performance ratio. As this study focuses on investigating the impact of PV on land use change, it is assumed during calculation that the efficiency of the PV module is set to 21% and the PR is set to 80% [53–55].

Setting constraints

Total area constraint: The total area under each scenario assumption should be consistent.

$$\sum_{g=1}^{7} X_g = 299,555 \tag{13}$$

Economic growth constraint: Ensure that the economic value of the optimized scenario is greater than or equal to the economic growth target of Henan Province in 2035 and that the economic value of the optimized scenario is greater than that under the ND scenario. The value of $\sum_{g=1}^{7} W_g A_g$ is shown in Table 8.

$$\sum_{g=1}^{7} X_g A_g \geq \sum_{g=1}^{7} W_g A_g \tag{14}$$

Table 8. Comparing the current situation in 2020 and the changes in different land use types under different scenarios (10^3hm^2).

Scenario	Farmland	Woodland	Grassland	Waters	Land for Construction	Unused Land
Status quo in 2020	114,922.8	109,490.22	54,139.32	6451.29	14,267.7	283.86
ND	7852.59	2256.03	−11,394.61	446.85	2513.97	3.42
CE	1608.8	2125.55	−3732.34	0.20	−0.70	−1.52
PVP	2067.16	646.57	−2712.43	−0.29	−0.70	3.42

Carbon emission constraint: Ensure that the carbon emissions of the optimized plan are lower than those under the ND scenario.

$$\sum_{g=1}^{7} X_g B_g \leq \sum_{g=1}^{7} W_g B_g \tag{15}$$

Area constraints for each type of land: The area constraints for each type of land shall be determined based on the current value and the ND scenario as the upper and lower limits and adjusted for different land types according to the development demands.

$$114,922 \leq X_1 < 122,775; 109,490 \leq X_1 < 111,746; 40,744 \leq X_3 < 54,139; 6451 \leq X_5 < 6898; 14,267 \leq X_6 \leq 16,781; X_7 < 285$$

3.3.2. Multi-Scenario Land Use Simulation Based on the PLUS Model

The PLUS model combines a rule mining framework using the Land Expansion Analysis Strategy (LEAS) module with a CA model based on various random seeds (CARS). The LEAS module is conducive to depicting spatiotemporal differentiation patterns in LULC, while the CARS module employs meta-cellular automata based on LULC data and drivers for efficient spatial simulation [49].

Model input settings

The LEAS module assesses the contribution of various types of influencing factors to land use changes by extracting the changes in LULC over two periods. This can help analyze the growth potential of different land types in the research area. In addition, the CARS module can simulate LULC competition at the urban patch level. It uses adaptive factors, neighborhood effects, and development probabilities to determine the direction of expansion of various land types in different scenarios.

Accuracy verification

In this study, the PLUS model was used to predict the LULC land pattern of Lingbao in 2020, and its accuracy was verified through comparison with the current LULC data in 2020. The overall accuracy generated by verification was 0.83, and the Kappa coefficient was 0.75, indicating that the model met the accuracy requirements for simulating future LULC in the research area [56].

Visual expression of scenarios

Land demand for the ND, CE, and PVP scenarios was inputted into the model. The land use patterns of the three scenarios in Lingbao in 2035 were visualized through the CARS module of the PLUS model.

4. Results

4.1. Comparison of LULC Changes in Different Scenarios

From 2020 to 2035, the LULC changes under various scenarios in Lingbao showed significant differences (Table 9 and Figure 3). Under the ND scenario, land areas for construction and farmland increased significantly. Significant changes in land use are exemplified by Figure 3e–h. Woodland, water, and unused land showed no significant increase, while those of grassland in the central and southern parts of the research area decreased significantly. Under the CE and PVP scenarios, the expansion of construction land in the central part of the research area and farmland in the southern part of the research area was restricted. The grassland in the central and southern parts of the research area was better protected (Figure 3), and the areas with various types of land did not significantly increase or decrease. This suggests that the two low-carbon development scenarios have shown remarkable results in restricting carbon sources, such as farmland and land for construction, and protecting carbon sinks, such as woodland, grassland, and watersheds, which highlights the concept of low-carbon urban development in the future.

Table 9. Comparison of relative value (absolute value) of benefits in different scenarios.

Type	Economic Benefits/10^8 Yuan	Carbon Emissions/10^4	Ecological Benefits/10^8 Yuan	Total Value/10^8 Yuan
Status quo in 2020	2399.38	105,564.33	51.06	32,783.28
	0.0	0.0	0.0	0.0
ND	2761.62	124,196.85	50.43	27,420.34
	362.24	18,632.52	−0.63	−5362.91
PVP	2400.36	105,560.00	50.90	32,785.40
	0.98	−4.33	−0.16	2.15
CE	2399.73	105,560.35	50.79	32,784.55
	0.35	−3.98	−0.27	1.30

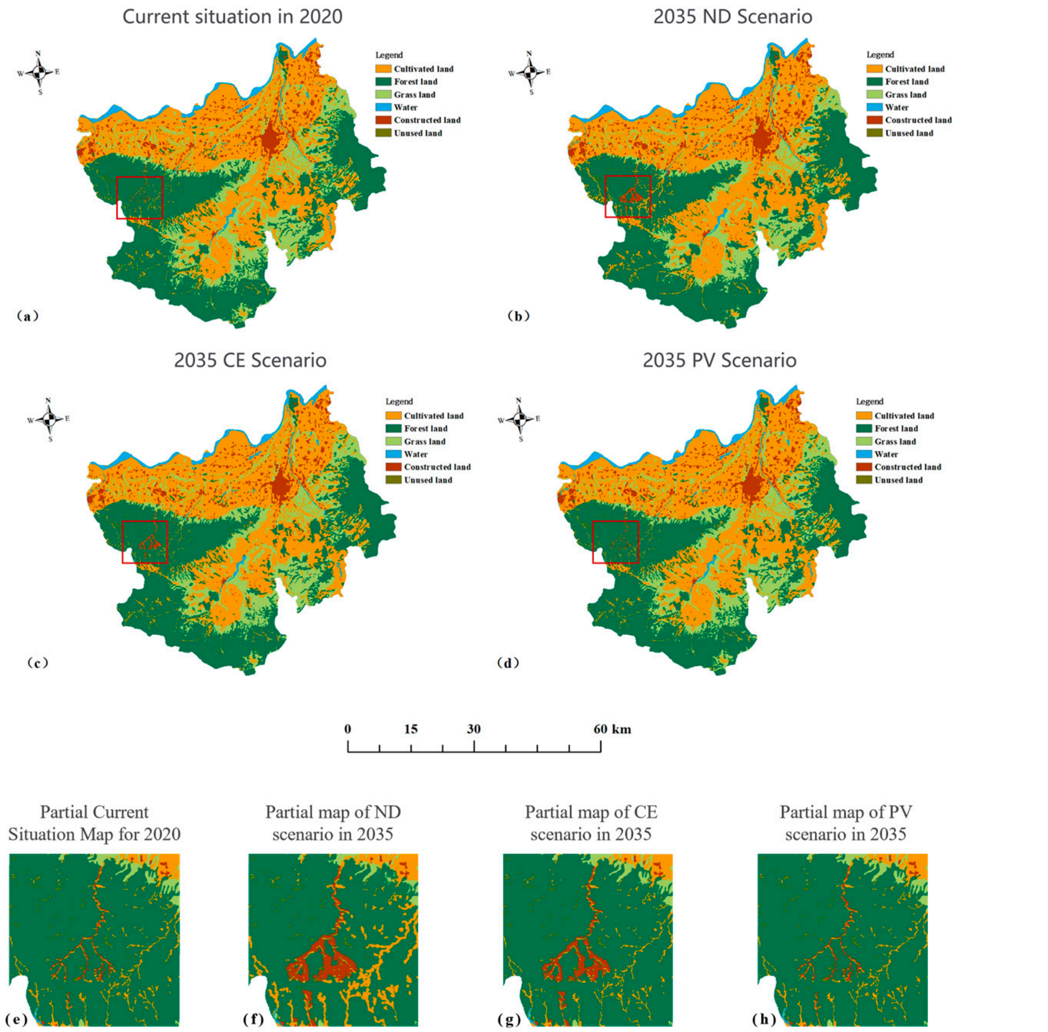

Figure 3. Land use patterns under different scenarios, (**a**) Current land use in 2020; (**b**) Natural development scenario; (**c**) Energy conservation and carbon reduction scenario; (**d**) PV penetration scenario. (**e**) Partial current Situation for 2020; (**f**) Partial map of ND scenario in 2035; (**g**) Partial of CE scenario in 2035; (**h**) Partial map of PV scenario in 2035.

Compared with the CE scenario, the PVP scenario presented a slight increase in the farmland area and a further decrease in woodland and grassland area, which might be related to the installation of distributed PV in woodland and grassland. The smaller reduction in the grassland area is mainly due to the conversion of part of the woodland to grassland in the south because the gentle slopes in the woodland part are more suitable for the installation of distributed PV compared to the grassland part of Lingbao (Figure 3). Overall, the ND scenario showed a substantial increase in farmland, land for construction, and woodland, while the extent of grassland decreased significantly at the same time. This change is mainly attributed to the low output value of the animal husbandry industry in Lingbao, which is often accompanied by encroachment on the grassland area due to urban development. Conversely, in the optimized scenarios (CE and PVP), more attention is paid to the protection of carbon sinks.

4.2. Comparison of Comprehensive Benefits and Carbon Reduction Analysis

The comprehensive benefits of various LUCC scenarios in Lingbao in 2035 differ significantly (Table 9). Compared with the ND scenario, the CE and PVP scenarios showed less carbon emissions, with carbon neutral contributions of 18,636.86 $\times$ 10^4 t and 18,636.5 $\times$ 10^4 t, respectively. At the same time, there was also a significant increase in ecological value, which saw overall value increase by RMB 5365.1 $\times 10^8$ and RMB 5364.2 $\times 10^8$, respectively. In the PVP scenario, the ecological benefits and carbon emission reductions were maximized. In summary, although the ND scenario has high economic benefits, it also leads to massive carbon emissions. By converting the carbon emissions into economic benefits in the form of standard coal, it was found that, compared with the other two types of scenarios, the total economic benefits of the ND scenario presented a negative growth trend over the status quo in 2020. Comparing the two types of low-carbon scenarios indicated that the PVP scenario had higher economic benefits, lower carbon emissions, and higher ecological benefits than the CE scenario.

5. Discussion

5.1. PV Development Contributions to Emission Reduction at the Land Use Level

PV solar power generation is an essential part of the future decarbonized energy economy [57] and an important direction to be considered for China's energy restructuring. In this study, the penetration of PV systems is included in the consideration of factors influencing urban development based on the previous CE scenario [13]. Through comparing the PVP sand CE scenarios, it is verified that the penetration of PV systems, to a certain extent, can bring additional economic benefits to the city while mitigating the pressure on urban ecological conservation and carbon emissions (Table 9). The main reason for the reduction of carbon emissions may be due to the fact that PV systems make full use of urban roofs and unused land for power generation [57], which lowers the pressure of power generation in the city and reduces carbon emissions from energy consumption. In one respect, the increase in economic aggregate is directly attributable to the generation of electricity by PV systems. However, the replacement of conventional fossil energy generation with PV cuts the cost of power generation and carbon reduction in the city [22], which further reduces the land demand for urban economic growth. The reduced demand for construction land is shifted to other land types, such as farmland and woodland, which generates new economic and ecological benefits. Overall, the method proposed in this study to correct the carbon emission factor based on the PV penetration scenario is feasible for investigating the effect of new energy development on land use changes and carbon reduction. In addition, there is still great potential for further exploring the effects of future PV systems on land use changes [58].

5.2. Trends in Land Use Changes in Lingbao in the Context of Carbon Neutrality

Changes in LULC have a material impact on carbon emissions from terrestrial ecosystems [59]. At the same time, changes in urban carbon emissions will indirectly affect changes in LULC through necessary factors influencing urban development, such as energy structure adjustment and constraints on ecological conservation targets [60]. In recent years, new energy systems represented by PV have developed rapidly and gradually become one of the key considerations required in urban planning. This study thoroughly analyzed the factors influencing land use changes from 2000 to 2020 and proposed three development scenarios (ND, CE, and PVP) in conjunction with two national and local policies (carbon neutrality goal and PV revitalization). Through scenario comparison, the complex influence mechanisms between urban LULC changes and economic development, ecological conservation, and carbon emissions were revealed. Specifically, under the ND scenario, the total area of farmland and construction land increases by 8%. The expansion of land for construction and farmland promoted rapid socio-economic development and farmland cultivation, while it was also accompanied by elevated energy consumption, possibly leading to more carbon emissions [61–63]. At the same time, increased land for construction and farmland encroached on the grassland area (25% reduction). Less grassland implies a decreased carbon absorption capacity of the city, which indirectly increases urban carbon emissions (Table 9). Under the CE and PVP scenarios, the growth in construction land and total farmland areas was under control, while woodland and grassland were better protected. The comparison of scenarios verified the strong correlation between changes in specific land types and urban development benefits, even at the county scale. This indicates that in the future, more attention should be paid to the expansion rate of land for construction in land use management in Lingbao while making full use of the natural background resources, such as farmland and woodland, to dynamically develop planting and forestry [64]. Moreover, it is also necessary to ensure the robust growth of the urban economy while reducing carbon emissions.

5.3. Research Deficiencies

Firstly, due to the classification limitation of the land use data used in this study, the area of wetland was counted as a watershed, which may lead to some errors in the calculation of the ecological benefit function. Secondly, the land use characteristics of Lingbao, with numerous mountains, gullies, and scattered construction land, may also lead to bias in the PLUS model simulation. Furthermore, the calculation of carbon emissions from PV systems is a complex process that requires not only the consideration of the whole life-cycle carbon emissions of PV panels when manufacturing them but also the assessment of farmland when selecting suitable land for PV installation. However, due to the strict restrictions on the use of farmland in China, where PV construction is prohibited on permanent basic farmland, and the difficulty of accessing such data, the carbon emission factor for farmland was not corrected in this study.

6. Conclusions

In this paper, with Lingbao, Henan Province, as an example, the impact of PV development on land use changes at the county level was thoroughly explored. The study constructed a multi-objective LUCC coupled model with carbon neutrality at its core, set three LUCC scenarios based on carbon emissions, and assessed the differences in the comprehensive benefits of different scenarios. The study results indicated that the farmland, woodland, grassland, and land for construction in Lingbao changed significantly under the three scenarios in 2035. Comparing the ND scenario with the two low-carbon CE and PV scenarios suggested that the intensive and carbon-reducing land-use pattern could cut over 18,600 $\times$ 10^4 t carbon emissions in Lingbao. It was also observed that changes in LULC were highly correlated with those in carbon emissions, which verified that the low-carbon development pattern also had a relatively significant impact on the changes in urban land use at the county level. Moreover, compared with the ND scenario, carbon reduction benefits from the PV and CE scenarios were 18,636.9 $\times$ 10^4 t and 18,636.6 $\times$ 10^4 t, respectively; the total added value was increased by RMB 5365.1 $\times$ 10^8 and RMB 5364.2 $\times$ 10^8, respectively. The PVP scenario reached the maximum value for carbon reduction benefits, ecological benefits, and total added value. This configuration became the optimal LUCC model among the three scenarios in Lingbao and highlighted the key role of reasonable LUCC optimization in achieving carbon neutrality goals and driving sustainable urban development while verifying that the development of PV was conducive to optimizing the urban land use structure and ensuring the achievement of carbon neutrality goals.

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Abbreviations

BAU	Business-as-unusual
BPNN	Back propagation neural network
CE/LE	Low carbon emissions
CNA	Carbon-neutral action
ESTDA	Exploratory spatiotemporal data analysis
FASOM	Forest and agricultural sector optimization model
HS	High carbon sequestration scenario
IPCC	Intergovernmental Panel on Climate Change
LC-MLUA	Low carbon multi-objective land use allocation
LMDI	Logarithmic mean divisia index
LPM	Linear programming model
LUCC	Land use/cover change
LULC	Land-use/Land-cover
MOGA	Multi-objective genetic algorithm
MOPSO	Multi-objective particle swarm optimization
ND	Natural development
NSGA-II	Non-dominated Sorting Genetic Algorithm II
PV	Photovoltaic
PVP	Photovoltaic penetration
PLUS	Patch-generating land use simulation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
OLS	Ordinary least squares

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