

Article

Analysis of Land Use Gravity Center Change and Carbon Emission Impact in Chengdu Plain of China from 2006 to 2022

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Abstract: As the economic center and major grain-producing area in Southwest China, the calculation of the carbon budget and the protection of cultivated land in the Chengdu Plain are of vital significance for China to achieve a carbon peak strategy and ensure food security. For the purpose of clarifying the trend of land use focus and carbon emissions in the Chengdu Plain, the carbon peak level of land use in 33 counties in the Chengdu Plain was explored. Based on the gravity center model and IPCC carbon emission coefficient method, the changing trend of land use gravity center and carbon emission in Chengdu Plain from 2006 to 2022 was clarified. PLS regression model and LMDI model were used to explore the main influencing factors of the carbon emission of cropland and the carbon emission of building land. PLUS model was used to simulate future land use patterns and carbon emissions. (1) The center of gravity of cropland, building land, water, and other and unused land shifted to the northeast by 4.23 km, 5.46 km, 8.44 km, and 31.58 km, respectively, and that of forest and grass shifted to the southeast by 11.12 km and 3.41 km, respectively. For major food crops, the centers of gravity of rice and maize moved northeastward by 15.47 km and 7.52 km, respectively, while wheat moved southwestward by 17.77 km. (2) From 2006 to 2022, carbon emissions from land use in the 33 counties of the Chengdu Plain are all on the rise, with a total increase of 13.552 million tons, and carbon sinks in the 31 counties continue to decline, with a total decrease of 0.691 million tons. (3) Under the natural scenario, carbon sink scenario, and carbon reduction scenario, the carbon emissions from land use decrease by 0.5391 million tons, 3.4728 million tons, and 4.5265 million tons from 2022, respectively. Among the 33 counties in the Chengdu Plain, 11 counties did not achieve carbon peak under the natural scenario, 5 counties did not achieve carbon peak under the carbon sink scenario, and all the counties achieved carbon peak under the carbon sink scenario. During the study period, there was a serious loss of cropland in the Chengdu Plain, mainly to building land in the central part of the Chengdu Plain and to forests within the Longmen Mountain, Longquan Mountain, and Leshan City, and there is a need to strengthen cropland protection in this region in the future. Under the natural scenario, carbon sink scenario, and carbon reduction scenario, land use in the Chengdu Plain region can achieve carbon peak, and the carbon reduction model will be more helpful for the counties to achieve carbon peak.

Keywords: multi-source data; land use gravity center change; PLUS model; carbon accounting; Chengdu Plain



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1. Introduction

China's Chengdu Plain, as the economic center of Southwest China, has serious energy consumption and carbon reduction pressures, and urgently needs to accelerate the pace of low-carbon development. The Chengdu Plain is an essential major grain-producing area in China, which serves as a linchpin in safeguarding the nation's food security. In June 2022, when President Xi Jinping inspected Meishan City, China, he emphasized that the

Chengdu Plain has a reputation as the ‘State of TianFu’, and that the red line of cropland must be strictly guarded and strive to create a higher level in the new era ‘Tianfu Granary’.

The center of gravity of land type is a principal index to reflect land change. Domestic and foreign scholars mainly use the displacement and trajectory of the center of gravity to analyze the spatial mobility and temporal change trend of regional elements [1,2]. The research on land use carbon emissions predominantly centers on carbon emission accounting [3–5], carbon emission influencing factors analysis [6–10], and land use low-carbon optimization [11–13]. Land use carbon emissions can be classified into direct carbon emissions and indirect carbon emissions. Direct carbon emissions are carbon emissions resulting from changes in land use types and changes in land management methods [14]. The accounting methods mainly include mechanism models [15–17], sample plot inventory methods [18], and remote sensing estimation methods [19,20]. Indirect carbon emissions are based on carbon emissions stemming from human socio-economic activities [21]. The accounting methods mainly include the measured method [22], the material method [23], and the emission coefficient method [24,25]. Concerning the main influencing factors of land use carbon emissions, cropland and building land predominantly contribute to carbon emissions. The regression model is a common method to analyze the influencing factors of cropland carbon emissions [26–28], and the LMDI model is used more in the analysis of building land carbon emissions [29–31]. The low-carbon optimization of land use is mainly to set different low-carbon development scenarios and simulate the future land use pattern [32], including early models like CA-Markov [33–35] model, CLUS-S [36,37] model, Flus [38,39] model, and the newer models represented by the PLUS [40–42] model. The early model has a good effect in simulating future land use and has been widely used, but it cannot dynamically model the patch changes in various land use types in time and space [43,44]. In contrast, the PLUS model offers enhanced accuracy in simulating land use spatial distribution, extensively applied in carbon emissions studies at regional [45], provincial [46,47], and municipal [48,49] scales across China. Nonetheless, prior studies exhibit several limitations: ① Cropland carbon emission accounting methods are too simple and seldom conducted at the county scale. ② Existing studies predominantly disregard the notable distinctions between the influencing factors of carbon emissions from cropland and building land. ③ Previous studies have mostly set future development scenarios around ecological priority or farmland protection priority when simulating future land use patterns, but lacked the development and enhancement of carbon scenarios.

The selection of research time nodes is based on the implementation of the Golden Land Project in Sichuan Province in 2006. The year 2010 is the starting year of the Chengdu Plain Urban Agglomeration Development Plan (2009–2020). In 2014, many counties in the Chengdu Plain entered the second batch of rural reform experiments in the country. In 2018, Sichuan Province issued the ‘Sichuan Rural Revitalization Strategic Plan (2018–2022)’. In 2022, when president xi jinping visited Yongfeng Village, Taihe Town, Dongpo District, and Meishan City, he emphasized that the Chengdu Plain should strive to create a higher level of ‘Tianfu Granary’ in the new era. In general, 2006, 2010, 2014, 2018, and 2022 are important nodes for the scale utilization and protection of cropland in the Chengdu Plain. These five important nodes are picked to represent the land use change trend of the Chengdu Plain in 2006–2022. In the hope of clarifying the changing trend of land use gravity center and the peak level of land use carbon in Chengdu Plain, based on multi-source data, the research investigated the changes in land use center of six land use types and three main food crops in the Chengdu Plain from 2006 to 2022, calculated carbon emissions of different land use types, and explored the impact of important influencing factors like social, economic, and resource input on the carbon emissions of cropland and the carbon emissions of building land. The study hypothesizes three scenarios: natural scenario (NS), carbon sink scenario (CSS), and carbon reduction scenario (CRS). The land use pattern and carbon emission of the Chengdu Plain in 2030 are simulated and analyzed, and the low-carbon path and low-carbon model of 33 counties in the Chengdu Plain are proposed.

2. Materials and Methods

2.1. Study Area

The Chengdu Plain is located in the central and western Sichuan Basin, China. It is located at 29°11' N–32°26' N north latitude and 103°1' E–105°15' E east longitude. It is about 380 km² long in the north and south, and about 180 km² wide in the east and west. It is a subtropical monsoon climate type. It is hot in summer and has less snow and ice in winter. The average annual precipitation is about 1000 mm. It has 12 major rivers such as the Minjiang River and Tuojiang River and dozens of tributaries. The main soil types include paddy soil, purple soil, and yellow soil, accounting for 44.32%, 26.19%, and 13.50% of the Chengdu Plain, respectively. The Chengdu Plain includes Chengdu City, Deyang City, Mianyang City, Meishan City, and some districts and counties in Leshan City, totaling 33 districts and counties (Figure 1), with an administrative area of 2.6242×10^4 km².

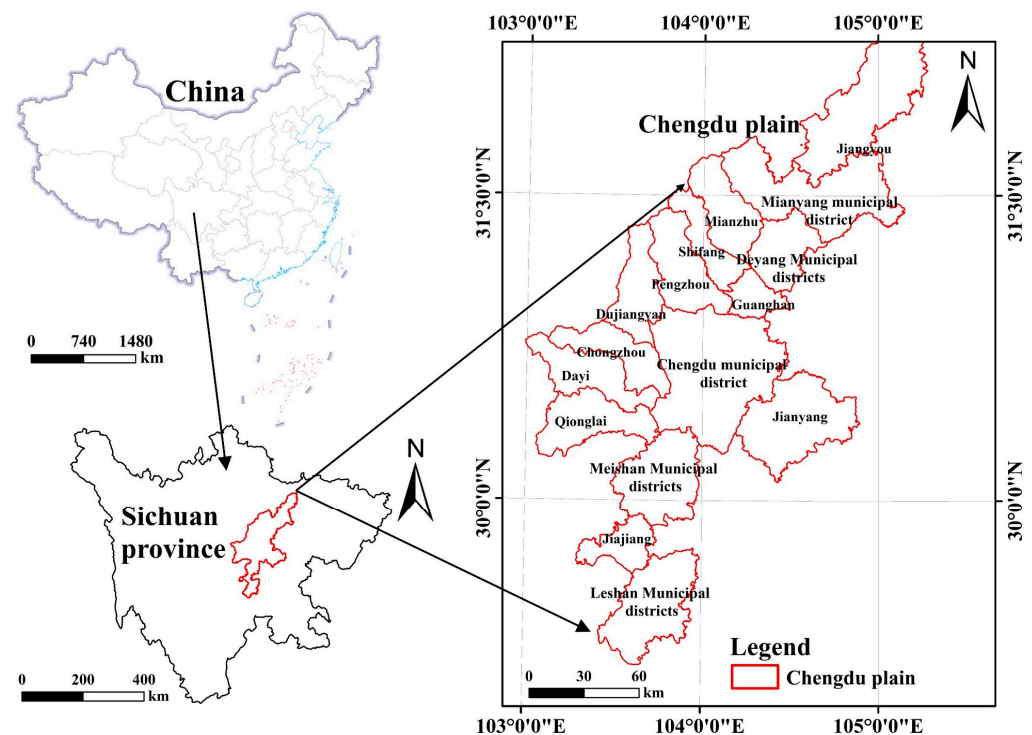


Figure 1. Chengdu Plain research area.

2.2. Data Sources

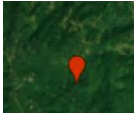
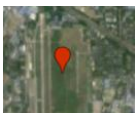
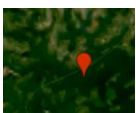
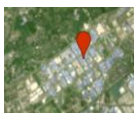
The data mainly include Landsat images, MODIS MCD15A3H data, socio-economic data, phenological data, temperature and rainfall data, soil type, ODIAC data, etc. (Table 1). Utilizing the GEE cloud platform, the code is written to complete the date and cloud screening, image splicing, cloud removal, and image cutting, and the cloud-free remote sensing image of the Chengdu Plain is captured. The typical objects are selected from the six land use types as training samples (Table 2), and the land use type data of 2006, 2010, 2014, 2018, and 2022 are obtained by supervised classification. The overall accuracy of supervised classification is more than 85%, and the Kappa coefficient is more than 80%, indicating that the classification results have high accuracy and meet the research requirements. The sown area of rice, wheat, and corn in the Chengdu Plain constitutes more than 70% of the total sown area of grain crops, and these three major grain crops are extracted. Because it is difficult to directly identify and extract rice, wheat, and corn in remote sensing images, crop area information is extracted based on phenological information. The field sampling verification was carried out in 2022, and a total of 300 samples were collected from the Chengdu Plain in spring and autumn. The overall accuracy of 2022 was 80.33% and the

Kappa coefficient was 70.15%, signifying improved accuracy in the extraction of rice, wheat, and corn crops.

Table 1. Data source.

Data Name	Source
Landsat5 and Landsat8 image	United States Geological Survey
MODIS MCD15A3H	National Aeronautics and Space Administration
Socio-economic statistics	Statistical Yearbooks and Annual Reports of Cities and Counties
phenological data	National Ecosystem Science Data Center
Temperature, rainfall, geomorphology, and soil data	Center for Resource Environmental Science and Data
Nighttime lighting data	National Earth System Science Data Center
Administrative division	National Geomatics Center of China
POI data	OpenStreetMap
ODIAC data	National Institute for Environmental Studies

Table 2. Interpretation identification of land use types in Chengdu Plain.

Land Type	Implication	Feature	Typical Sample
Cropland	Meaning land on which crops are grown, including mainly paddy land and dry land.	Mostly distributed in strips and blocks	
Forest	Refers to land on which trees, bamboos, and shrubs grow, mainly including tree woodland, shrubland, woodland, and garden land.	Uniformly distributed in blocks and patches	
Grass	Land on which herbaceous plants predominate, including mainly natural pasture, artificial pasture, and other grasslands.	Textural features are distinct and non-uniformly distributed	
Water	Refers to the land of natural land water and water facilities. Mainly includes rivers, reservoirs, pits, and ponds.	True colors tend to be blue when synthesized	
Building land	Refers to industrial, mining, transport, and other land in urban and rural settlements and beyond.	Neatly arranged, mostly long or rectangular in shape	
Other and unused land	Refers to unused land, mainly including bare land, bare rock, etc.	Greyish-white bare rock with no vegetation on the surface	

2.3. Research Methodology

2.3.1. Center of Gravity Model

The regional center of gravity model is mainly based on the spatial position of a specific research area as the specific research object.

$$D = \left[(X_{t+1} - X_t)^2 + (Y_{t+1} - Y_t)^2 \right]^{1/2} \quad (1)$$

$$\begin{aligned} \theta &= \arctan\left(\frac{Y_{t+1} - Y_t}{X_{t+1} - X_t}\right) & X_{t+1} - X_t &\geq 0 \\ \theta &= \pi + \arctan\left(\frac{Y_{t+1} - Y_t}{X_{t+1} - X_t}\right) & X_{t+1} - X_t &< 0 \end{aligned} \quad (2)$$

X_i and Y_i are the latitude and longitude coordinates of the center of gravity of a certain type of land use type; D and θ are the center of gravity migration distance and angle of a certain land use type in a specific range.

2.3.2. Carbon Sink Accounting

(1) Farmland carbon sink: Crop carbon sequestration refers to the process by which crops convert CO_2 in the air into carbohydrates through photosynthesis. The process of fixing carbon in crops for their own growth and development is one of the important ways to achieve carbon sinks.

$$CS_c = \sum_{i=1}^n z_i \times \delta_i \times d_i \times h_i \quad (3)$$

CS_c is the carbon sink of cropland; z_i is the carbon absorption ratio of i -th crop (Table 3); δ_i is the economic yield of i -th crop; d_i is the dry ratio of i -th crop; h_i is the economic coefficient of i -th crop.

Table 3. Parameters of main crops in Chengdu Plain.

Crops	Carbon Absorption Rate	Economic Coefficient	Dry Ratio	Root-Shoot Ratio	Nitrogen Ratio of Straw or Root
Rice	0.410	0.489	0.855	0.125	0.008
Wheat	0.490	0.434	0.870	0.166	0.005
Corn	0.470	0.438	0.860	0.170	0.006
Beans	0.450	0.425	0.860	0.130	0.018
Potatoes	0.420	0.667	0.450	0.050	0.011
Peanut	0.450	0.556	0.900	0.200	0.018
Rapeseed	0.450	0.271	0.820	0.150	0.005
Vegetable	0.450	0.830	0.150	0.250	0.008
Fruit	0.450	0.700	0.100	-	-

Table 3 shows the carbon sequestration rates, economic factors, dry weight ratios, root crown ratios, and straw or root nitrogen ratios of nine major crops in the Chengdu Plain, which can be used to calculate the carbon sink of major crops in the Chengdu Plain.

(2) Carbon sinks of forest, grass, water, and other and unused land: Forest, grass, water, and other and unused land mainly play a role in carbon sinks. The IPCC inventory model was used to estimate the carbon sinks of the four land types.

$$CS_t = \sum_{i=1}^6 x_i \times c_i \quad (4)$$

CS_t is the total amount of carbon sinks in forest, grass, water, and other and unused land; x_i is the area of i -th land type (hm^2); c_i is the carbon emission coefficients of i -th land type, with general reference to the carbon absorption coefficients of 0.6046, 0.0206, 0.2530, and $0.0005 \text{ t} \cdot \text{hm}^{-2} \times \text{a}^{-1}$ for forest, grass, water, and other and unused land, respectively [50,51].

2.3.3. Accounting for Carbon Sources

Land use carbon emissions include cultivated land agricultural production, fossil fuel combustion, cement production, and natural gas combustion. The carbon emissions of cultivated land agricultural production mainly include carbon emissions from agricultural resource input, CH_4 emissions from rice cultivation, and N_2O and CH_4 emissions from livestock and poultry breeding. In order to facilitate calculation and comparison, CO_2 , N_2O , CH_4 , etc. are uniformly converted to standard C equivalents. According to the IPCC Fourth Assessment Report, the conversion C equivalent standard is that the greenhouse effect caused by 1 t N_2O is equivalent to the greenhouse effect caused by 298 t CO_2 , and the greenhouse effect caused by 1 t CH_4 is equivalent to the greenhouse effect caused by

25 t CO₂. In total, 1 t CO₂ contains 0.2727 t C, and 1 t N₂O and 1 t CH₄ contain about 81.2646 t C and 6.8175 t C, respectively.

(1) Carbon emissions from agricultural resources input: Carbon emissions from agricultural resources input mainly come from the use of chemical fertilizers, pesticides, agricultural film, diesel oil consumed by agricultural machinery, and energy consumed by tillage and irrigation. The formula is as follows:

$$CE_c = \sum_{i=1}^n \varphi_i \times \beta_i \quad (5)$$

CE_c is the carbon emission of agricultural resource investment; β_i is the amount of i -th agricultural resource input; φ_i is the carbon emission coefficient of i -th agricultural resource input; according to the existing studies, the carbon sink coefficients of fertilizer, pesticide, agricultural film, agricultural diesel, tillage, and irrigation are 0.8956 kg/kg [52], 4.9341 kg/kg [53], 5.18 kg/kg [53], 0.5927 kg/kg [54], 312.6 kg/hm⁻² [55], and 4.75 kg/hm⁻² [53].

(2) Rice carbon emissions: CH₄ emissions from rice cultivation account for a relatively high proportion of CH₄ emissions in China, and also have a greater impact on global CH₄ emissions [56].

$$CE_r = \varphi_r \times S \times 6.8175 \quad (6)$$

CE_r is the carbon emission of rice (t); φ_r is the methane emission factor of rice field; taking the emission factor of single-season rice recommended by the Guidelines for the Preparation of Greenhouse Gas Inventories in Sichuan Province as the standard, $\varphi_r = 156.2$ (kg/hm²); S is the sowing area of rice (hm²).

(3) N₂O emissions from cultivated land: N₂O emissions from cultivated land include direct and indirect emissions. Direct emissions include nitrogen fertilizer (agricultural resources have been accounted for in carbon emissions), manure, and straw returning to the field. The direct emission factor is selected from the 'Guidelines for the preparation of greenhouse gas inventories in Sichuan Province'. The recommended value is 0.0109 tN₂O/tN.

$$CE_t = ((N_c + N_j) \times 0.0109 + N_2O_d + N_2O_l) \times 81.2646 \quad (7)$$

N_c is livestock manure nitrogen; N_j is straw returning nitrogen; N_2O_d is N₂O emission caused by atmospheric nitrogen deposition; N_2O_l is N₂O emission caused by runoff leaching; CE_t is the N₂O-to-carbon emission of cultivated land.

(4) Carbon emissions from livestock and poultry breeding: Carbon emissions from livestock and poultry breeding are mainly produced by gastrointestinal fermentation and the excreta of livestock and poultry, including N₂O emissions from animal manure management, CH₄ emissions from animal manure management, and CH₄ emissions from the gastrointestinal fermentation of poultry.

$$CE_y = CH_{4y} \times 6.8175 + N_2O_y \times 81.2646 \quad (8)$$

N_2O_y is livestock and poultry breeding N₂O; CH_{4y} is CH₄ for livestock and poultry breeding; CE_y is the carbon emission of livestock and poultry breeding.

2.3.4. Partial Least Squares (PLS) Regression

Combining the existing research results and the actual situation of the Chengdu Plain, the most important influencing factors of carbon emissions from cropland include population, economic development, resource investment, planting level, and planting structure factors (Table 4), and the population factors package urbanization rate (UR). Economic development factors include rural inhabitant per capita disposable income (RDI) and average agricultural output value (AAOV). Resource investment factors include energy consumption intensity (ECI), fertilizer application intensity (FAI), pesticide application

intensity (PAI), and agricultural film application intensity (AFAI). Planting level factors include mechanization level (ML), irrigation rate (IR), and farmland operation scale (FOS). Planting structure includes multiple-crop index (MCI) and food crop rate (FCR).

Table 4. Index system of influencing factors of cropland carbon emission.

Type	Norm	Computational Principle
Population	UR	Urban population/Total population
Economic development	RDI	—
	AAOV	GDP of primary industry/Cropland area
Resource investment	ECI	Diesel consumption/Cropland area
	PAI	Pesticide application rate/Cropland area
	FAI	Fertilizer application rate/Cropland area
	AFAI	Agricultural film usage/Cropland area
Planting level	ML	Power of agricultural machinery/Cropland area
	IR	Irrigated area/Cropland area
	FOS	Cropland area/Agricultural workers
Planting structure	MCI	Crop acreage/Cropland area
	FCR	Grain crop planting area/Crop acreage

The specific steps of PLS regression analysis are shown in the literature [57]. According to the size of Variable Importance in Projection (VIP), the explanatory importance of independent variables to dependent variables can be determined.

$$VIP = \sqrt{k \sum_h^m Rd(y, t_h) w_{hj}^2 / Rd(y, t_h)} \quad (9)$$

$Rd(y, t_h) = r^2(y, t_h)$. Reflecting the precision of variation when the variable y is explained by the principal component t_h , it represents the ability of the principal component t_h to explain the variable y , and $r(y, t_h)$ is the correlation coefficient between y and t_h . When $VIP > 1$, it is an extremely important indicator, which has very strong explanatory significance for the dependent variable; when $0.8 < VIP < 1$, it is a generally important indicator, which has general explanatory significance for the dependent variable; when $VIP < 0.8$, it is an unimportant indicator, which has basically no explanatory significance for the dependent variable.

2.3.5. LMDI Model

The LMDI model has been widely used in related studies due to its advantages of full decomposition, no residuals, and consistency between additive and multiplicative decomposition results [58]. The LMDI additive decomposition is used in the study.

$$\Delta CE = CE_t - CE_0 = \Delta CI + \Delta BI + \Delta EI + \Delta GI + \Delta PI \quad (10)$$

$$\varphi_c = \frac{\Delta CI}{\Delta C}, \varphi_B = \frac{\Delta BI}{\Delta C}, \varphi_E = \frac{\Delta EI}{\Delta C}, \varphi_G = \frac{\Delta GI}{\Delta C}, \varphi_P = \frac{\Delta PI}{\Delta C} \quad (11)$$

ΔCE is the amount of changes in carbon emissions from building land; CE_0 and CE_t are the carbon emissions from building land at the beginning and the end, respectively; ΔCI , ΔBI , ΔEI , ΔGI , and ΔPI are the amount of changes in carbon emissions from building land due to five factors, namely, carbon emission intensity (CEI), use efficiency (UE), energy intensity (EI), economic development (ED), and population size (PS), respectively; and φ_c , φ_B , φ_E , φ_G , and φ_P are the contribution rates of ΔCI , ΔBI , ΔEI , ΔGI , and ΔPI , respectively.

2.3.6. Multi-Scenario Land Use Pattern Simulation

Referring to the relevant research results [40,59], considering the situation of land use in the Chengdu Plain, 18 main driving factors were selected from the social economy and

natural environment. Natural factors include elevation, slope, average annual precipitation, average annual temperature, and distance to water. Socio-economic factors include population density, per capita GDP, distance to various roads (main roads and railways), distance to airports, high-speed rail stations, government distance, POI nuclear density, and nighttime light data.

The study hypothesis NS, CSS, and CRS for the Chengdu Plain is to achieve the peak carbon target by 2030. First, under the NS, assuming that the land use of the Chengdu Plain did not take any restrictions, the land use pattern maintained a natural development trend. Second, under the premise of ensuring food security, forest, grass, and water are set as the main sources of carbon sinks, and priority is given to protecting these land types to increase regional carbon sink capacity under the CSS. Third, under the CRS, in order to ensure food security, the building land is determined as the primary source of carbon emissions, and the area growth of building land needs to be strictly controlled.

Combined with the provisions of the ‘Sichuan Provincial Land Spatial Planning (2021–2035)’ and ‘Chengdu High Standard Farmland Building Plan (2021–2030)’, the upper limit of cropland outflow area in Chengdu Plain is set to 15%, and the upper limit of building land area increase is set to 20%. According to the agricultural protection pattern of the ‘Chengdu land space master plan’, the agricultural protection area is taken as the restriction condition of land transfer. Under the CSS, the cropland area is set to decrease by 15%. The area of building land was increased by 20%, and the cropland was transferred to the area of forest, grass, and water, which was allocated according to the proportion of cropland transferred from 2006 to 2022 (Table 5). Other and unused land refer to the results of the NS. Under the CRS, the area of cropland is reduced by 10% and the area of building land is increased by 15%. The calculation methods of forest, grassland, water, and other and unused land are the same as those of the CSS.

Table 5. Prediction of land use demand in three scenarios of Chengdu Plain in 2030 (km²).

Scenario	Cropland	Forest	Grass	Water	Building Land	Other and Unused Land
NS	7037.73	11,631.42	167.23	704.04	6656.77	9.20
CSS	9149.09	10,398.19	168.93	669.09	5811.89	9.20
CRS	9687.28	10,111.04	168.04	661.10	5569.73	9.20

Based on the proportion expansion of each category in the Chengdu Plain from 2006 to 2022, the domain weights of cropland, forest, grass, water, building land, and other and unused land were determined to be 0.0394, 0.2448, 0.0033, 0.0294, 0.4607, and 0.0004, respectively. In 2030, the carbon absorption coefficients of forest, grass, water, and other and unused land will be the same as before. The carbon emission coefficients of cropland and building land are based on the carbon emissions of cropland and building land per unit area from 2006 to 2022, and predicted by EXCEL trend line.

3. Results

3.1. Analysis of Gravity Center Change in Land Use Types

3.1.1. Analysis of Gravity Center Changes in Six Land Use Types

The movement direction of the center of gravity for cropland, forest, and other and unused land in the Chengdu Plain has strong continuity in 2006–2010, 2010–2014, 2014–2018, and 2018–2022, while the change in the center of gravity of grassland, water, and building land has no continuity. (Figure 2). From 2006 to 2022, the transfer area of cropland in the central and southwestern regions of the Chengdu Plain was large, resulting in a 4.23 km shift in the center of gravity of cropland to the northeast (Table 6). The area of forest showed an expansion from the Longmen Mountains to the southeast, and the forest in the Longquan Mountains and Jianyang City increased steadily, making the center of gravity of the forest move 11.12 km to the southeast. The grass and water have relatively fixed spatial distribution, and their center of gravity changes in a closed loop, moving 3.41 km and

5.46 km, respectively. Because the position of the river itself is relatively fixed, the inflow of water is concentrated near the water area, so the center of gravity of the water moves less distance. Combined with Table 6, it can be seen that the distance of the center of gravity in each stage of the water is 2014–2018 < 2018–2022 < 2006–2010 < 2010–2014, and the expansion rate of the water along the direction of the center of gravity is also 2014–2018 < 2018–2022 < 2006–2010 < 2010–2014. The urbanization speed of Deyang City and Mianyang City is faster than that of Leshan City and Meishan City, which leads to the center of gravity of building land in the Chengdu Plain moving to the northeast by 8.44 km. The northeast inflow area of other and unused land is larger than the rest area, which makes the center of gravity move 31.58 km to the northeast. Overall, from 2006 to 2022, the reduction area of cropland in the central and western directions of the Chengdu Plain is higher than that in the northeast direction. The expansion area of water, building land, and other and unused land in the northeast direction is significantly higher than that in the southwest direction, and the increase area of forest and grass in the southeast direction is higher than that in the northwest direction.

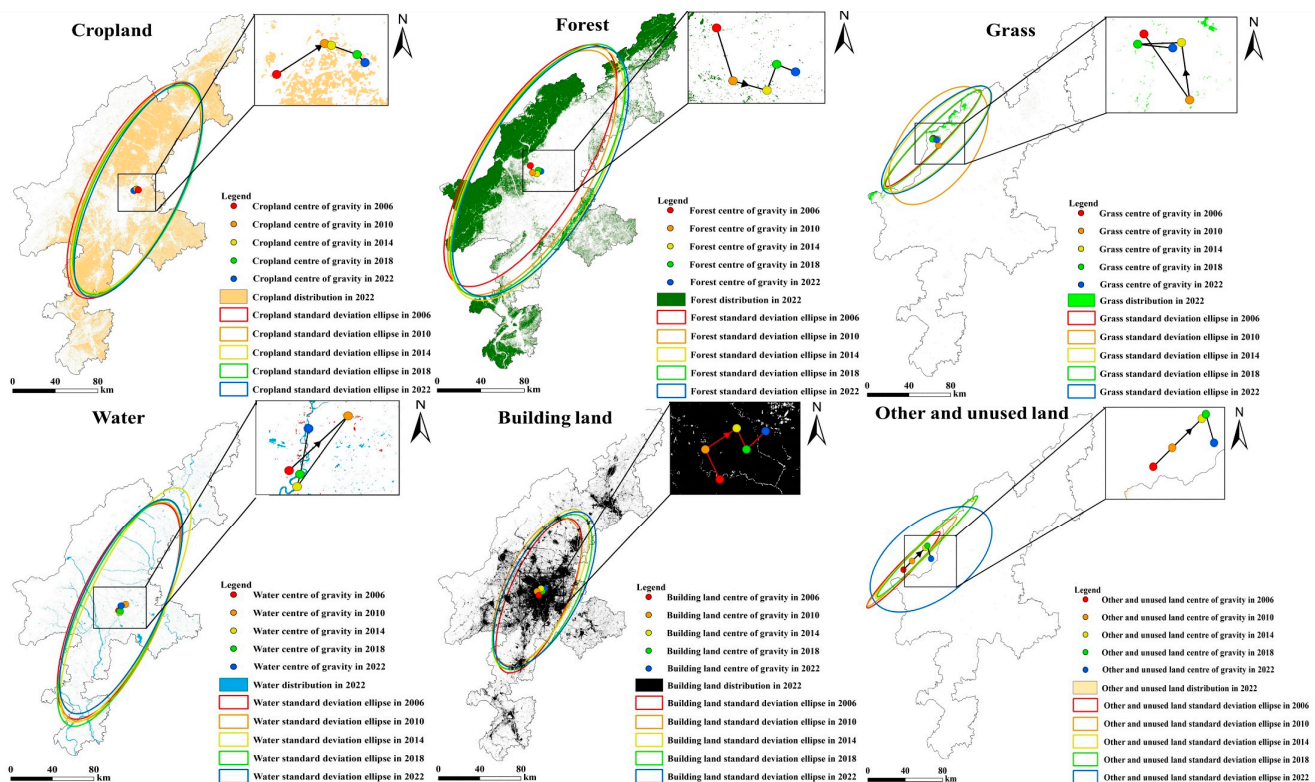


Figure 2. The change in the center of gravity of land use types in the Chengdu Plain from 2006 to 2022.

Table 6. The moving direction and length of the center of gravity of six land use types (km).

Land Type	2006–2010		2010–2014		2014–2018		2018–2022		2006–2022	
	Direction	Length	Direction	Length	Direction	Length	Direction	Length	Direction	Length
Cropland	northwest	2.63	southeast	0.34	southeast	1.30	southeast	0.54	northwest	4.23
Forest	southeast	7.08	southeast	4.27	northwest	3.53	southeast	2.44	southeast	11.12
Grass	southeast	7.01	northwest	6.03	northwest	4.57	southeast	3.87	southeast	3.41
Water	northwest	9.36	southwest	10.17	northwest	4.71	northwest	5.12	northwest	5.46
Building land	northwest	4.31	northwest	4.85	southeast	2.95	northwest	3.40	northwest	8.44
Other and unused land	northwest	12.5	northwest	19.24	northwest	3.24	southeast	14.11	northwest	31.58

3.1.2. Analysis of Gravity Center Changes in Major Grain Crops Rice, Wheat, and Maize

The changing trend of the gravity center of rice, wheat, and maize in the Chengdu Plain is obviously different. The change in the gravity center of rice has obvious consistency in 2006–2010, 2010–2014, 2014–2018, and 2018–2022, and the gravity center of wheat and maize has irregular change (Figure 3). From 2006 to 2022, the outflow area of rice cultivation in the central and southwestern Chengdu Plain was higher than that in the northeastern region, and it was mainly converted to other crop cultivation. The center of gravity of rice moved 15.47 km to the northeast (Table 7). The wheat outflow area in the northeast of Chengdu Plain is higher than that in the southwest, and the proportion of outflow to rice and other crops is relatively high. The wheat center of gravity moves 17.77 km to the southwest. The outflow area of corn at each stage is not spatially clustered, and the proportion of outflow to rice and other crops is relatively high. The center of gravity changes in a round-trip manner, and the corn center of gravity moves 7.52 km to the northeast.

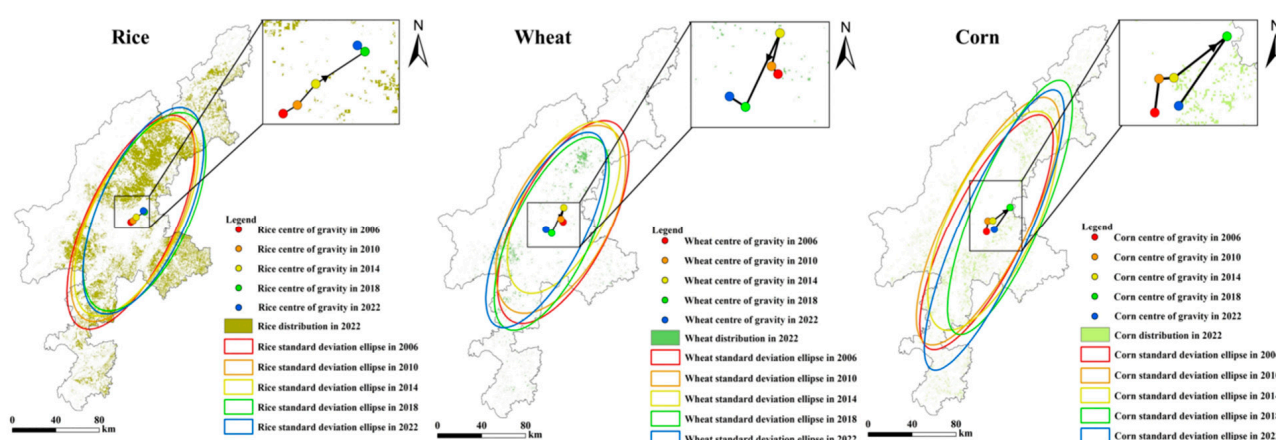


Figure 3. The change in the gravity center of rice, wheat, and corn in the Chengdu Plain from 2006 to 2022.

Table 7. The moving direction and length of the center of gravity of rice, wheat, and corn (km).

Crops	2006–2010		2010–2014		2014–2018		2018–2022		2006–2022	
	Direction	Length	Direction	Length	Direction	Length	Direction	Length	Direction	Length
Rice	northwest	2.63	northwest	4.32	northwest	9.17	southeast	1.47	northwest	15.47
Wheat	northwest	3.16	northwest	10.88	southwest	25.79	northwest	6.19	southwest	17.77
Corn	northwest	9.74	west	4.45	northwest	19.95	southwest	24.45	northwest	7.52

3.2. Spatio-Temporal Changes in Carbon Source and Carbon Sink in Chengdu Plain

3.2.1. Time Changes in Carbon Source and Carbon Sink in Chengdu Plain

From a temporal perspective, focusing on carbon sources, the total carbon emissions of the Chengdu Plain increased by 13.552 million tons from 2006 to 2022. The proportion of carbon emissions from building land in the total carbon emissions from 2006 to 2022 was 81.62%, 88.56%, 90.99%, 92.91%, and 94.33%, respectively, showing an increasing trend (Table 8). The carbon emissions of cropland showed a declining trajectory year by year. From 2006 to 2022, the carbon emissions of cropland decreased by 1.6948 million tons, a decrease of 44.56%. Overall, the carbon emissions in the Chengdu Plain are mainly from building land, and the proportion is still rising. Shifting the focus to carbon sink, from 2006 to 2022, the carbon sink effect of forest has been significantly improved. The carbon absorption of forest is 0.3783, 0.4587, 0.5262, 0.5440, and 0.5909 million tons, respectively, and the contribution rate to carbon sink is 14.16%, 18.18%, 23.40%, 27.46%, and 28.09%, respectively. The carbon sink of cropland showed a downward trend, and the proportion of cropland carbon sink to total carbon sink was 85.33%, 81.28%, 75.89%, 71.75%, and 71.11%,

respectively, which decreased by 14.19% in 16 years. It shows that cropland is the most important place to realize carbon sink, but the carbon sink capacity is declining. The carbon sink effect of the water area was very small and fluctuated. During the 16-year period, it only increased by 0.0024 tons, an increase of about 17.02% compared with 2006.

Table 8. Carbon emission of land use types in Chengdu Plain from 2006 to 2022 (10^4 t).

Year	Cropland Carbon Emission	Cropland Carbon Sinks	Forest	Grass	Water	Building Land	Other and Unused Land	Carbon Emission	Total Carbon Sink	Net Carbon Emission
2006	356.39	−227.88	−37.83	−0.03	−1.41	1582.69	0.00	1939.08	−267.15	1671.93
	18.38%	85.30%	14.16%	0.01%	0.53%	81.62%	0.00%	100%	100%	
2010	288.09	−205.05	−45.87	−0.04	−1.33	2230.17	0.00	2518.26	−252.29	2265.97
	11.44%	81.28%	18.18%	0.02%	0.53%	88.56%	0.00%	100%	100%	
2014	258.95	−170.63	−52.62	−0.04	−1.55	2614.40	0.00	2873.35	−224.84	2648.51
	9.01%	75.89%	23.40%	0.02%	0.69%	90.99%	0.00%	100%	100%	
2018	207.82	−142.16	−54.40	−0.03	−1.55	2722.16	0.00	2929.98	−198.14	2731.84
	7.09%	71.75%	27.46%	0.02%	0.78%	92.91%	0.00%	100%	100%	
2022	186.91	−149.59	−59.09	−0.03	−1.65	3107.37	0.00	3294.28	−210.36	3083.92
	5.67%	71.11%	28.09%	0.01%	0.78%	94.33%	0.00%	100%	100%	

3.2.2. Spatial Variation in Carbon Source and Carbon Sink in Chengdu Plain

Viewed from a spatial distribution perspective, the annual average change rates of carbon emissions, carbon sinks, and cropland carbon emissions have obvious aggregation. (1) In the annual average rate of change in carbon emissions, there are two rapid growth types, which are Shuangliu District and Qingbaijiang District. The average annual growth rate of Shuangliu District is the highest, which is 5.36% (Figure 4a). The carbon emissions of 18 counties are in medium-speed growth, mainly in Chengdu municipal district, Deyang municipal district, and Mianyang City. The remaining 13 counties are growing slowly, indicating that the Chengdu Plain municipal district, Deyang municipal district, and Mianyang City as pivotal areas for future carbon emission control. (2) In the annual average rate of change in carbon sinks, there are more types of changes and more obvious spatial aggregation. There are five counties in a state of rapid decline, chiefly situated in the main urban area of Chengdu (Figure 4b), with only Wenjiang District in a state of rapid decline. There are eight counties in the state of medium-speed decline, predominantly located in the primary urban area of Chengdu and Meishan City. There are 17 counties in a state of slow decline, distributed in the edge counties of Chengdu, Deyang City, and Mianyang City. The carbon sink of Guanghan City and Shizhong District shows a slow growth trend, which is worthy of attention. In general, the decline in carbon sink level has become a common trend in the 33 counties in the Chengdu Plain. In the future, the decline in carbon sink capacity in the primary urban area of Chengdu should be slowed down and the number of counties achieving carbon sink growth should be increased. (3) In the annual average change rate of Cropland carbon emissions, there are nine counties with rapid decline, which are distributed in the Chengdu municipal district (Figure 4c). The rapid decline type is mainly distributed in Chengdu. There are 12 counties with medium-speed decline, mainly distributed in Chengdu, Leshan, and Mianyang, and 6 with slow decline, mainly distributed in Deyang. Overall, the reduction rate of carbon emissions from cropland in Chengdu is greater than that in other districts and counties. It is vital to speed up the supervision of carbon emissions from cropland in Deyang City, Dongpo District, and Jiangyou City.

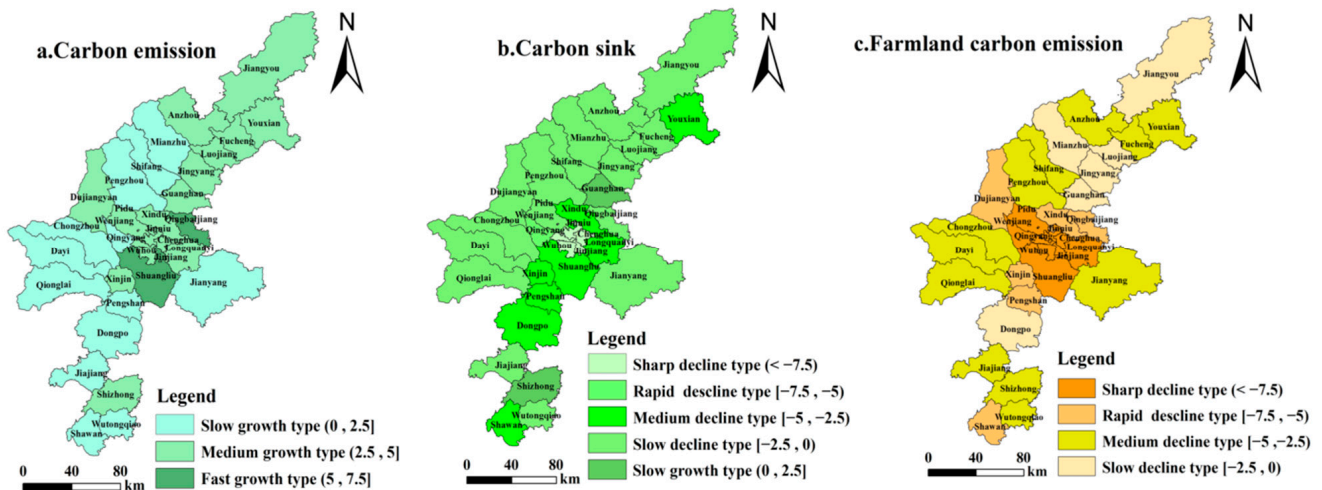


Figure 4. Spatial distribution of annual average change rate in Chengdu Plain from 2006 to 2022.

3.3. Analysis of the Main Influencing Factors of Cropland Carbon Emissions

Utilizing SPSS26, PLS regression analysis was conducted. Considering that the first four principal components have more than 80% explanatory power, four principal components were selected to analyze the independent variables and dependent variables, and the effect of the regression model was analyzed from the regression coefficient, VIP value, and regression model verification.

Among the PLS regression results of the 12 indicators, (1) UR, RDI, and ML are negatively correlated with carbon emissions per unit of cropland (Table 9). It is mainly because the increase in urbanization, RDI, and ML will promote the reduction in agricultural resource investment and green development, and reduce the generation of carbon emissions. (2) AAOV, ECI, PAI, FAI, AFAI, IR, FOS, MCI, and FCR are positively correlated with carbon emissions per unit of cropland, mainly because ECI, IR, PAI, FAI, and AFAI are the main modes of agricultural resource investment, which will generate a large amount of carbon emission. MCI is an important reflection of the intensity of agricultural cultivation, and the increase in MCI will bring more agricultural resource investment and consumption, and FCR is due to the fact that rice cultivation will produce a large amount of carbon emission. AAOV and average carbon emission are positively correlated, indicating that the Chengdu Plain is still in the stage of pursuing yield rather than green ecological products. The positive correlation between FOS and land-per-capita carbon emissions indicates that the Chengdu Plain has not yet achieved the improvement of the use rate of agricultural resource investment through large-scale operation, and is still in the pre-scale stage. (3) It is worth noting that the 12 influencing factor indicators have an impact on cropland carbon emissions, and will also have a positive promotion or negative inhibition effect on cropland carbon sink capacity, and we should not pursue cropland low carbon emissions, but should take the road of promoting cropland low carbon emissions combined with cropland high carbon sinks.

According to Figure 5, the regression equation calculated using the PLS model has a good fitting effect, indicating that the equation more accurately quantifies the linear relationship between the land-averaged cropland carbon emissions in Chengdu county and the various influencing factors, which provides good data support for realizing the low-carbon development of cropland. According to Figure 6, UR, RDI, ECI, PAI, FAI, and MCI have $VIP > 1$, which are extremely important indicators. The $VIP \in (0.8\sim1.0)$ for AFAI, IR, FOS, and FCR indicates that this category of indicators has a certain impact on land-averaged carbon emission. The VIP of AAOV and ML is <0.8 , which has less influence on land-averaged carbon emissions and is an unimportant indicator. Overall, UR, FCR, and MCI are indicators that cannot be suppressed for the low-carbon development of cropland at present, and the carbon emissions stemming from agricultural resource investment in

the replanting process can be reduced in the future. Among the remaining adjustable important impact indicators, the degree of explanation of the carbon emission intensity of cropland is $ECI > FAI > PAI > FOS > AFAI$, indicating that energy saving research and the development of agricultural machinery in the future is the preferred choice to reduce ECI, promote fertilizer and pesticide reduction, and increase efficiency, and developing eco-agriculture is an important entry point for reducing carbon emission intensity of cropland and intensification. Greening the scale of farmland operation and improving the rate of agricultural film recycling are important supplements to low-carbon development.

Table 9. PLS regression results.

Variant	Non-Standardized Coefficients	Standardized Coefficient
UR	−0.01	−0.03
RDI	−0.36	−0.44
AAOV	1.72	0.10
ECI	380.82	0.32
PAI	91.61	0.01
FAI	43.69	0.11
AFAI	15.69	0.29
ML	−0.50	−0.06
IR	63.34	0.06
FOS	96.87	0.06
MCI	93.58	0.37
FCR	162.99	0.19
Constant	1.69	−

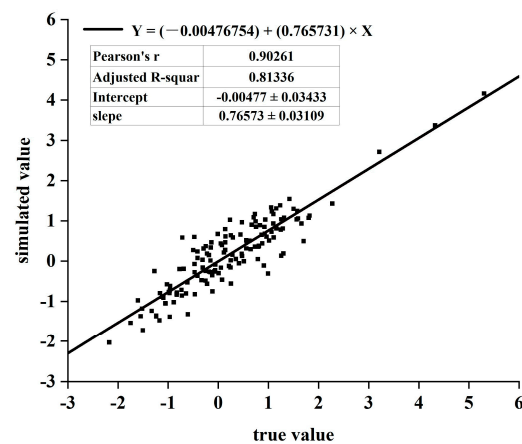


Figure 5. Comparison of simulated and true values.

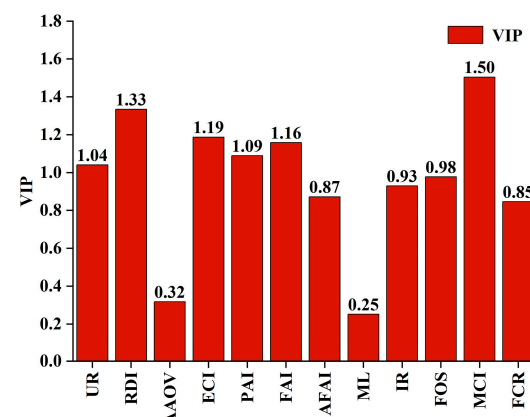


Figure 6. VIP value of each index.

3.4. Influencing Factors of Carbon Emissions of Building Land

According to Figure 7a, from 2006 to 2022, the influence of EI factors on carbon emissions from building land shows obvious spatial differentiation characteristics and is basically inhibitory. Within the primary urban area of Chengdu, the inhibitory effect of EI on carbon emissions decreased first and then increased, from 0.9014 million tons in 2006 to 2.2391 million tons in 2022. The main urban area of Chengdu shows a continuous upward trajectory, from 0.8205 million tons in 2006 to 3.1153 million tons in 2022. The EI inhibition effect of the remaining counties basically exhibited a trend characterized by an initial increase followed by a subsequent weakening, from 1.7681 million tons in 2006 to 1.9888 million tons in 2022. It is worth noting that from 2018 to 2022, the inhibitory effect of EI on carbon emissions from building land in the Chengdu municipal district increased rapidly, while the inhibitory effect in other counties was relatively stable. Overall, the inhibitory effect of EI in the Chengdu municipal district is much higher than that in other districts and counties. In recent years, the optimization of energy structure in the Chengdu municipal district has been further accelerated.

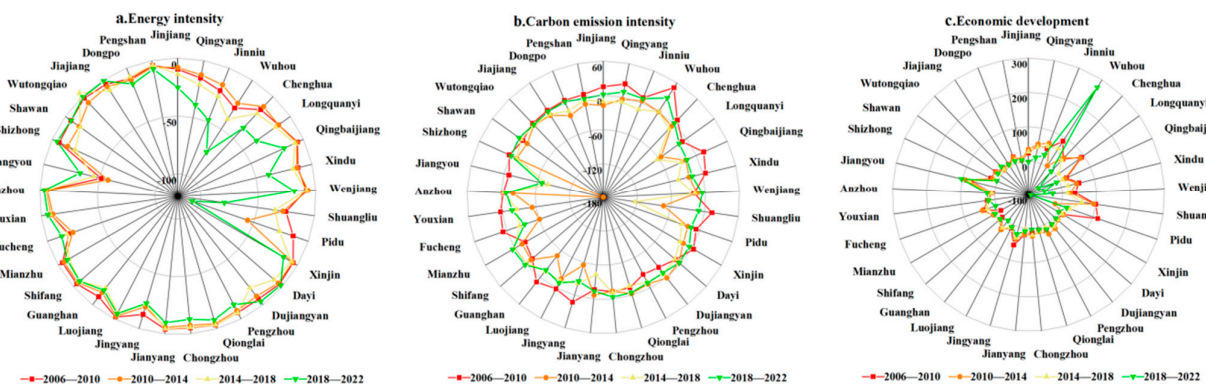


Figure 7. Decomposition of EI, CEI, and ED of carbon emissions from building land in 33 counties from 2006 to 2022.

From 2006 to 2022, the contribution value of county CEI showed obvious spatial differences (Figure 7b), mostly showing an inhibitory effect. The inhibitory effect of CEI within the primary urban areas of Chengdu, Deyang, Mianyang, and Leshan indicated a trend of initial increase followed by subsequent decrease, with 2010 as the inflection point. The values of the four periods of 2006–2010, 2010–2014, 2014–2018, and 2018–2022 were 1.0123 million tons, 5.7065 million tons, 2.731 million tons, and 1.2772 million tons, respectively. The inhibitory effect of CEI within the primary urban area of Chengdu displayed a trend from increasing to decreasing with 2014 as the inflection point. The values of the four periods were 0.0048 million tons, 2.2765 million tons, 3.3757 million tons, and 0.9125 million tons, respectively. The remaining counties fluctuated. It shows that reducing the CEI of building land has become more and more challenging over time, and traditional carbon reduction methods are difficult to meet the new low-carbon development requirements.

According to Figure 7c, from 2006 to 2022, ED factors basically promoted the carbon emissions of building land in each county of the Chengdu Plain. The carbon emissions resulting from the development of the county economy in Chengdu basically increased first and then decreased with 2010 as the inflection point. The values of the four periods of 2006–2010, 2010–2014, 2014–2018, and 2018–2022 were 5.4298 million tons, 5.9521 million tons, 3.5911 million tons, and 1.682 million tons, respectively. The carbon emissions resulting from ED in Jingyang District, Luojiang District, Guanghan City, Shizhong District, and Dongpo District showed a continuous downward trend, from 1.3599 million tons in 2006–2010 to 0.3496 million tons in 2018–2022, while the remaining counties showed fluctuating changes. It generally reflects the trend that the Chengdu Plain economy has gradually

transformed into a green and low-carbon direction after 2014, but the development level of low-carbon economy in each county is quite different. By 2022, the ED of 7 counties in 33 counties has changed from promoting carbon emissions to inhibiting, and all of them are located in the municipal district of Chengdu, indicating that the municipal district of Chengdu is ahead of the other counties in the development of a low-carbon economy.

From 2006 to 2022, the increase effect of PS on carbon emissions within the primary urban area of Chengdu exhibited a pattern of decreasing first and then increasing with 2010 as the inflection point (Figure 8a). The values of the four periods of 2006–2010, 2010–2014, 2014–2018, and 2018–2022 were 0.1662 million tons, 0.0214 million tons, 0.0594 million tons, and 0.9384 million tons, respectively. The main urban area and Fucheng District of Chengdu showed an increasing trend year by year, with 0.712 million tons in 2006–2010 increasing to 6.2733 million tons in 2018–2022, while the remaining counties showed fluctuating changes. From 2018 to 2022, the increase in carbon emissions from building land generated by the increase in PS in Chengdu’s municipal districts has increased significantly. Overall, from 2006 to 2022, the carbon emissions resulting from the high PS within the Chengdu municipal district and Fucheng District are much higher than those in other counties, and the gap with other counties has been further widened in recent years.

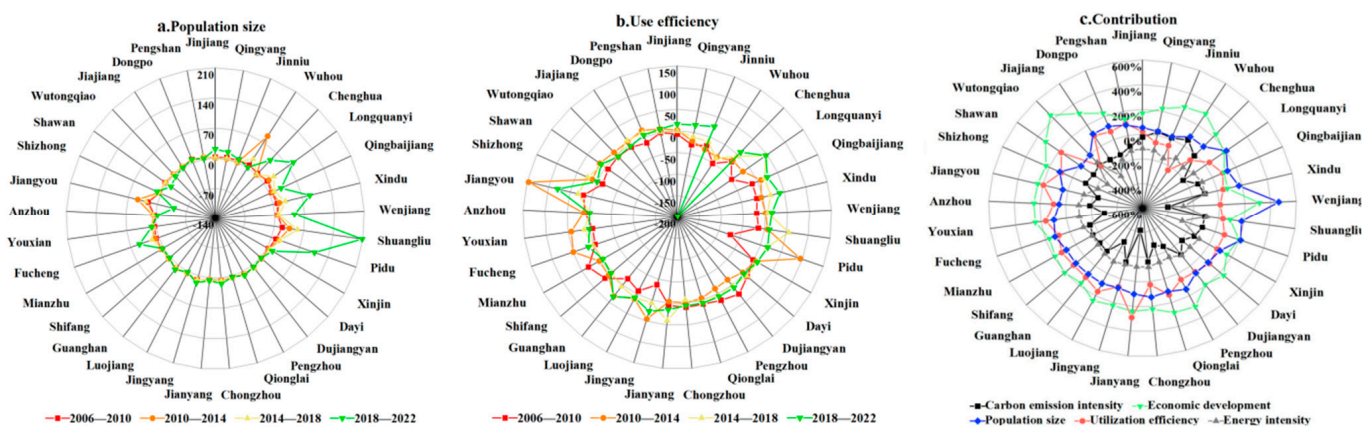


Figure 8. Decomposition of PS, UE, and contribution of carbon emissions from building land in 33 counties from 2006 to 2022.

According to Figure 8b, from 2006 to 2022, the 33 counties in the Chengdu Plain gradually changed from the promoting effect of UE to the increasing effect, from 23 counties in 2006 to 7 counties in 2022. The impact of UE on each county shows a small range of regional differences. The UE of eight counties in Jinjiang District, Qingyang District, Jinniu District, Chenghua District, Longquanyi District, Qingbaijiang District, and Xindu District of Chengdu City has gradually changed from inhibiting carbon emissions to promoting carbon emissions, and the promotion effect has been increasing. From 2006 to 2010, its effect surged from −1.7446 million tons to 1.9229 million tons in 2018–2022, while the rest of the counties showed fluctuating changes. In general, in urban development, the expansion of building land area is more, resulting in large carbon emissions, and the low UE of building land has become a common trend in the 33 counties of the Chengdu Plain.

In terms of carbon emission contribution, there is no obvious regional difference in PS among counties, which constitutes the primary factor driving the increase in carbon emission of building land in the 33 counties (Figure 8c). The contribution of UE, PS, CEI, and EI shows evident regional variations. In terms of increasing carbon emissions from building land, the contribution of PS in 18 counties of Chengdu is greater than the contribution of UE, and the contribution of UE in the remaining 15 counties is greater than the contribution of PS. In terms of inhibiting carbon emissions from construction land, the contribution of CEI surpasses that of EI in a total of 11 counties in the main urban area of Chengdu, Leshan City, and Meishan City, while the contribution of EI exceeds that of CEI in the remaining 22 counties.

3.5. Multi-Scenario Simulation and Low-Carbon Path Analysis of Land Use Pattern

We compared the current land use types and simulated land use types in the Chengdu Plain in 2022, and verified the accuracy. The Kappa coefficient simulation was used to measure the spatial position consistency of the land use type map. The Kappa coefficient value was greater than 0.75, indicating that the spatial position of the two types of land use types was consistent. The Kappa coefficient test was performed at a sampling rate of 0.01, and the value was 0.752, confirming the PLUS simulation results were consistent with the real results, and could better simulate the prospective spatial distribution pattern of land use within the Chengdu Plain. The three scenario parameters were integrated into the PLUS, and the results are shown in Figure 9.

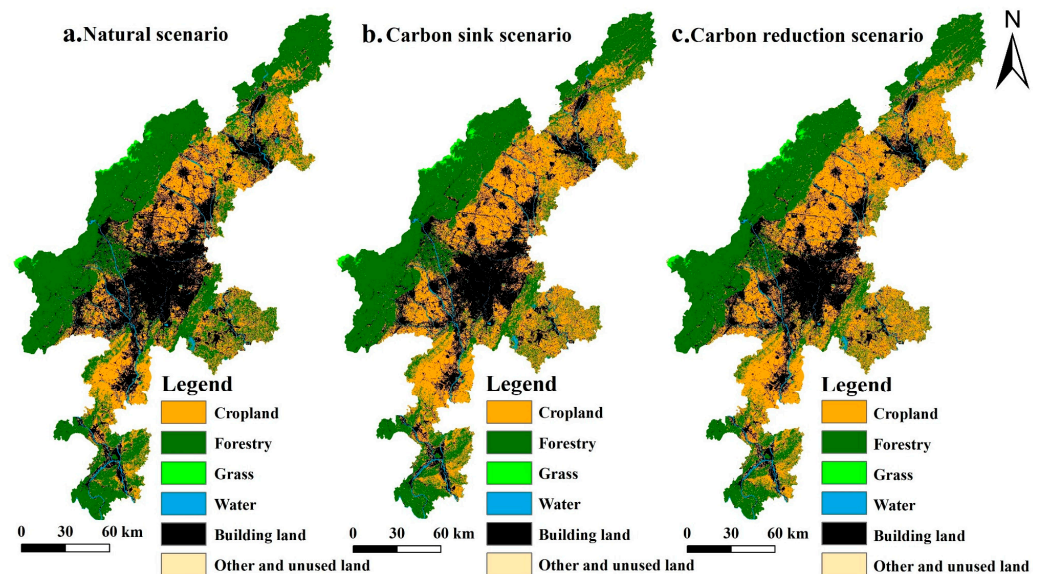


Figure 9. Land use demand projections under three scenarios in 2030.

3.5.1. Differences in Land Use Area under Three Scenarios

According to Figure 9, it can be seen that cropland and forest are still the main land use types in the Chengdu Plain prospectively. The spatial pattern of land use types remains largely consistent across three scenarios. Forest is mainly distributed in Longquan Mountains, Longmen Mountains, and Leshan City. Building land is predominantly distributed in the central region of the Chengdu Plain. Deyang City and Mianyang City also have a large increase, and grass and water still maintain a relatively stable spatial distribution.

- (1) According to Table 10, under the NS, the area of cropland is 7042.46 km², taking 26.88%; the area of forest is 11,626.25 km², representing 44.37%; the area of grass is 167.23 km², comprising 0.64%; the area of water is 704.04 km², taking up 2.69%; the area of building land is 6656.77 km², covering 25.41%; and the area of other and unused land is 4.47 km² covering only 0.02%. The area size is forest area > cropland area ≈ building land area > water > grass area > other and unused land area. In general, under the NS, the loss of cropland is serious, and forest has become the major land type. The area of building land is basically the same as that of cropland, and the land use pattern is hard to support the demand for food security.
- (2) Under the CSS, the cropland area is 9150.77 km², representing 34.92%, and the forest area is 10,394.06 km², taking 39.67%. The grass area is 168.99 km², constituting 0.64%. Water is 668.13 km², covering 2.55%. The building land area is 5812.08 km², representing 22.18%, and the other and unused land area is 7.20 km², covering only 0.03%. The area size is cropland area > forest area > building land area > water > grass area > other and unused land area. In general, the loss of cropland under the CSS is weaker than that under the NS. Cropland is the major land type, and the land use pattern basically supports the demand for food security.

- (3) Under the CRS, the area of cropland is 9688.97 km², constituting 36.98% of the total area, while the forested area encompasses 10,106.95 km², taking 38.57%. The grass area is 168.10 km², covering 0.64% of the total area. Water is 660.14 km², equivalent to 2.52%. The building land area is 5569.91 km², comprising 21.26%, and the other and unused land area is 7.16 km², covering only 0.03%. The area size is cropland area > forest area > building land area > water > grass area > other and unused land area. In general, under the CRS, the loss of cropland is the least and the food security is the highest.

Table 10. The area of six land use types in the Chengdu Plain under the three scenarios in 2030 (km²).

Land Use Type		Cropland	Forest	Grass	Water	Building Land	Other and Unused Land
2022	Area	10,763.25	9767.63	167.05	652.03	4843.40	7.86
	Area	7042.46	11,626.25	167.23	704.04	6656.77	4.47
NS	Variations	−3720.79	1858.62	0.18	52.01	1813.37	−3.39
	Percentage	26.88%	44.37%	0.64%	2.69%	25.41%	0.02%
CSS	Area	9150.77	10,394.06	168.99	668.13	5812.08	7.20
	Variations	−1612.48	626.43	1.94	16.10	968.68	−0.66
CRS	Percentage	34.92%	39.67%	0.64%	2.55%	22.18%	0.03%
	Area	9688.97	10,106.95	168.10	660.14	5569.91	7.16
CRS	Variations	−1074.28	339.32	1.05	8.11	726.51	−0.70
	Percentage	36.98%	38.57%	0.64%	2.52%	21.26%	0.03%

3.5.2. Changes in the Center of Gravity of the Six Land Use Types

According to Figure 10, among the six land types, the center of gravity of forest, water, building land, and other and unused land in the Chengdu Plain moves in the same direction in the NS, CSS, and CRS. The centroid of forest moves to the southeast direction, while water moves to the northeast direction. Similarly, building land and other and unused land also migrate to the northeast. The moving distance of the center of gravity of the land type is NS > CSS > CRS (Table 11), indicating that the future changes in the four land types have a very obvious trend. The center of gravity movement of cropland and grass in the Chengdu Plain is not consistent. According to the analysis of the moving direction of the center of gravity, the expansion area of building land, water, and unused land in Mianyang City and Deyang City in the northeast of the Chengdu Plain will be higher than that in Leshan City and Meishan City in the southwest of the Chengdu Plain in the future. The increase rate of forest in the southeast direction will be higher than that in the northwest direction of Longmen Mountain. Forest land and grassland have great differences in the direction of area transfer due to different future development scenarios.

Table 11. The moving direction and length of the center of gravity of six land use types in the Chengdu Plain under the three scenarios (km).

Type	NS		CSS		CRS	
	Direction	Length	Direction	Length	Direction	Length
Cropland	northwest	0.54	southwest	0.49	southeast	0.27
Forest	southeast	6.29	southeast	2.14	southeast	1.18
Grass	northwest	12.63	southeast	0.41	southwest	0.36
Water	northwest	4.01	northwest	1.64	northwest	0.74
Building land	northwest	3.38	northwest	3.02	northwest	2.14
Other and unused land	northwest	20.21	northwest	15.28	northwest	9.06

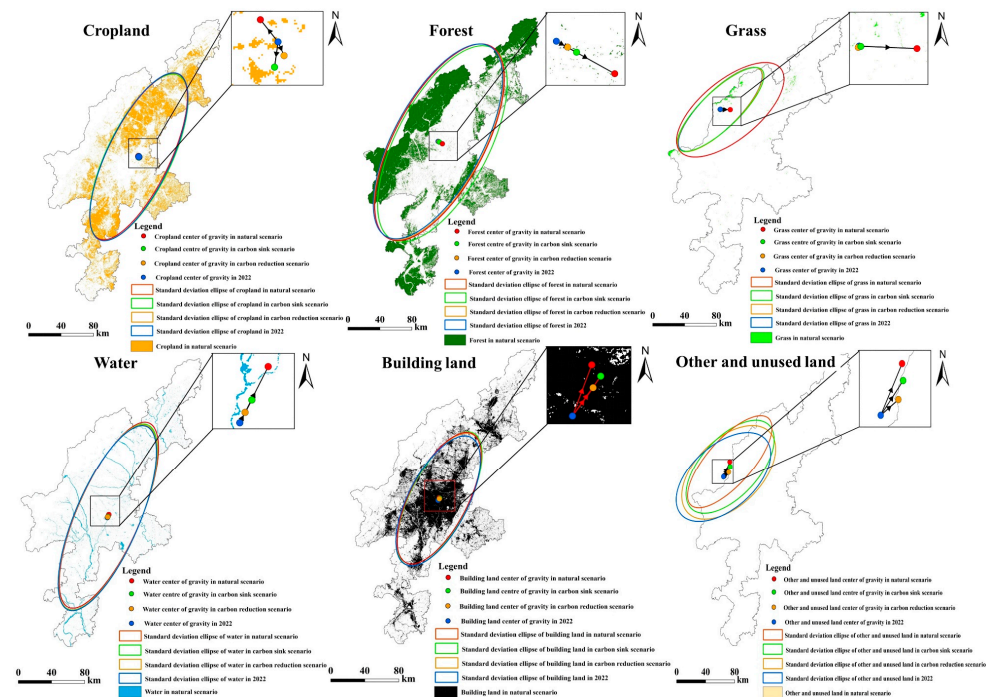


Figure 10. The gravity center changes in six land use types in the Chengdu Plain under the three scenarios from 2022 to 2030.

3.5.3. Analysis of Land Use Carbon Emissions under Three Scenarios in Chengdu Plain

According to Table 12, in the NS, the Chengdu Plain for 2030 amount is 30.301 million tons, representing a decrease of 0.5391 million tons compared to 2022 levels, thereby indicating the attainment of the carbon peak target by 2030. The carbon emission of cropland decreases by 0.5379 million tons, which primarily contributes to this achievement. Under the CSS, the carbon emission in the Chengdu Plain in 2030 will be 27.3664 million tons, marking a decrease of 3.4728 million tons relative to 2022 levels, and the reduction will be between the NS and the CRS. Under the CRS, the land use carbon emission of the Chengdu Plain in 2030 will be 26.3127 million tons, which will be reduced by 4.5265 million tons compared with 2022, which is the scenario with the largest decrease in carbon emission. The carbon emission of building land will decrease by 3.8877 million tons, which is the main way to achieve carbon peak.

Table 12. The area of six land use types in the Chengdu Plain under the three scenarios in 2030 (10⁴ t).

Land Use Type		Cropland	Forest	Grass	Water	Building Land	Other and Unused Land	Total Carbon Emissions
2022	Carbon emissions	37.32	−59.09	−0.03	−1.65	3107.37	0.00	3083.92
NS	Carbon emissions	−16.47	−70.29	−0.03	−1.78	3118.59	0.00	3030.01
	Variations	−53.79	−11.2	0.00	−0.13	11.22	0.00	−53.91
CSS	Carbon emissions	−22.42	−62.84	−0.03	−1.69	2823.62	0.00	2736.64
	Variations	−59.74	−3.75	0.00	−0.04	−283.75	0.00	−347.28
CRS	Carbon emissions	−23.2	−61.11	−0.03	−1.67	2718.6	0.00	2631.27
	Variations	−60.52	−2.02	0.00	−0.02	−388.77	0.00	−452.65

According to Table 13, in 2030, the Chengdu Plain as a whole can achieve carbon peaks under the NS, CSS, and CRS. Under the NS, there are 11 counties that can not achieve carbon peaks (Xindu District, Qingbaijiang District, Pengzhou City, Chongzhou City, Jingyang

District, Luojiang District, Guanghan City, Shifang City, Mianzhu City, Anzhou District, and Pengshan District), mainly distributed in Deyang City and its neighboring counties and the western counties of Chengdu, and the remaining counties have achieved carbon peaks. Under the CSS, five counties (Jingyang District, Guanghan City, Shifang City, Anzhou District, and Pengshan District) cannot achieve carbon peaks, of which Deyang City has three, accounting for the highest proportion, and the remaining counties have achieved carbon peaks. Under the CRS, the 33 counties in the Chengdu Plain can achieve carbon peaks. Overall, the CRS is more helpful than the CSS and the NS to achieve the carbon peak target in the 33 counties of the Chengdu Plain.

Table 13. Carbon emission of land use types under three scenarios in 33 counties in 2030 (10⁴ t).

County	NS	CSS	CRS	County	NS	CSS	CRS
Jinjiang	74.99	74.10	73.59	Jianyang	32.54	28.97	27.83
Qingyang	130.64	130.19	130.15	Jingyang	146.06	131.71	122.45
Jinniu	146.68	145.82	145.44	Luojiang	33.32	28.34	24.87
Wuhou	248.32	248.21	248.17	Guanghan	113.77	94.83	85.92
Chenghua	127.79	126.36	125.97	Shifang	58.69	44.58	38.90
Longquanyi	114.00	106.00	102.77	Mianzhu	69.92	52.30	45.21
Qingbaijiang	69.47	56.37	55.09	Fucheng	128.25	120.60	115.62
Xindu	171.22	145.42	139.71	Youxian	42.93	39.62	36.56
Wenjiang	63.44	59.20	58.63	Anzhou	51.06	42.73	34.72
Shuangliu	256.22	232.45	228.32	Jiangyou	300.16	281.66	262.84
Pidu	119.56	102.31	101.93	Luoshi	48.46	46.24	44.50
Xinjin	48.61	38.80	37.88	Shawan	35.09	35.69	35.13
Dayi	33.69	25.78	25.57	Wutongqiao	14.99	14.56	14.02
Duijiangyan	63.23	60.31	59.80	Jiajiang	21.41	19.39	17.96
Pengzhou	79.93	51.11	48.46	Dongpo	58.59	50.74	44.79
Qionglai	33.47	26.59	25.88	Pengshan	36.92	32.50	30.01
Chongzhou	56.58	43.14	42.58	aggregate	3030.01	2736.64	2631.27

3.5.4. Comparison of Mutual Learning Preferred Carbon Peak Mode

In the NS, 11 counties did not reach the peak, 5 counties in the CSS, and 0 counties did not reach the peak in the CRS. In order to compare and select the best carbon peak scenario for the 33 counties in the Chengdu Plain, the study proposes a comparative and mutual learning model for selecting the best carbon peak (Figure 11).

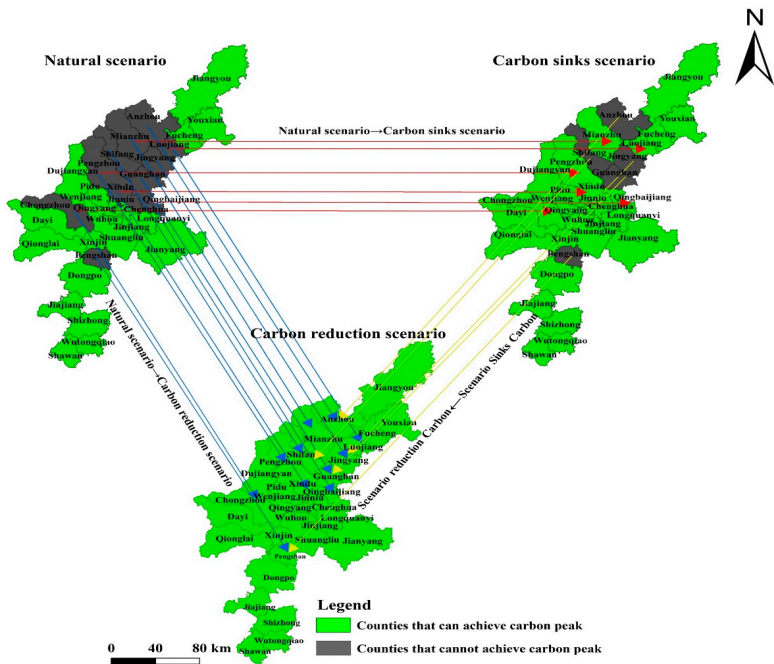


Figure 11. Comparison of mutual learning preferred carbon peak mode.

Under the NS, the 11 counties that do not peak have two path options. First, the 11 counties can choose the CRS mode to realize carbon peak. Second, six counties, Xindu District, Qingbaijiang District, Pengzhou City, Chongzhou City, Luojiang District, and Mianzhu City, can choose the CSS mode to realize peak carbon. Under the CSS, five counties that have not peaked, Jingyang District, Guanghan City, Shifang City, Anzhou District, and Panshan District, can choose the CRS mode to realize peak carbon.

4. Discussion

The carbon emissions of cropland in the Chengdu Plain reduced to 52.45% from 2006 to 2022, which was basically the same as Lu's [60] opinion. The effects of RDI, FOS, and FCR on carbon emissions from cropland are basically the same as those of Huang, Guo, and Niu [61–63]. The carbon emissions caused by economic development increased first and then decreased [64], and the economic development of some districts and counties changed from promoting carbon emissions to inhibiting carbon emissions, which basically corresponded with the study results of Yu [65]. The CRS is more conducive to the low-carbon development of land use than the NS and the CSS, which corresponds with the research results of Wu [66].

The study puts forward suggestions for low-carbon development in the Chengdu Plain with food security and dual-carbon purposes: ① The area of cropland in the Chengdu Plain is reduced by about 40%, mainly transferred to building land in the central Plain and woodland in Longmen Mountains, Longquan Mountains, and Leshan City. In the future, it is vital to enhance the protection of cropland in this area. ② In the main grain crops, the proportion of wheat sown area in the total sown area decreased by about 34%, with the largest decline. It is necessary to increase scientific research on wheat, improve wheat quality and planting income, and increase wheat planting area, prospectively. ③ In the 21 counties of the Chengdu Plain where the unrealized cultivated land was converted from carbon source to carbon sink, priority should be given to accelerating the promotion of energy-saving agricultural tools, actively promoting the use of organic fertilizers and green pesticides instead of traditional pesticides and fertilizers, and gradually improving the quality of farmland scale management. ④ Chengdu non-municipal area, Deyang City, Mianyang City, Leshan City, and Meishan City should speed up the promotion of a low-carbon energy consumption structure. ⑤ It is necessary to speed up the construction of new areas such as the Eastern New Area of the Chengdu Plain, the Chengde New Area, and the Meishan Area of the Tianfu New Area; reduce the development intensity and population density of the primary urban area of Chengdu; and ease the resources of the primary urban area. ⑥ Build a strong national integrated computing power network national hub (Chengdu–Chongqing region) node, provide technical support for economic transformation and upgrading, and promote the development of the green service industry of Chengdu and the development of industrial Internet in other districts and counties.

The research explores the nexus between the transfer of land use center and carbon emissions, simulates the land use pattern of the Chengdu Plain under three scenarios, and proposes a low-carbon path, but there are still some shortcomings that need to be further explored. Carbon emissions accounting can scale up the accuracy of accounting with more accurate image information and more quantitative statistical data. Three simulation scenarios were designed, and other scenarios need to be further simulated and improved. Using multi-period time node data to show the continuity of data changes, the data analysis is rough, and further refined analysis is needed.

5. Conclusions

Utilizing multi-source data, this research analyzed the changes in land use centers of six land use types and three major grain crops of rice, wheat, and corn in the 33 counties of the Chengdu Plain from 2006 to 2022, calculated carbon footprints, and explored the impact of important influencing factors like social, economic, and resource input on the carbon emissions of cropland and building land. The three scenarios of NS, CSS, and CRS

are hypothesized to simulate and analyze the nexus between land use pattern and carbon emission in the Chengdu Plain from 2022 to 2030, and the low-carbon path and mode of the 33 counties in the Chengdu Plain are put forward.

- (1) From 2006 to 2022, the center of gravity of land use in the Chengdu Plain changed significantly, with cropland and forest land shifting to the northeast and southeast, grassland and water center changing slightly, while the center of gravity of building land and unused land shifted significantly to the northeast. The outward area of rice predominantly focused on the central and southern parts of the Plain, resulting in the shift of its central core to the northeast, while the outward area of wheat and maize was scattered, and the change in the center of gravity was not obvious.
- (2) The carbon emissions in the Chengdu Plain demonstrated a continuous upward trajectory in general, carbon emissions increased by 13.552 million tons, carbon sinks have demonstrated a diminishing trend, with a decline of 0.5679 million tons. The carbon emissions of the 33 counties are on the rise, and the carbon sinks of 31 counties are negative. The increase rate of carbon emissions in Chengdu municipal districts and Mianyang City is greater than that of other districts and counties. The primary urban area of Chengdu has witnessed a more substantial decline in carbon sinks relative to other regions. Furthermore, the reduction in cropland carbon emissions within Chengdu has surpassed the spatial variance observed across other districts and counties.
- (3) Under the NS, CSS, and CRS, the land use sector of the Chengdu Plain can fulfill the carbon peak target by 2030. Within the 33 counties in the Chengdu Plain, 11 counties are anticipated to fall short of reaching the carbon peak under the NS, while 5 counties may not achieve the target under the CSS, and 0 counties can not achieve the target under the CRS. This indicates that adopting a carbon emission reduction model will help the counties achieve the carbon peak target. At the same time, the study also proposes targeted low-carbon paths for the 33 counties in the Chengdu Plain to meet the data support in different counties.

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