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Unpacking the Sub-Regional Spatial Network of Land-Use Carbon Emissions: The Case of Sichuan Province in China

Qianyu Zhao [1,2], Boyu Xie [1] and Mengyao Han [2,3,4,*]

1 School of Public Administration, Sichuan University of China, Chengdu 610065, China; zhaoqianyu@scu.edu.cn (Q.Z.); x1773451136@163.com (B.X.)
2 Department of Land Economy, University of Cambridge, Cambridge CB3 9EP, UK
3 Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
4 Centre for Environment, Energy and Natural Resource Governance (C-EENRG), University of Cambridge, Cambridge CB2 3QZ, UK
* Correspondence: hanmy@igsnrr.ac.cn

Abstract: Land, as an essential resource for social, economic and ecological activities, is regarded as a key factor in material production. Against the background of rapid social and economic transition, land-use carbon emissions have gradually drawn due attention. However, few studies have been conducted to explore the spatial relationship of land-use carbon emissions at the sub-regional level, especially within Sichuan Province, China. This study is aimed at unpacking the spatial network of land-use carbon emissions in Sichuan Province by employing the panel data from 2006 to 2021 and using the method of Social Network Analysis. The results indicate that the net land-use carbon emissions of various prefecture-level divisions in Sichuan generally showed an inverse and asymmetrical "V-shaped" trend. The network correlation was improved and the stability was enhanced, gradually developing into a multi-centric structure. In addition, the spatial relationship among different clusters in the network undergoes a transition from intra-regional to inter-regional spillover. Based on these findings, the carbon balance zoning policy was discussed to provide references for how to coordinate roles and positions in the network when optimizing land-use carbon emission management policies in sub-regional areas with rapid social and economic development.

Keywords: spatial network; land-use carbon emissions; social network analysis; carbon balance zoning; Sichuan

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1. Introduction

Land, an essential resource for social, economic and ecological activities, is regarded as a key factor in material production. Land use changes (LUC) generate fundamental impacts on carbon emissions and hence contribute to climate change, especially against the background of rapid social and economic transition and given the increasing energy consumption for better human livelihoods and well-being [1,2]. According to the report issued by the Intergovernmental Panel on Climate Change (IPCC), the natural response of land to human-induced environmental change caused a net sink of approximately 11.2 $GtCO_2$ yr^{-1} between 2007–2016 (equivalent to 29% of total CO_2 emissions) [3]. Highlighting land-use carbon emission reduction activities to promote sustainable land use, fulfilling the goal of carbon neutrality and actively responding to climate change is thus of great importance for policy-makers. In addition, cooperation is desperately needed within regions in terms of carrying out carbon emission reduction activities and between such regions [4]. Different levels and types of collaboration have been carried out worldwide since the adoption of the United Nations Framework Convention on Climate Change in 1992. The spatial network of land-use carbon emissions in the collaborative process has been restructured as well [5]. Specifically, the network centrality and the roles within the network clusters of different countries have changed over time in the collaboration of engaging in land-use carbon emission reduction activities. Some countries gradually became the center of the network, while others were at the edge and play net spillover roles within the cluster [6].

As the second-largest economy and one of the largest carbon emitters, China plays a pivotal role in the collaborative network to achieve the goal of global carbon neutrality. China is also facing significant challenges in reducing carbon emissions in the context of a substantial social and economic transition. The gross domestic product (GDP) per capita increased from CNY 385 in 1978 to CNY 85,698 in 2022, an increase of 221.59 times. The urbanization rate also increased from 17.92% to 65.22% during the same period. The rapid social and economic transition indicates that China needs to take more effective actions to achieve its carbon neutrality goals. At the 75th General Assembly of the United Nations in 2020, China, for the first time, proposed achieving a carbon peak by 2030 and carbon neutralization by 2060 [7]. Since that time, a national "double control" system to control the carbon emission quantity and intensity was put forward, and a national action plan for a carbon peak by 2030 was launched to highlight ten key actions in terms of promoting carbon reduction activities. Top-down actions promoted by China's central government have generated positive and significant carbon emission reduction effects. According to the data released by the Carbon Emission Accounts and Datasets (CEADs) for emerging economies, the carbon emissions per unit of GDP are decreasing, although the temporal trend of China's total carbon emissions is generally increasing. In 2021, carbon emissions per unit of GDP in China were reduced by 3.8% compared to 2020 and experienced a cumulative decrease of 50.8% compared to 2005 [8]. Amid COVID-19 lockdowns and a real estate slump, the emissions barely changed from 2021 to 2022, but the overall yearly decline was the first since structural reforms drove emissions lower in 2015 [9]. These effects cannot be achieved without the provincial efforts in the country since China's central government breaks down carbon emission reduction tasks to each province. More importantly, specific and executable carbon emission reduction action plans and policies are developed at the provincial level. Attention should thus be paid to provinces as an important sub-regional type in analyzing the network relationship of land-use carbon emissions. In addition, China is still seeing rapid social and economic development, which means that its land use would accordingly undergo dynamic changes, and related land-use carbon emission reduction activities still face great challenges [10]. The allocation of land use quotas, such as the addition of construction land and the amount of preserved arable land, is also generally achieved within a province, which is similar to the decomposition system of carbon emission reduction tasks. Thus, it is indispensable to analyze the spatial network of land-use carbon emissions within a province to better understand China's land-use carbon emission management system.

However, less attention has been given to the spatial network of land-use carbon emissions within a province both in China and around the world. In fact, the sources and sinks of carbon from LUC are significant in global, national, regional, and sub-regional carbon budgets [11–14]. Therefore, extensive studies have focused on calculating carbon emissions from LUC. Several different models, datasets and methods have been applied. Among them, Smith and Rothwell (2013) examined land-use carbon emissions between 1700 and 2000 using a simple mechanistic carbon-cycle model with regional and ecosystem specific parameterizations based on the global gridded data, finding that the estimation result was smaller than the native values from the Global Change Assessment Model result due to lower net reforestation in the Representative Concentration Pathway (RCP) 4.5 gridded land-use data product [15]. Mahowald et al. (2016) explored the role of human land use and land cover change in modifying the terrestrial carbon budget in simulations forced by RCP8.5 using the Community Earth System Model and estimated a cumulative carbon loss of 490 Pg C between 1850 and 2300 [16]. Despite extensive research on measuring and simulating large-scale and long-interval land-use carbon emissions at the global level [17–21], analyzing land-use carbon emissions at national and regional levels has attracted much attention. The differences are that studies at national and regional levels usually focused on a shorter time span and lower scale area [22–24]. For example, Hung et al. (2021) used the coefficient method and aggregated remote sensing data between 2002 and 2012 in Vietnam to calculate carbon emissions in the fields of land use, land use change, and forestry [25]. Compared with the analysis at global, national and regional levels, spatially explicit information on land-use carbon emissions at the sub-regional level is of value for the implementation of local carbon emission mitigation policies. Ulrich et al. (2023) estimated the carbon fluxes related to land use and land cover change in the state of Baden-Württemberg in Germany based on four types of data resources, providing a solid carbon emission analysis to local authorities [14]. To formulate feasible local policies, sub-regional land-use carbon emissions should be given more attention and require more exploration.

Land-use carbon emissions are closely related to the social, economic and ecological activities which have spatial relationships [26,27]. In addition to estimating the sources and sinks of carbon from LUC at different levels, the spatial network or relationship of carbon emissions was also explored to further understand the correlation structure of carbon emissions within or across regions [6,28,29]. Social Network Analysis (SNA) subsequently was regarded as a prevalent method to explore spatial relationships [28,30]. Using SNA and data from 1995 to 2018, Yu et al. (2022) analyzed the overall characteristics of the spatial correlation network of 41 cities in the Yangtze River Delta region in China and clarified the roles of cities in the land-use carbon emission network [31]. Wang et al. (2018) classified provinces into four clusters based on the internal relationship of the carbon emission network of various provinces in China using data from 2008 to 2014 [32]. Compared with the conventional spatial relationship analysis based on attribute data, SNA uses relational data to identify the key nodes and clusters in the carbon emission network, which could provide a new perspective to understand the internal structure of the spatial network of land-use carbon emissions [33]. In addition, feasible local carbon emission reduction policies, such as carbon balance zoning, can be introduced and optimized based on the analysis of spatial networks or relationships combining attribute data and relational data. However, few studies have shed light on this combination to analyze the spatial network within a province and provide policy implications for local authorities. Against this background, our study takes Sichuan Province in China as the case and uses the data from 2006 to 2021 to explore the sub-regional spatial network of carbon emissions from LUC, which could enhance our understanding of the local carbon emission spatial relationships in two ways: (i) analyzing the features, clusters, and evolutions of the spatial network of land-use carbon emissions at the sub-regional level; and (ii) providing a reference for local carbon emission management policies through a comprehensive analysis based on attribute data and relational data.

2. Materials and Methods

2.1. Study Area

Situated in southwest China (Figure 1), Sichuan Province is of great importance in providing support for national development strategies, including the "Belt and Road" initiative, the "Yangtze River Economic Belt" strategy and the "Chengdu-Chongqing Dual-City Economic Circle" strategy. Its strategic position among provinces has brought unprecedented development opportunities to the province. According to data released by the National Bureau of Statistics of China, the GDP of Sichuan Province increased from CNY 2651.80 billion in 2013 to CNY 5674.98 billion in 2022, achieving a growth rate of 1.14 times and ranking sixth among 31 provinces of mainland China. In the meantime, the urbanization rate rose from 44.96% to 58.40%, which promoted significant social transformation within the province. A total of 21 prefecture-level divisions form the administrative structure of the province, with the headquarters located in Chengdu. The population was 83.74 million in 2022. Complex and diverse terrain is distributed on a territory land area of 486,000 km^2. The rapid development and strategic position among provinces in China make Sichuan Province a typical case to help understand the sub-regional spatial relationship of land-use carbon emissions from LUC.

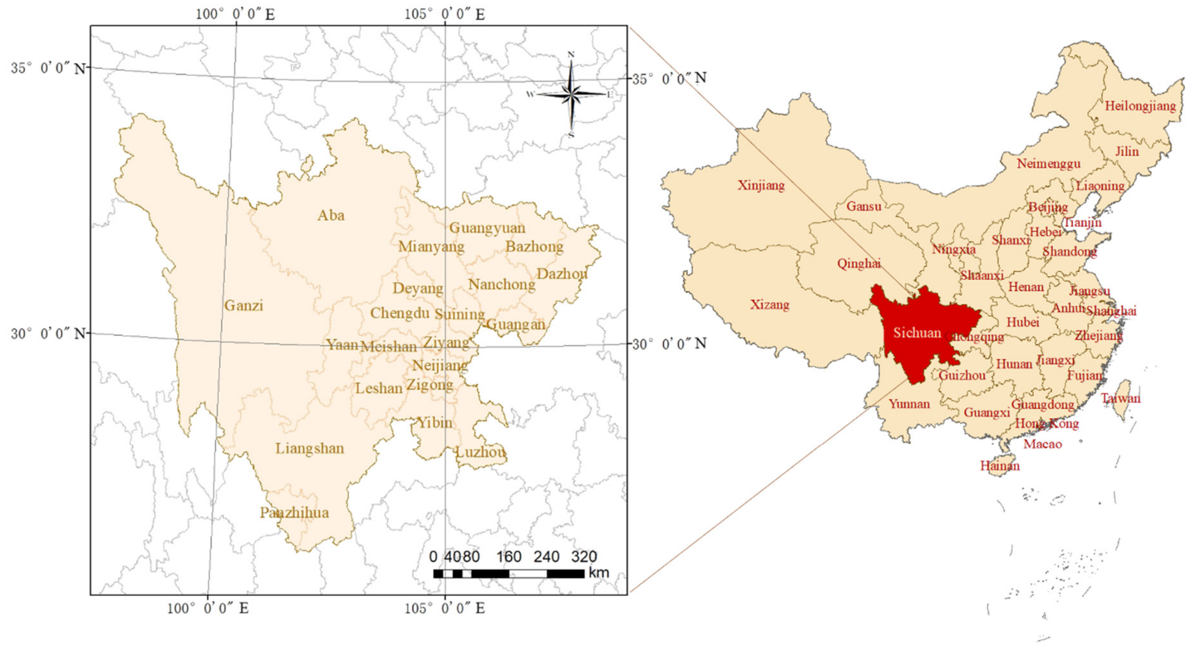

Figure 1. Geographical Location of the Study Area. Note: GS(2020)4619.

Specifically, Sichuan's rapid development and strategic position brought about dramatic LUC and posed great challenges to its carbon emission reduction plans, which makes it a suitable case to analyze carbon emissions from LUC. As shown in Figure 2, the area of woodland, which is a land use type associated with carbon sinks, increased by 8925.20 km^2 from 2006 to 2021, while the area of grassland decreased by 4365.84 km^2 and the water area decreased slightly. Two primary sources of carbon emissions for LUC, namely, cultivated land and construction land, had different trends. The area of cultivated land decreased by 7741.83 km^2, while that of construction land increased by 8925.20 km^2. The construction land per unit area generally carries more economic, social and ecological activities, and the carbon emissions are correspondingly larger. Therefore, areas such as Sichuan Province with rapid development are usually associated with dramatic increases in construction land and carbon emissions and warrant more effective action plans to manage land-use carbon emissions.

In December 2016, Sichuan Province was selected as the second batch of carbon emission trading pilots in China. To pilot Chinese Certified Emission Reduction (CCER) transactions, a series of local policies need to be formulated or optimized. Among them, an energy consumption control plan for production activities on different types of lands was formulated in 2017. Since then, energy consumption in land use activities in Sichuan has been under control. According to the data issued by the China Energy Statistical Yearbook (2007–2022), the consumption of different types of fossil energy in Sichuan has decreased or increased at a lower rate in recent years. For example, the consumption of raw coal was 83.88 million tons in 2006, increased to 114.09 million tons in 2011, decreased to 101.17 million tons in 2016, and further decreased to 79.71 million tons in 2021. In fact, various actions have been taken in practice within the province to promote carbon emission reduction activities from LUC before being selected as the pilot, such as strengthening the management of agricultural, industrial and mining lands and promoting the recuperation of grasslands, forests and wetlands. Thus, it is possible to analyze the spatial network of land-use carbon emissions within Sichuan Province to provide policy references for local authorities in China and other developing countries intending to implement similar pilot programs.

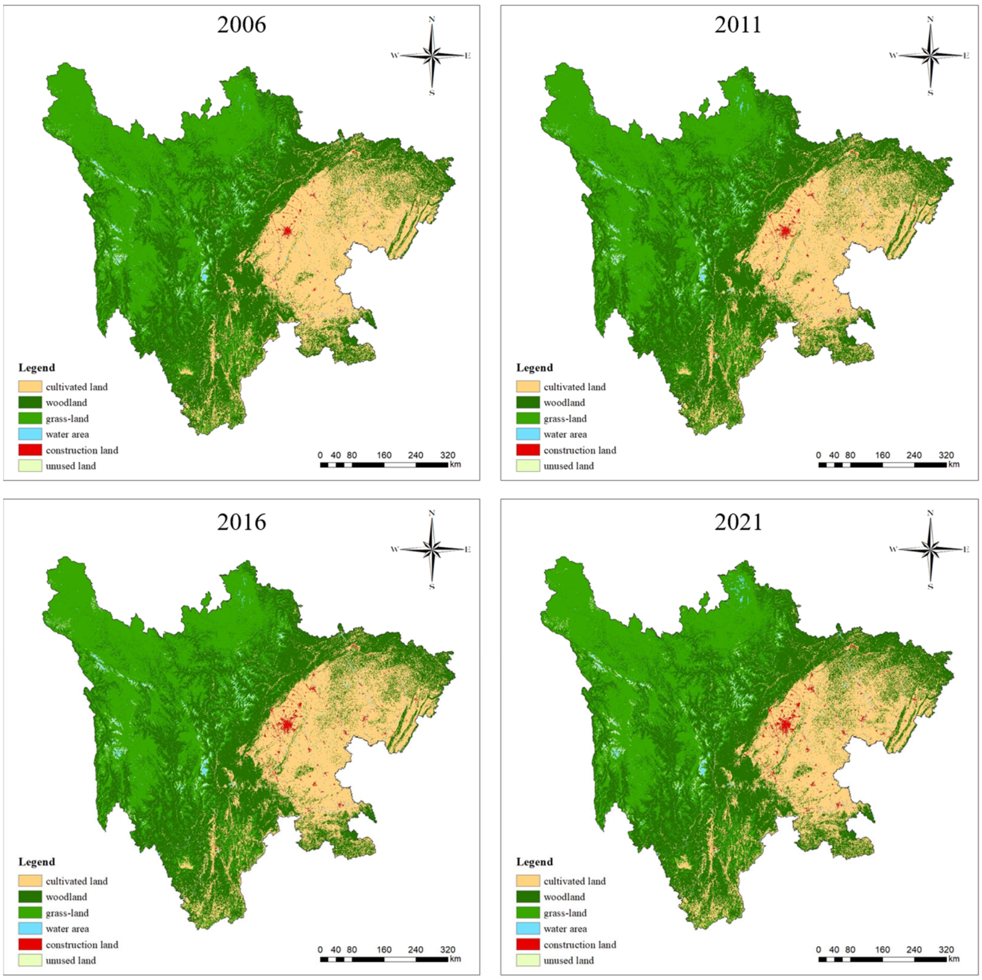

Figure 2. Land Use Changes of the Study Area.

2.2. Data Sources

The annual China Land Cover Dataset (CLCD) is adopted to analyze LUC in our study. This dataset employs 335,709 Landsat images on the Google Earth Engine (GEE) platform to construct a 30 m resolution annual land cover monitoring database of China [34,35]. As a sequential and high-resolution dataset, it has been used as the basic dataset to analyze LUC in several studies since it is able to reflect the rapid development and a series of ecological projects (e.g., Gain for Green) in China and reveal the anthropogenic implications of LUC under the condition of climate change (e.g., Liu et al. (2023) [36]). To explore the dynamics of the spatial network of land-use carbon emissions within Sichuan Province, we built a pooled prefecture-level dataset based on CLCD with time series of 2006, 2011, 2016 and 2021. We chose 2006 as the base year for two reasons. Firstly, 2006 marked a milestone, as it was the year when China's carbon emissions first surpassed those of the United States, making China the world's largest carbon emitter [37,38]. Secondly, there was a significant lack of energy consumption data for various prefecture-level divisions in Sichuan before 2006. Subsequently, an accessible dataset with widely used 5-year intervals from 2006 to 2021 was built.

Statistical data for the relevant years used in this study include population, energy consumption, and GDP, which were mainly obtained from the Sichuan Statistical Yearbook, China Energy Statistical Yearbook, and Statistical Bulletins of 21 prefecture-level divisions. Following the study of Sun et al. (2022) [28], a linear regression method was employed to fit the trend and interpolate the missing data in divisions with limited data gaps. China's county-level carbon emission data in the Carbon Emission Accounts and Datasets (CEADs) and the carbon emission inventories of 290 Chinese cities were also used to interpolate the missing data in divisions with consecutive data gaps [39,40]. The data of spatial distance between prefecture-level divisions in Sichuan Province were obtained from the platform of China's City Distance.

2.3. Methods

2.3.1. Model of Land-Use Carbon Emission Measurement

This study adopts the most widely used carbon emission coefficient method to calculate the prefecture-level land-use carbon emissions of Sichuan Province [41,42]. The classification system of land use types is defined based on the classification of land use types in the CLCD database and China's national standard of "Classification of Land Use" (Standard No. GB/T 21010–2017) and with reference to the state conditions of land cover in Sichuan. Finally, land use types were divided into six categories: cultivated land, woodland, grassland, water area, construction land, and unused land. Among them, the carbon emissions of cultivated land, woodland, grassland, water area, and unused land were calculated using the direct emission coefficient. The equation is as follows:

$$C_e = \sum S_i \cdot V_i \tag{1}$$

where C_e is the total land-use carbon emissions excluding the emissions of construction land. S_i is the area of land use type i (i = 1,2, ..., 5, representing cultivated land, woodland, grassland, water area and unused land, respectively). V_i is the land-use carbon emission coefficient per unit area of land use type i. V_i is defined based on the study of Lan et al. (2012) [43] and Ji et al. (2023) [44]. Positive values of V_i represent emissions and negative values represent absorption.

The carbon emissions of construction land were calculated using the indirect carbon emission coefficient method due to the large number of economic activities and human living activities carried by construction land. The calculation was processed by measuring the fossil energy consumption and population respiration according to the 2019 IPCC Guidelines for National Greenhouse Gas Inventories based on the following equations:

$$C_c = C_f + C_p \tag{2}$$

$$C_f = \sum E_j \times \theta_j \times f_j \tag{3}$$

$$C_p = N \times b \times 365 \tag{4}$$

where C_c denotes the total carbon emissions of construction land. C_f is the carbon emissions of fossil energy consumption, and C_p is the carbon emissions of the population. E_j represents the energy consumption of fossil type j. According to the IPCC guidelines, the fossil types included in this study are raw coal, coke, natural gas, gasoline, diesel, fuel oil, liquefied petroleum gas, and kerosene, and j = 1,2, ..., 8. θ_j is the coefficient of converting the energy consumption of fossil fuel type j into standard coal. f_j is the carbon emission coefficient of fossil fuel type j. The related coefficients are shown in Table 1. N is the population, and b is the daily carbon emissions per person. Following the study of Wei and Chen (2021) [45], b was defined as 0.2455 kg carbon per person per day. The total carbon emissions of each prefecture-level division in Sichuan Province (C) were the sum of C_e and C_c.

$$C = C_e + C_c \tag{5}$$

Table 1. Energy Standard Coal Conversion Coefficient (ESCCC) and Carbon Emission Coefficient (CEC).

Fossil Types	ESCCC (10^4 tce/10^4 t)	CEC (10^4 tce/10^4 t)
Raw coal	0.7559	0.7143
Coke	0.8550	0.9714
Natural gas	0.4483	1.2143
Gasoline	0.5538	1.4714
Diesel	0.5921	1.4571
Fuel oil	0.6185	1.4286
Liquefied petroleum gas	0.5042	1.7143
Kerosene	0.5714	1.4714

2.3.2. Model of Land-Use Carbon Emission Spatial Network Analysis

- Modified gravity model and spatial correlation matrix

Following the studies of Sun et al. (2022) [28] and Yu et al. (2022) [31] and applying the traditional gravity model with variables related to land-use carbon emissions, a modified gravity model was built to measure the spatial correlation degree and to construct a spatial correlation matrix of land-use carbon emissions. The modified gravity model has been widely used to measure spatial interactions. It was inspired by the law of universal gravitation and initially introduced to the field of economics by Walter Isard to analyze the interactions between two regions involving distance parameters and scale parameters [46]. The core concept of this model is that the interaction between two regions is directly proportional to the scale parameters and inversely proportional to the distance parameters [47]. The carbon emission ties between two divisions are thus directly proportional to their carbon emission scales and inversely proportional to their spatial distance [6]. However, divisions with larger carbon emission scales but lower economic development levels might be at the edge of the spatial network of carbon emissions. Therefore, we built a modified gravity model that not only included the carbon emission scale and distance factors between two divisions but also incorporated economic and social factors that influence the spatial connection of land-use carbon emissions between two divisions. The equation is as follows:

$$Q_{mn} = \frac{C_m}{C_m + C_n} \cdot \frac{\sqrt[3]{N_m C_m G_m}\sqrt[3]{N_n C_n G_n}}{D_{mn}^2/(I_m - I_n)^2} \tag{6}$$

where Q_{mn} is the correlation degree of land-use carbon emissions between division m and division n. C and N are the same as defined above. G, D, and I denote the gross domestic product, the spatial distance between m and n, and the per capita income, respectively. Based on this model, the gravity matrix of land-use carbon emissions is obtained. The average value of gravity in each row is taken as a comparison value. A value greater than the average level is recorded as 1, otherwise, it is recorded as 0. The spatial correlation matrix is then constructed.

- Social Network Analysis model and spatial network characteristics
  - (a) Overall spatial network characteristics

In this study, the indicators of four dimensions, network density (ND), network correlation (NC), network hierarchy (NH), and network efficiency (NE), are chosen to analyze the overall network structure of land-use carbon emissions in Sichuan Province. ND indicates the closeness of the node association in the entire network structure. The higher the network density, the closer the connections between nodes. NC reflects the stability or robustness of the network structure. The greater the degree of correlation, the more stable the network structure. NH measures the degree of asymmetry of the spatial correlation network. A higher value of hierarchy indicates that the individual node plays a "leading" role in the spatial network and has a controlling effect on the flow of elements within the network. NE measures the number of network connection lines, and the lower the network efficiency is, the more stable and complex the spatial network of land-use carbon emissions. The corresponding equations of ND, NC, NH, and NE are shown as follows:

$$ND = \frac{r}{k(k-1)} \tag{7}$$

$$NC = 1 - \frac{v}{k(k-1)/2} \tag{8}$$

$$NH = 1 - \frac{s}{\max(s)} \tag{9}$$

$$NE = 1 - \frac{\delta}{max(\delta)} \tag{10}$$

where k is the number of nodes in the network and r is the number of actual relationships. $k(k-1)$ denotes the maximum possible number of network relationships. v is the number of unreachable node pairs within the network. s is the number of symmetrically reachable node pairs, and $max(s)$ is the maximum number of symmetrically reachable node pairs in the network. δ is the number of redundant lines in the network, and $max(\delta)$ is the maximum number of possible redundant lines.

(b) Network structure characteristics of individual nodes

The spatial network characteristics of individual nodes were analyzed using three indicators: degree centrality (DC), betweenness centrality (BC) and closeness centrality (CC). DC measures the centrality of a node in the network. The higher DC is, the closer the node is to the center of the network. BC reflects the intermediary role of a node in the network. When a node is on the shortest distance of more node pairs, its value of BC will be higher. If BC is higher than the average value, its intermediary role in controlling and regulating land-use carbon emissions in other divisions will be stronger. CC measures the ability of a node in the network not being controlled by other nodes. When the CC of a node is higher than the average value, the distance between the node and other nodes in the network is relatively close, and correspondingly it will have more advantages in promoting factor flows within the network. The equations of DC, BC, and CC are shown as follows:

$$DC = \frac{d_m}{(k-1)} \tag{11}$$

$$BC = \frac{2\sum_m \sum_n \frac{h_{mn}(\tau)}{h_{mn}}}{[(k-1)(k-2)]} \tag{12}$$

$$CC = \frac{\sum_m g_{mn}}{(k-1)} \tag{13}$$

where d_m is the number of nodes directly associated with node m. h_{mn} is the number of shortest paths from node m to node n. $h_{mn}(\tau)$ is the number of those paths that pass through node τ. Thus, $h_{mn}(\tau)/h_{mn}$ measures the probability that a third node τ is on the shortcut between nodes m and n. g_{mn} is the distance of the shortest path from node m to node n.

(c) Network structure characteristics of clusters

The Block Model of SNA is used to analyze the cluster network structure of the land-use carbon emissions of Sichuan Province. Through spatial clustering, the internal structure state and the role of each member in the association network are depicted. Members with the same role form a cluster. The interaction mechanisms and influence paths among the clusters can be evaluated via a density matrix and image matrix of the network. Following the study of Sun et al. (2022) [28], we chose an iteration criterion of 0.2 and a maximum partition density of two and obtained four cluster types (Table 2). Assuming that cluster B_k includes b_k nodes, the maximum number of possible relationships of all members in the network will be $b_k(k-1)$, and the maximum number of possible internal relationships is $b_k(b_k-1)$. Thus, the ratio of expected internal relationships of cluster B_k in the rational situation is $(b_k-1)/(k-1)$, which is used as an indicator to determine the type of cluster. By using the relationships of nodes to identify the clusters within the network, nodes having similar relationships with other nodes can be classified into the same group. Given that the position of a node in the network is determined not only by the node itself but also by other nodes connecting to it, it is more suitable to use social network cluster analysis to identify the roles of the clusters within the network than to use normal cluster analysis which is generally based on indicator values to classify different clusters.

Table 2. The Division of Cluster Types.

Ratio of Internal Relationships	Ratio of Accepted Relationships	
	≈0	**>0**
$\geq (b_k-1)/(k-1)$	Bidirectional spillover cluster	Net beneficiary cluster
$< (b_k-1)/(k-1)$	Net spillover cluster	Brokers cluster

3. Results

3.1. Land-Use Carbon Emission Measurement Results

Based on the panel data collected from CLCD and other related statistical materials, the prefecture-level land-use carbon emissions of Sichuan Province were calculated. According to the results shown in Figure 3 and Table 3, the net land-use carbon emissions of various prefecture-level divisions in Sichuan Province showed an overall trend of increasing first and decreasing from 2006 to 2021 afterwards, except that Luzhou, Mianyang, Guang'an, and Dazhou showed different trends. Chengdu, as the headquarter of the province, has maintained the pressure of ranking first in net land-use carbon emissions over the years, although the emissions varied and decreased in the long run. The net land-use carbon emissions of Ganzi and A'ba remained negative, indicating that the carbon compensation rates of these two divisions are relatively high, which could thus play essential roles in carbon sink functions in Sichuan Province. Other divisions showing an initial increase followed by decreasing land-use carbon emissions are mainly affected by provincial carbon emission policies, especially those launched after Sichuan was selected as the national carbon emission trading pilot in 2016. The central government's first round of environmental protection supervision in Sichuan Province started in 2016. The superposition of the above factors jointly contributed to the reduction of land-use carbon emissions in most prefecture-level divisions within and after 2016. In addition, land-use carbon reduction activities are related to LUC, which is a slow process and needs to be coordinated with economic and social development [48,49]. This may be the reason why land-use carbon emissions in Luzhou, Mianyang, Guang'an, and Dazhou showed different characteristics compared with other cities.

According to a quantitative research report on the degree of regional cooperation in the "Chengdu-Chongqing Dual-City Economic Circle", Luzhou, Mianyang, Guang'an, and Dazhou were relatively active in regional collaborative development activities [50]. Thus, there might be lags in coordinating economic and social development and land-use carbon emission reduction actions in these four divisions. In summary, on the one hand, the results shown in Figure 3 and Table 3 shed light on the effectiveness of the carbon emission reduction policies launched in 2016 and after 2016 within Sichuan Province. On the other hand, the results reflect the heterogeneity in the trade-offs between carbon emission reduction activities and local economic and social development.

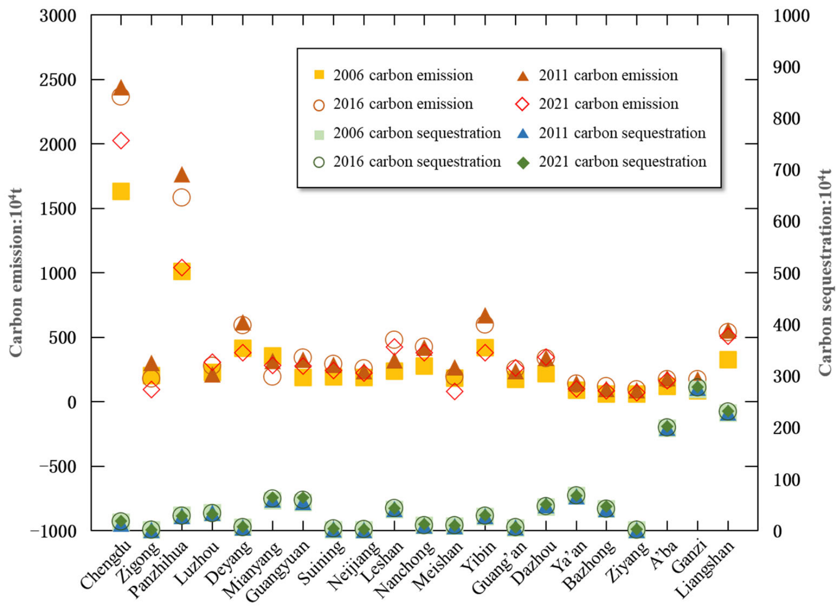

Figure 3. Carbon Emission and Carbon Sequestration of Different Prefectural-level Divisions within Sichuan.

Table 3. Land-use Carbon Emissions of Different Prefecture-level Divisions within Sichuan.

Prefecture-Level Divisions	Net Carbon Emissions from LUC (10^4 t)			
	2006	2011	2016	2021
Chengdu	1616.342	2423.794	2349.454	2007.995
Zigong	200.060	299.599	176.580	94.701
Panzhihua	983.071	1734.065	1554.043	1013.417
Luzhou	192.149	177.543	245.389	274.453
Deyang	408.255	612.795	586.253	374.641
Mianyang	299.691	256.433	133.906	218.615
Guangyuan	134.121	268.563	281.175	212.513
Suining	192.084	285.521	289.036	236.673
Neijiang	186.097	235.673	254.253	221.905
Leshan	198.759	281.096	434.076	380.609
Nanchong	265.829	409.410	416.904	366.848
Meishan	173.676	257.715	184.637	68.921
Yibin	392.790	644.051	569.767	350.725
Guang'an	170.038	232.763	248.672	255.512
Dazhou	171.693	291.092	290.736	297.374
Ya'an	23.236	75.615	72.691	33.513
Bazhong	18.318	55.492	79.262	39.867
Ziyang	60.034	86.826	95.591	67.770
A'ba	−79.964	−17.817	−24.923	−37.450
Ganzi	−189.255	−102.977	−105.254	−183.496
Liangshan	98.047	324.702	309.262	275.431

3.2. Land-Use Carbon Emission Spatial Network Analysis

3.2.1. Overall Spatial Network Characteristics of Land-Use Carbon Emissions

The results shown in Table 4 and Figure 4 reflect that the spatial correlation network of land-use carbon emissions was improved and that the network stability was enhanced in Sichuan from 2006 to 2021. Specifically, the network density (*ND*) of land-use carbon emissions showed an asymmetrical "N-shaped" trend of a fluctuating increase, reflecting that the interactions among nodes in the spatial network were strengthened over time. Interestingly, we found that the overall density value of the spatial network in Sichuan in 2016 was the lowest in the whole study interval. This is perhaps because each division focused on the work of environmental protection inspection in 2016, and the increase in the mean gravity blurred the identification of the spatial correlation relationship among divisions. The network correlation (*NC*) of land-use carbon emissions showed an asymmetrical "V-shaped" trend, with the inflection point appearing in 2011. The overall increase in *NC* from 2006 to 2021 reflected the enhanced stability of the entire spatial network in Sichuan, which was further verified by the results of the network hierarchy and efficiency. The network hierarchy (*NH*) of land-use carbon emissions in Sichuan, measuring the asymmetry of the spatial correlation network, showed an opposite trend to *NC*. The decline in the *NH* value of land-use carbon emissions indicates that the dependence of the spatial correlation network on a single node or a few nodes is reduced. This result is consistent with the prefecture-level development situation within Sichuan Province in recent years. With the implementation of a series of sub-regional development strategies, Sichuan Province has promoted the coordinated development of various divisions while enhancing the links and promoting the flow of factors among regions. Thus, the development process depends more on the entire network than just on a central division. Figure 4 also shows that, in the process of development, the regional network has gradually transformed from a single center to multiple centers. In addition, the decrease in network efficiency (*NE*) from 0.905 in 2006 to 0.747 in 2021 reflects the increase in the interconnection within the land-use carbon emission network, further verifying the improvement of network stability.

Table 4. Overall Network Structure Characteristics of Land-use Carbon Emissions within Sichuan.

Indicators	Overall Network Structure Characteristics			
	2006	**2011**	**2016**	**2021**
ND	0.145	0.162	0.141	0.231
NC	0.356	0.333	0.372	0.427
NH	0.521	0.611	0.521	0.333
NE	0.905	0.837	0.879	0.747

3.2.2. Spatial Network Characteristics of Nodes of Land-Use Carbon Emissions

Although the overall spatial network structure of land-use carbon emissions within Sichuan Province shows increased correlation and enhanced stability, the changes of individual nodes (divisions) in the network are heterogeneous. According to the results shown in Table 5, the status of some nodes in the network (such as Deyang, Mianyang, Meishan, and Ziyang) improved, while the status of other nodes declined or remained unchanged (such as Panzhihua, Dazhou, and Chengdu). The heterogeneity of the status changes of different nodes reflects that the relative centrality of each node in the network varies over time even though the value of the degree centrality (*DC*) might remain unchanged. A possible reason for this is that in the process of development, some divisions have relatively more enhanced flow of production factors with central nodes, especially those related to carbon emissions such as population, investment, and technology, while others do not have such an enhanced flow level [51]. In addition, changes in the ability of each node to be unaffected by other nodes and to influence other nodes also varied across time but were consistent with the trend of decreasing dependence on a single center in the overall network. Specifically, Chengdu maintained the central position concerning both the independence and influence on other nodes in the network, which could be verified by the highest value of its betweenness centrality (*BC*) and closeness centrality (*CC*). Deyang, Mianyang, and Ziyang also have higher *BC* and *CC* values above the average, of which Deyang and Mianyang have gradually developed into network centers. These two divisions have better economic location conditions and governance abilities, hence showing more connections with other cities while remaining relatively independent. The *BC* and *CC* values of Panzhihua, Guangyuan, Dazhou, and A'ba remained extremely low in 2006 and 2021. These divisions are geographically located in the fringe area of the province with an economically lagging development level. Thus, it is difficult for these divisions to control or dominate the land-use carbon emissions of other divisions in the network although they might be active in regional collaborative development activities. Compared with the results of land-use carbon emissions and the characteristics of the overall spatial network, it could be inferred that through the flow of production factors such as population, technology, and capital within Sichuan Province, the positions of different nodes have changed, reshaping a multi-centric network structure of land-use carbon emissions.

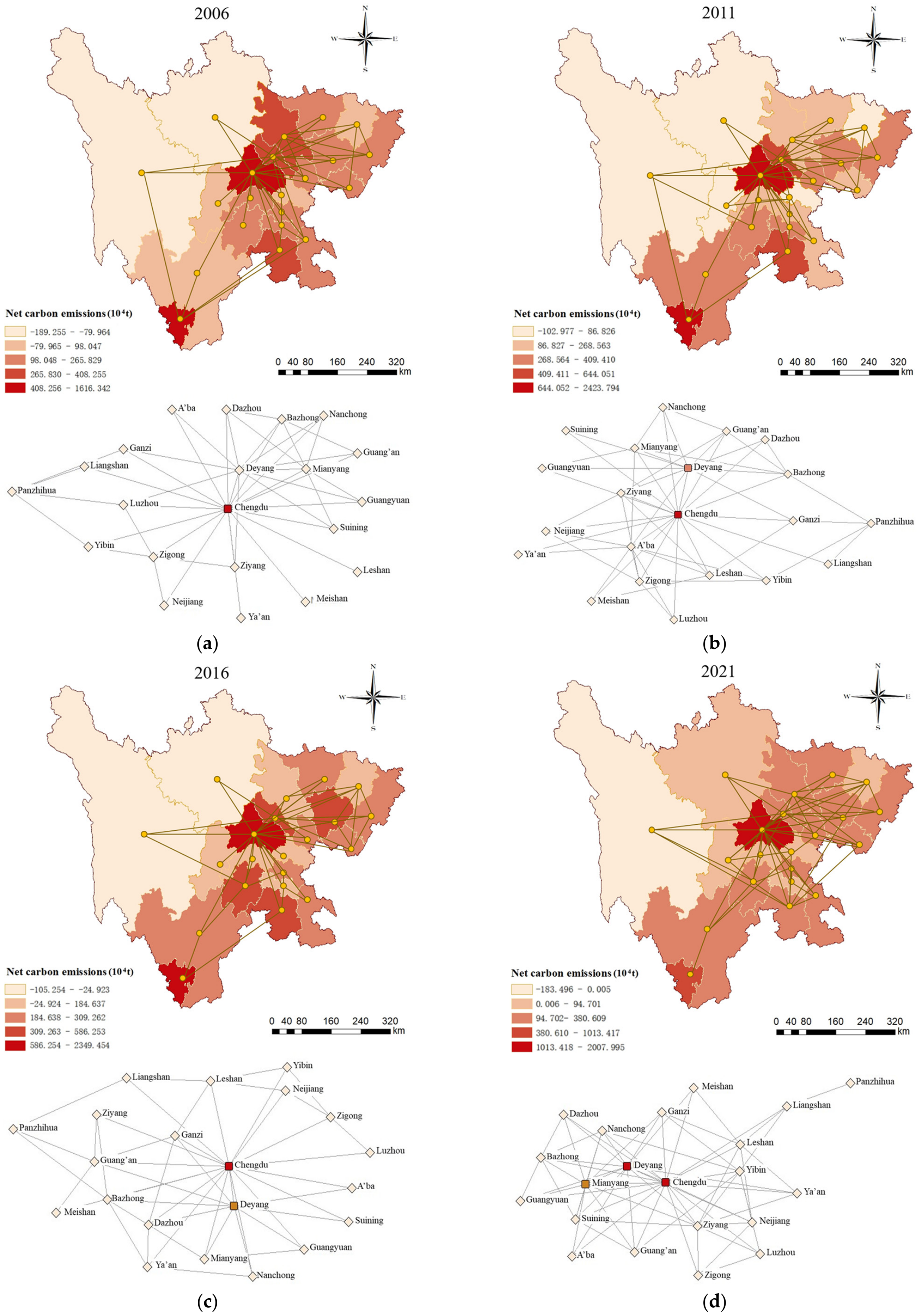

Figure 4. Spatial Network Structures and Network Relationships of Land-use Carbon Emissions in Sichuan, 2006, 2011, 2016, and 2021. Note: The spatial network structures are located at the upper of the subfigures, and the network relationships are located at the lower of the subfigures.

Table 5. Spatial Network Centrality of Different Prefecture-level Divisions within Sichuan.

Prefecture-Level Divisions	*DC*		*BC*		*CC*	
	2006	**2021**	**2006**	**2021**	**2006**	**2021**
Chengdu	95.000	95.000	66.842	40.544	95.238	95.238
Zigong	25.000	20.000	1.711	0.132	57.143	54.054
Panzhihua	20.000	5.000	1.404	0.000	40.816	36.364
Luzhou	20.000	20.000	3.004	0.132	55.556	54.054
Deyang	60.000	70.000	13.026	11.342	71.429	74.074
Mianyang	35.000	55.000	1.579	4.412	58.824	66.667
Guangyuan	15.000	20.000	0.000	0.000	52.632	54.054
Suining	15.000	35.000	0.000	0.579	52.632	58.824
Neijiang	10.000	30.000	0.000	0.763	51.282	57.143
Leshan	5.000	35.000	0.000	3.351	50.000	60.606
Nanchong	15.000	30.000	0.000	0.588	52.632	57.143
Meishan	5.000	15.000	0.000	0.088	50.000	52.632
Yibin	15.000	40.000	1.798	4.719	54.054	62.500
Guang'an	15.000	25.000	0.000	0.325	52.632	55.556
Dazhou	20.000	20.000	0.000	0.000	54.054	54.054
Ya'an	5.000	20.000	0.000	0.088	50.000	54.054
Bazhong	25.000	35.000	0.351	0.658	55.556	58.824
Ziyang	15.000	50.000	0.175	4.772	52.632	64.516
A'ba	10.000	15.000	0.000	0.000	51.282	52.632
Ganzi	15.000	25.000	2.412	0.561	54.054	55.556
Liangshan	10.000	20.000	1.382	10.105	52.632	55.556

3.2.3. Spatial Network Characteristics of Clusters of Land-use Carbon Emissions

The iterative convergence method of the Concor module in Ucinet software was adopted to identify the cluster types in Sichuan. The results are shown in Table 6. According to the results, the spatial effect of land-use carbon emissions in Sichuan has mainly undergone a transition from intra-regional to inter-regional spillover. The divisions included in each cluster in different years varied slightly, although the cluster types changed considerably, which reflects that the members within the cluster have experienced a certain extent of coordinated and consistent development. Specifically, the central divisions, i.e., Chengdu, Mianyang, and Deyang, remained consistently in the first cluster of the spatial network [52]. Their cluster type transitioned from a "Bidirectional Spillover Cluster" in 2006 to a "Net Benefit Cluster" in 2011 and 2016 and then reverted to a "Bidirectional Spillover Cluster" in 2021. With their economic and transportation advantages, the central divisions could attract various factors and serve as the primary recipient of production factors. Meanwhile, the central divisions also play a role in the outward transmission of the flow of factors such as capital and technology, which is the main reason for the transition of the central divisions from "Net Benefit Cluster" to a "Bidirectional Spillover Cluster". In addition, it is interesting to find that Suining, Bazhong and Nanchong, another three divisions were included in the first cluster in 2021. Their cluster type transitioned from "Broker Cluster" in 2006, 2011, and 2016 to "Bidirectional Spillover Cluster" in 2021, indicating that their focus on developing external relationships paid off and their abilities to attract production factors were enhanced.

The second cluster in the network, which included Guang'an, Ganzi, A'ba, Dazhou, etc., was identified as the "Broker Cluster" in 2006, 2011, and 2016 and transformed to the "Net Spillover Cluster" in 2021. Among them, Guang'an and Dazhou showed different land-use carbon emission trends from 2006 to 2021. Combining the results of their carbon emission trends with the transformation of their cluster types, it can be observed that although these two divisions struggled to be integrated into the "Chengdu-Chongqing Dual-City Economic Circle" strategy, they still faced challenges regarding the outflow of resources [53]. Meishan and Ziyang, two divisions affected both by the strategies of "Chengdu-Deyang-Meishan-Ziyang" intra-city integration and the "Chengdu-Chongqing

Dual-City Economic Circle", have experienced a development trend from the coordination in the early stage to the difference in the later stage within the network. The cluster type of Ziyang transformed from "Broker Cluster" in 2006 to "Bidirectional Spillover Cluster" in 2011 and 2016 and then reverted to "Broker Cluster", while that of Meishan changed to "Net Spillover Cluster". This could be mainly attributed to the difference in geographic and economic location conditions. Upon further examination of the members included in the third and fourth clusters, it was observed that the compositions changed considerably over time, indicating a lower stability in cluster structure. This is primarily because the economic development levels of these divisions were at or below the intermediate range in the province, leading to spillover effects of land-use carbon emissions in their development process. In addition, it is worth noting that in 2021, Ganzi and A'ba were also included in the "Net Spillover Cluster". This was likely due to a series of poverty alleviation policies that had promoted land development activities in these two regions in recent years and resulted in carbon spillover effects.

Comparing the four clusters within the network, we find that the first and second clusters exhibited greater stability over time, especially the central divisions. Among them, the centrality of Mianyang and Deyang increased, while the centrality of Chengdu maintained the same level. Other divisions demonstrated a relatively more diverse range of changes in the cluster characteristics of land-use carbon emissions. We further calculated the network density of each cluster and graphed the density network to explore the relationships in between [54], as shown in Figure 5. The overall structure of the clusters showed a "network-type" characteristic. The first cluster held a central position and was linked to the second, third, and fourth clusters from 2006 to 2021. However, the relationship between the first and second clusters was comparatively unstable, although their internal sectors were relatively stable. In addition, the relationships between the first and second clusters were unidirectional in 2011 and 2021. This was partially because of the carbon sink spillover effect from the second cluster to the first cluster. The second cluster also held a unidirectional relationship with the fourth cluster while maintaining a bidirectional connection with the third cluster. The third cluster held a stable bidirectional connection with the fourth cluster, which indicated a mutually beneficial relationship. By combining the above results, it could be inferred that while the overall correlation of the land-use carbon emission network of Sichuan Province had been strengthened, the internal correlations of different clusters showed a tendency to be weakened due to the intensifying development differentiation among divisions.

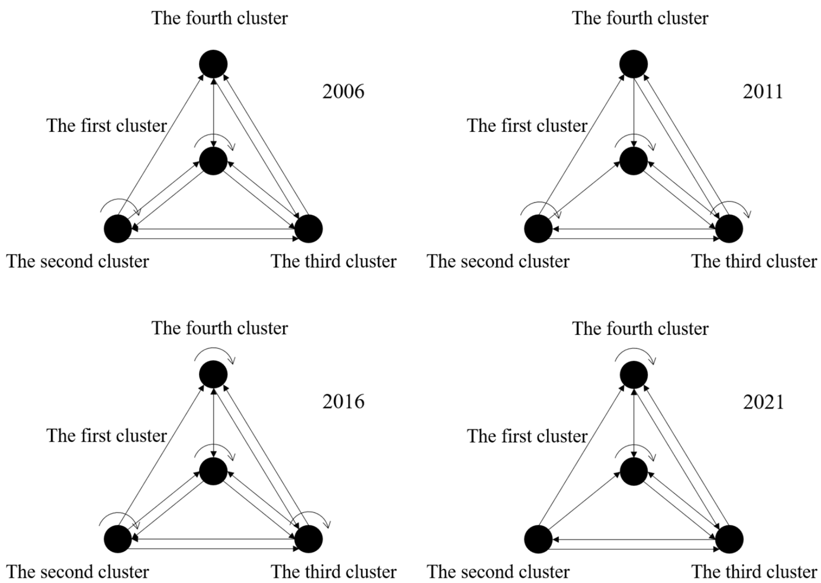

Figure 5. Relationships of Clusters of Land-use Carbon Emission Network in Sichuan, 2006, 2011, 2016, and 2021.

Table 6. Clusters of the Land-use Carbon Emission Network in Sichuan, 2006, 2011, 2016, and 2021.

Year	Cluster No.	Cluster Type	Division	Number of Relations Received		Number of Relations Issued		Ratio of Expected Internal Relations (%)	Ratio of Actual Internal Relations (%)
				Inside	Outside	Inside	Outside		
2006	The First Cluster	Bidirectional Spillover Cluster	Chengdu; Mianyang; Deyang	6	32	6	6	10	50
	The Second Cluster	Broker Cluster	Guang'an; Ganzi; Meishan; Ziyang; Suining; Guangyuan; A'ba; Nanchong; Leshan; Bazhong; Dazhou	3	6	3	26	50	10
	The Third Cluster	Net Spillover Cluster	Panzhihua; Zigong	0	7	0	8	5	0
	The Fourth Cluster	Net Spillover Cluster	Luzhou; Ya'an; Yibin; Neijiang; Liangshan	0	7	0	12	20	0
2011	The First Cluster	Net Beneficial Cluster	Chengdu; Mianyang; Deyang	6	29	6	6	10	50
	The Second Cluster	Broker Cluster	Guang'an; Ganzi; Suining; Guangyuan; A'ba; Nanchong; Bazhong; Liangshan; Dazhou	5	3	5	23	40	18
	The Third Cluster	Bidirectional Spillover Cluster	Yibin; Meishan; Ya'an; Neijiang; Luzhou; Ziyang; Zigong	14	7	14	9	30	61
	The Fourth Cluster	Net Spillover Cluster	Panzhihua; Leshan	0	4	0	5	5	0
2016	The First Cluster	Net Beneficial Cluster	Chengdu; Mianyang; Deyang	6	27	6	6	10	50
	The Second Cluster	Broker Cluster	Guang'an; Ganzi; Suining; Guangyuan; A'ba; Nanchong; Bazhong; Dazhou	8	2	8	19	35	30
	The Third Cluster	Bidirectional Spillover Cluster	Yibin; Liangshan; Ya'an; Neijiang; Luzhou; Zigong	5	4	5	8	25	38
	The Fourth Cluster	Bidirectional Spillover Cluster	Panzhihua; Ziyang; Meishan; Leshan	1	6	1	6	15	17
2021	The First Block	Bidirectional Spillover Cluster	Chengdu; Mianyang; Deyang; Nanchong; Bazhong; Suining	27	32	27	9	25	75
	The Second Cluster	Net Spillover Cluster	Guang'an; Ganzi; Meishan; Guangyuan; A'ba; Dazhou	0	5	0	24	25	0
	The Third Cluster	Net Spillover Cluster	Panzhihua; Leshan; Yibin; Zigong	0	15	0	15	15	0
	The Fourth Cluster	Broker Cluster	Luzhou; Ya'an; Neijiang; Ziyang; Liangshan	3	15	3	19	20	14

4. Discussion and Policy Implications

Against the background of rapid development and urbanization, activities aimed at reducing land-use carbon emissions in Sichuan and other sub-regional areas will continue to face significant challenges, especially in regard to simultaneously supporting different levels of development strategies while meeting the development needs for different divisions. Therefore, more effective policies should be formulated to better address these challenges. Before delving any further into the discussion, it is necessary to review the related policies recently issued by Sichuan Province to identify the focus of policy optimization. In general, Sichuan Province has issued a series of land-use carbon emission reduction plans, including promoting multi-level collaborative innovation for carbon emission reduction within prefecture-level divisions. For example, according to the "Sichuan Province Collaborative Efficiency Enhancement Action Plan for Pollution Reduction and Carbon Emission Reduction" issued by seven departments, including the Provincial Energy Bureau, in July 2023, each prefecture-level division is required to formulate local collaborative efficiency enhancement action plans for pollution reduction and carbon emission reduction. In addition, the implementation of carbon emission reduction tasks will be included in the provincial-level ecological and environmental protection inspection and local party-government joint accountability assessment. Carbon emission management policies were also adopted in other areas in China and across the world [55–58]. Hedemann-Robinson (2017) argued that there were various levels of challenges the European Union needed to address in the legislative engagement of different member states in relation to environmental inspections, which reflected the difficulty in environmental cooperative governance [57]. Considering the close connection between land use activities and carbon emission reduction, more effective policies should focus on optimizing the management of land-use carbon emissions from the perspective of cooperation and at the sub-regional level.

The optimization of land-use carbon emission management of prefectural-level divisions in Sichuan primarily involves adopting decentralized actions at present. However, a spatial and systemic cooperation network has not been formed within the province. Furthermore, this is not only the case in Sichuan but also the reality faced by other areas. Consequently, formulating an effective carbon emission reduction plan and taking it into consideration in the foundational work of spatial planning in provincial or state land use management is crucial [59,60]. The key problem of formulating an effective carbon emission reduction plan then emerges. Given that land-use carbon emissions are spatially connected within a province or a state and that different divisions have different positions and play various roles within the network, another problem is how to integrate the spatial network with local economic development realities and formulate division-specific plans. Under these constraints, carbon balance zoning could provide a way to solve the above problems [61–63].

Based on low-carbon objectives, using indicators such as carbon emissions and ecological carrying capacity, and focusing on the spatial relationship and the cluster types and roles, carbon balance zoning could be formulated to develop a spatial and systemic network for land-use carbon emission management optimization of different regions [45,62]. Taking Sichuan Province as a case, we tried to combine the attribute data of ecological carrying capacity and the economic contribution coefficient of carbon emissions and relational data of spatial network analysis with the newest data to conduct carbon balance zoning. A total of four main carbon balancing zones were classified: carbon sink zone, low-carbon zone, economic zone, and high carbon zone based on the attribute data of ecological carrying capacity and the economic contribution coefficient of carbon emissions. Overlaying the main classification types with the spatial network cluster analysis based on relational data, seven carbon balancing zones were finally classified: carbon sink functional zone, low-carbon development zone, decentralized linkage zone, total carbon emission control zone, general linkage zone, core linkage zone, and high carbon optimization zone. The overlay zoning results are shown in Figure 6. The analysis of different zones is conducted based on the zoning results of Sichuan Province, which could also provide insights for other sub-regional areas to conduct carbon balance zoning and optimize carbon emission management policies.

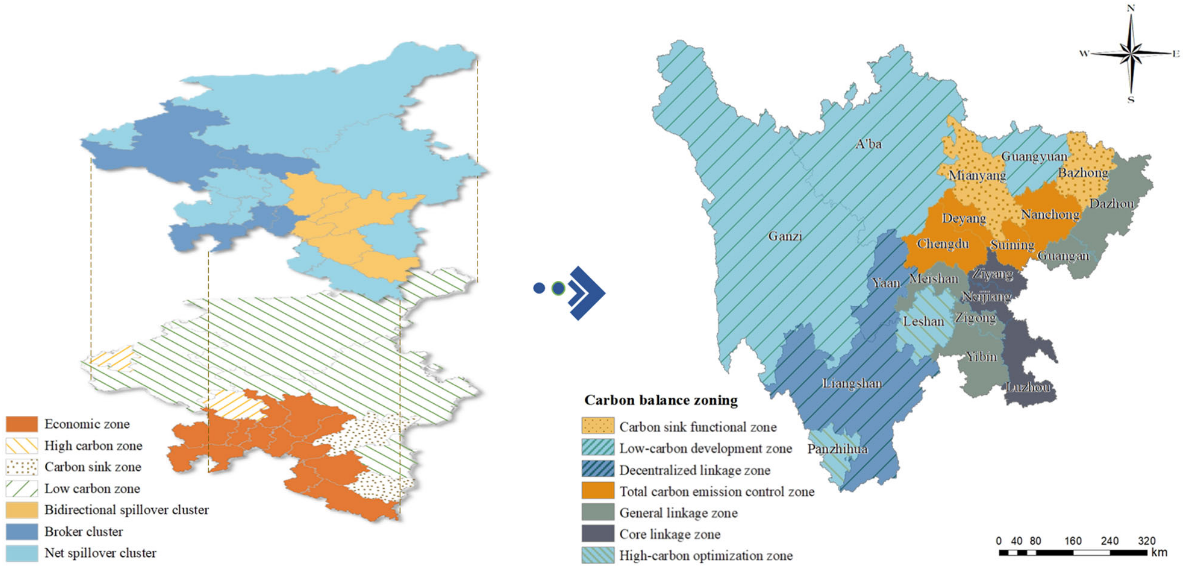

Figure 6. Carbon balance zoning of Sichuan Province.

(a) Carbon sink functional zone: In Sichuan's case, examples include Mianyang and Bazhong. There are natural scenic spots such as Sichuan Xuebaoding Nature Reserve and Sanjianghu National Wetland Park. This zone could represent areas with relatively high economic contribution coefficients of land-use carbon emissions. This zone should make full use of existing carbon sink resources and protect such resources, maintain a stable economic growth rate, vigorously develop local tourism, and encourage local industries to thrive.

(b) Low-carbon development zone: In Sichuan's case, examples include A'ba, Ganzi, and Guangyuan. This zone represents areas with strong carbon sequestration capacity and rich carbon sink resources but low levels of economic and social development. Therefore, this region should focus on developing low-carbon green industries according to local conditions, and transforming ecological advantages into economic advantages.

(c) Decentralized linkage zone: In Sichuan's case, examples include Liangshan and Ya'an. This zone has a high land-use carbon compensation rate and relatively low economic benefits per unit of carbon emissions. This type of zone should focus on the transformation of its economic development paths, through which the zone can drive the adjustment of the energy consumption structure, accelerate technological innovation, and enhance its economic strength. The zone should also play the role of an intermediate "bridge" in the network and establish more ecological connections with surrounding areas to share the land-use carbon source pressure.

(d) Total carbon emission control zone: In Sichuan's case, examples include Chengdu, Deyang, Suining, and Nanchong. This zone usually has sub-regional centers and lies at the center of the entire carbon emission network. Therefore, the economic development advantage is prominent, and the carbon sink capacity is weak. Since the total carbon emissions are generally high, this type of zone should focus on protecting the ecological environment and realizing coordinated development, accelerating technological modernization, and achieving energy conservation and emission reduction. Furthermore, it should also make full use of the core position to radiate surrounding areas and drive their economic development and technological progress.

(e) General linkage zone: In Sichuan's case, examples include Meishan, Zigong, Yibin, Dazhou, and Guang'an. This zone is spatially connected to other areas with a land-use carbon emission spillover effect. It represents areas with relatively abundant resources and industrial transfer, which results in carbon emissions overflow. Therefore, this zone should make full use of its energy advantages, improve energy utilization, and pay attention to ecological protection while controlling energy consumption and focusing on energy-saving development.

(f) Core linkage zone: In Sichuan's case, examples include Luzhou, Neijiang, and Ziyang. The regional average GDP is relatively high, and the ecological pressure is moderate. This zone plays a "broker" role in the spatial network. Therefore, its linkage with the surrounding areas is strong. This area should continue to control carbon sources and reduce the impact on the surrounding areas. Moreover, it should engage in stabilizing and optimizing the source of land-use carbon sinks, alleviating the carbon pressure of the whole province, and better exerting the linkage effect.

(g) High carbon optimization zone: In Sichuan's case, examples include Panzhihua and Leshan. This zone represents areas with a high total amount of carbon emissions and low ecological carrying capacity. This type of zone should establish the development strategy of ecological priority and green development, strictly control the energy consumption and pollution discharge of enterprises, accelerate technological reform, and build a green and low-carbon industrial system, thus achieving low-carbon sustainable development.

Local governments play an essential role in achieving land-use carbon emission reduction goals. Decomposing the task of reducing land-use carbon emissions to the local level can facilitate the development of more specific, flexible, and adaptable carbon reduction plans. Furthermore, local governments can encourage and support local innovation, achieving collaborative governance of carbon emission reduction across different regions by directly managing and controlling land resource utilization [64]. Therefore, it is of practical significance to optimize the management of land-use carbon emissions at the local level [65,66]. Effective policies should also focus on approaches to enhance local governments' capacity to manage land-use carbon emission reduction activities. However, there are challenges for local governments in terms of promoting sub-regional cooperative land-use carbon emission reduction activities, including how to take the position and function of different divisions in the spatial network into consideration and how to promote cooperation across divisions. Taking Sichuan Province as a representative case to unpack the sub-regional spatial network of land-use carbon emissions, we attempt to apply the research findings to the local land-use planning system by conducting carbon balance zoning analysis. The results of our study are expected to provide references for the optimization of local carbon emission management policies in the following two aspects.

First, the position and function of different divisions in the spatial network should be considered when formulating local land-use carbon emission reduction policies. There is a close connection between land use activities and carbon emissions, and the differences in economic and social development levels determine the different situations in which land resources are used [10,67,68]. Thus, the divisions with different economic and social development levels have various positions and functions in the land-use carbon emission network. Taking the positions and functions of the divisions in the spatial network into account when formulating carbon emission policies can make them more reasonable and targeted. Second, coordinated governance across divisions and differentiated zoning for carbon balance management should be included in the optimization of land-use carbon emission reduction policies. Land-use carbon emissions are spatially connected and have spillover effects. Thus, coordinated governance is necessary for an enhanced and sustainable spatial network of land-use carbon emissions, especially regarding the protection of nature reserves, the development of jointly built industrial parks, and other cross-regional land use issues.

5. Conclusions

Faced with global warming challenges, green, low-carbon, and sustainable development has become the goal of various countries and cities worldwide and is also the current focus of China's government. Among them, land use, as an important factor behind the rapid increase in carbon emissions and thus resulting in global warming, has long drawn the attention of the government in terms of identifying suitable approaches to sustainably use land. It is crucial to deeply tap the enormous potential of carbon emission reduction in land use and optimize related measures to use land. Different levels of spatial networks have been developed in efforts to reduce carbon emissions and promote sustainable land use. In addition, extensive studies have explored the estimation of the sources and sinks of carbon emissions from LUC based on attribute data and unpacked the spatial network of land-use carbon emissions based on relational data. However, few studies have shed light on combining the measurement of land-use carbon emissions and the analysis of spatial networks with local economic and ecological realities to formulate local land use management plans. Thus, the differences in roles and functions of different areas within the spatial network of land-use carbon emissions could not be adequately taken into consideration. Furthermore, not enough attention has been paid to the spatial network of land-use carbon emissions within a province, which is a typical sub-regional area and plays a fundamental role in achieving carbon emission reduction goals.

Taking Sichuan Province as a case study, this study aims to unpack the spatial network of land-use carbon emissions of different prefecture-level divisions within the province. Panel data from 2006 to 2021 and an applicable method of Social Network Analysis were employed. The characteristics of the spatial network of Sichuan Province were analyzed, and a carbon balance zoning policy was formulated. We found that the net land-use carbon emissions of various prefecture-level divisions in Sichuan Province generally showed a trend of initially increasing and then decreasing from 2006 to 2021. In addition, the spatial correlation network of land-use carbon emissions was improved and the network stability was enhanced. However, through the flow of carbon-emission-related production factors such as population, technology, and capital within Sichuan Province, the positions of different nodes gradually changed, developing into a multi-centric network structure. In addition, the spatial effect has undergone a transition from intra-regional to inter-regional spillover, with weakening internal correlations of different clusters in the network. Based on these findings, we proposed a planning tool for carbon balance zoning to better consider the roles and functions of different divisions in the spatial network when formulating local land-use carbon emission reduction policies. The findings of our study are expected to provide references for the optimization of land-use carbon emission management policies in sub-regional areas with rapid social and economic development. These areas, as essential sources of carbon emissions with high growth potential, may contribute a crucial role in global decarburization efforts. With available datasets, future studies can focus on smaller-scale spatial networks to further extend sub-regional land-use carbon emission research within these areas.

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