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The Impact of Urbanization Growth Patterns on Carbon Dioxide Emissions: Evidence from Guizhou, West of China

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Abstract: Little attention has been paid to the impact of future urban expansion patterns on carbon emissions based on the existing urban pattern of a region. This study used the Central Guizhou Urban Agglomeration as the study area, and the relationships between regional urbanization and CO_2 emissions in the study area were analyzed based on historical data. Urban growth patterns were then simulated in four scenarios that focused on the next 15 years, and they were based on the cellular automaton model. In each different scenario, the CO_2 emissions were predicted, and some implications regarding the impact of those emissions were provided. The results showed that as urban land-use intensity increases, CO_2 emissions first increase then decrease; however, the rate of decline for CO_2 emissions is much slower than the rate at which it rises. Moreover, in the next 15 years, urban expansion will lead to a significant increase in CO_2 emissions. The CO_2 emissions were found to be lowest in the spatial agglomeration scenario and highest in the spatial dispersion scenario. The spatial agglomeration scenario was conducive to understanding how CO_2 emissions eventually peak; however, different cities in the study area should adopt different urban expansion patterns. These research results can provide a reference guide for the government with regard to urban planning.

Keywords: urban growth; CO_2 emission; Guizhou province; urban planning

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1. Introduction

Urban areas account for three percent of the Earth's land area; however, currently, half of the world's population lives in these areas. They are the main areas of economic activity and the main sources of greenhouse gas emissions, accounting for about 85% of total carbon dioxide (CO_2) emissions [1]. With the acceleration of urbanization in recent decades, big cities continue to grow, and small towns develop rapidly. The agglomeration, expansion, and dispersion expansion of urban spaces have accelerated at different levels [2]. Urban growth has increased energy consumption in industry, the transportation sector, and places of residence, resulting in a rapid upsurge of CO_2 emissions [3,4]. Urban growth is an inevitable part of human development, and thus, how to control the resultant CO_2 emissions has become a key problem that needs to be addressed.

Research on urbanization and CO_2 emissions mainly focuses on three themes. The first concerns the empirical relationships found between urbanization levels and CO_2 emissions; results have shown positive, negative, and inverted U-shaped relationships [5–7]. Using the time series data of different countries, many scholars have demonstrated that urbanization increases carbon emissions [8,9]. Several scholars have found that compact cities reduce the energy consumption of residents. The compact planning of urban transit systems was believed to be causing CO_2 emissions to decrease per capita, and a negative correlation was found between per capita CO_2 emissions and population density in the transportation sector [7]. In addition, an inverted U-shaped relationship between urbanization and carbon emissions has been demonstrated, which means that with the expansion of urban spaces, carbon emissions first increase and then decrease [10,11].

The second topic focuses on evaluating the impact of historical urban expansion patterns on CO_2 emissions [11,12]. For example, Carpio [12] analyzed urban expansion from 1990 to 2019 using satellite images of the Monterrey Metropolitan Area, Mexico, to determine the relationship between the area's expansion and carbon emissions. Li [13] explored the impact that urban expansion had on ecosystem services between 1990 and 2019, taking into account the different rates of urban expansion and city sizes. Numerous studies have demonstrated that the impact of urban growth on CO_2 emissions manifests in three ways [14]. The first is "production", which refers to the process of urbanization as the process of industrialization; the use of fossil fuel energy in industrial production processes is the main source of CO_2 emissions [15,16]. The second is "land", which refers to the process of urbanization as the process of transforming agricultural land into construction land; this leads to the reduction of carbon storage areas, thus affecting the overall impact of carbon emissions [14,17]. The third is "people", which refers to the process of urbanization as the process of population agglomeration. An increase in the urban population leads to an increase in building construction, transportation use, and the energy consumption of urban residents [7,18]. The effects of urban morphology and urban planning on the spatial patterns of CO_2 emissions in cities have also been examined [1,19].

The third topic concerns the consequences of carbon emissions, as revealed by urban expansion simulations of the future, and how they may support urban development decisions [20–22]. Some studies have focused on simulating future urban land-use change and predicting carbon storage losses caused by the expansion of urban fabric into forests, farmlands, and other carbon storage areas [23,24]. These studies mainly focus on the impact of land-use changes caused by urban expansion and the resultant CO_2 emissions. In addition, some other studies explored simulated urban expansion scenarios with eco-environmental constraints, that were based on cellular automaton data. For example, Zhang [25] developed a framework, which was based on a modified CA model, in order to simulate a scenario wherein an urban area expands and develops in a 'low-carbon' manner. Chen [20] assessed the impact that urban expansion will have on carbon storage areas in the future, using the belt and road initiative scenario, cropland protection scenario, and ecological protection scenario.

Although the impact of urbanization on carbon emissions has been widely studied, further research is still needed. Urban expansion has different spatial patterns, such as spatial agglomerations or spatial dispersions, which have been confirmed by many studies [2,26]. The spatial patterns of urban expansion in a region can potentially have a significant impact on the layout of industrial, housing, and transportation infrastructures, and could thus result in different levels of energy consumption and energy efficiency [19]. Some existing studies have noted the impact of historical urban expansion patterns on CO_2 emissions [11,12,27]; however, the conclusions drawn from studying historical processes may not be applicable to the development of future solutions. The impact of future urban expansion patterns (based on the impact of existing urban expansion patterns) on CO_2 emissions needs to be further studied. At present, studies which simulate future urban expansion scenarios mainly consider the impact that land-use changes or policy interventions have on CO_2 emissions. Little attention has been paid to the impact of future urban expansion patterns on carbon emissions based on the existing urban patterns of a region. In addition, most studies focus on carbon emissions in economically developed regions [4,6,25]; however, underdeveloped regions, especially urbanized agglomerations within those underdeveloped regions, rapidly develop at a faster rate than areas within economically developed regions, and they also have the fastest-growing carbon emission rate in China. Furthermore, with this in mind, analysis focusing on urbanized agglomerations in the West of China is the most logical course of action.

Moreover, this study aims to explore the impact of future urban growth patterns on CO_2 emissions, and to provide guidance for urban planning. First, using an urban agglomeration in the center of the Guizhou Province as a case study, CO_2 emissions were mapped onto a high resolution spatial grid; then, the impact of urbanization on CO_2 emissions in the urban area was analyzed. From this analysis, a relationship between urbanization and CO_2 emissions in the urban area was derived. Four scenarios of different urban growth patterns were simulated using the CA model as a basis, and for each scenario, the CO_2 emissions were predicted for the next 15 years. This study can provide important guidance in the field of urban planning with regard to choosing urban growth patterns.

2. Framework

Generally speaking, urbanization is regarded as a phenomenon that is related to the population concentration in a specific region, and the high-density and intensive land use of human settlements [3,4]. Urbanization is considered to be one of the main causes of increased CO_2 emissions [3,28]. Most studies show that all modes of urban growth cause CO_2 emissions to increase in the initial growth stage; however, with further growth, CO_2 emissions gradually decrease [6,19]. At the same time, urban growth may reduce CO_2 emissions per unit land area due to intensive land use [29]. Exploring the relationship between urbanization and CO_2 emissions (or CO_2 emissions per unit land area) can help us to better understand the impact of urbanization on CO_2 emissions in cities [30].

Urban land growth mainly occurs in three main forms: spatial agglomeration, spatial dispersion, and a synergistic combination of the two [2,31]. Regarding spatial agglomeration, new urban land is mainly concentrated around big cities, causing the urban area to either 'fill in' space or 'spread out'. This urban growth pattern realizes how the agglomeration of population, industry, and transportation occurs in the original big city. Regarding spatial dispersion, new urban land is mainly concentrated around small towns, in different regions, in the form of urban spreading. The dispersion of urban growth means that the population, economy, and transportation network is concentrated on a smaller scale, and growth can occur in multiple spaces, such as multiple small towns or small cities. The synergy between spatial agglomeration and spatial dispersion means that the growth of new urban land is relatively balanced between spatial agglomeration and dispersion modes (Figure 1). For a given region, the choice of different spatial growth modes has an important impact on the urban scale, layout mode, and land-use intensity of each city in the region, thus affecting the total CO_2 emissions and the CO_2 emissions per unit land area [6,19,30].

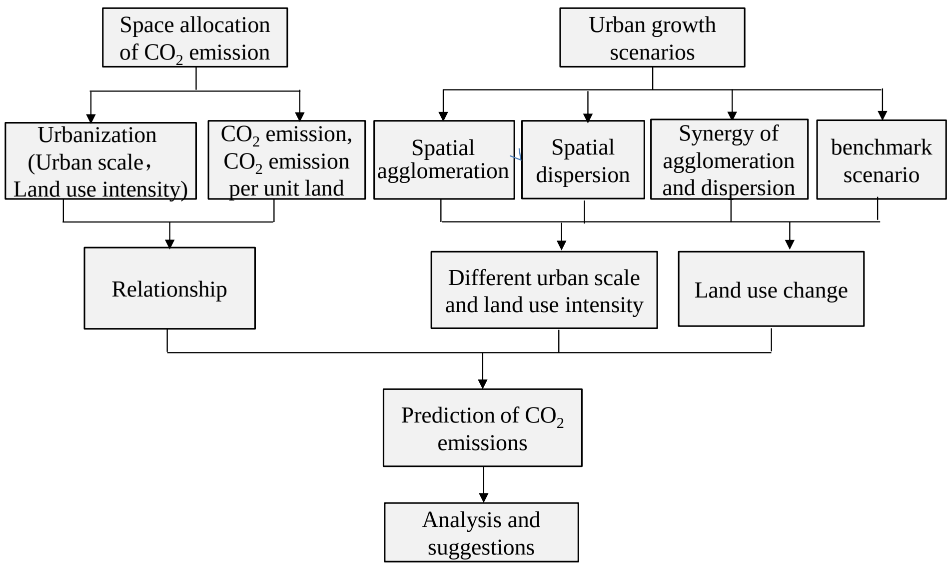

Figure 1. Framework of urban expansion and carbon emissions.

First, this study spatially mapped out CO_2 emissions and obtained their spatial distribution in the study area. The CO_2 emissions of each city in the study area were also obtained. The impact of urbanization—including urban scale and land-use intensity—on the total CO_2 emissions, or CO_2 emissions per unit land area, in urban areas, was explored. Then, four spatial urban growth scenarios were simulated, using the CA model as a basis, in order to analyze potential urban growth and the resultant CO_2 emissions over the next 15 years (to 2035). The CO_2 emissions of the four scenarios were predicted and analyzed (Figure 1). Finally, this paper discusses the impact of spatial urban growth on CO_2 emissions, and provides corresponding suggestions for urban development.

3. Materials and Methods

3.1. Study Area

Most studies focus on the impact that urbanization has on CO_2 emissions in eastern China, or in some of its more developed provinces. Less attention is paid to the less economically developed provinces in western China [4,6,25]; however, these provinces in western China are in the initial stages of rapid urban expansion, and their CO_2 emissions are also rapidly increasing, especially in the Guizhou province, which is experiencing rapid urbanization and industrialization. To balance urban expansion and control of carbon emissions in the future, it is important to explore the impact of urbanization growth patterns on CO_2 emissions, in order to provide support for future urban planning in Guizhou. Thus, we selected Guizhou to be the representative province for western China, as our case study.

The study area is the urban agglomeration in the center of the Guizhou Province, with an area of 53,800 km^2 (Figure 2). It covers 33 counties in six cities (districts) of Guizhou. The Central Guizhou Urban Agglomeration is the key urbanization area in Guizhou, which has great potential for economic development. It is a transportation hub in Southwest China, an important transit area for northwestern and coastal areas, and an important part of the Yangtze River economic belt. The landform of the study area is characterized by plateau–mountainous areas, with an average elevation of about 1100 m; this is consistent with the area's characterization as a place that has "eight mountains, one source of water, and one field." Both the terrain and economy restrict the expansion of the city.

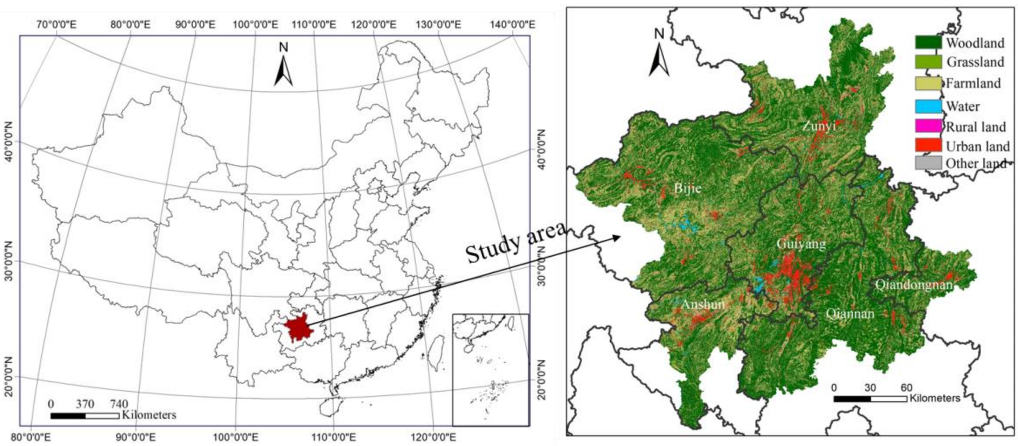

Figure 2. Location of the study area.

With the implementation of the western development strategy of China, the Guizhou economy has ushered in a stage of rapid development. By the end of 2019, the GDP of Guizhou Province reached CNY 1676.934 billion (about USD 248.2 billion, according to the average exchange rate in 2019), with an annual growth rate of 8.3% [32]. The growth rate has been one of the highest in China for nine consecutive years, and it has ranked first for three consecutive years [32]. As the core economic region of the Guizhou Province, the study area has seen increasing rates of industrialization and urbanization, and its energy demands are steadily growing; moreover, its carbon emissions have increased significantly in recent years. The situation regarding energy conservation and emission reduction is grim and worrying.

3.2. Accounting for CO_2 Emissions and Space Allocation

3.2.1. Accounting for CO_2 Emissions

The CO_2 emissions in this study mainly include energy-related and process-related CO_2 emissions. Energy-related CO_2 emissions are emitted during the combustion of fossil fuels, and they can be calculated using Equation (1) [15]:

$$CE_{ij} = FC_{ij} \times NCV_i \times CC_i \times OR_{ij} \quad (1)$$

where CE_{ij} is the CO_2 emissions for fossil fuel type i in socioeconomic sector j. FC_{ij} is the consumption of fossil fuel type i in socioeconomic sector j, obtained from China's energy statistical yearbooks and Guizhou's statistical yearbooks in 2009 and 2019. NCV_i and CC_i are the net calorific value and carbon emissions per unit of net heat generated by fossil fuel i. OR_{ij} is the oxidation rate during fuel combustion. The energy-related CO_2 emissions include 17 fossil fuels in 47 sectors.

Process-related CO_2 emissions mainly refer to the CO_2 emissions from industrial production processes. The main source of process-related CO_2 emissions in China is cement production, accounting for approximately 75% of the total CO_2 emissions produced during industrial production processes [15]; therefore, in this study, the CO_2 emissions from cement production were calculated as follows:

$$CP_k = FC_k \times CF_k \quad (2)$$

where CP_k is the CO_2 emissions from cement production and FC_k is the activity factor of cement production in year k, which was obtained from the official dataset of the National Bureau of Statistics. CF_k is the emission factor for cement production, which was 0.2906 [15].

3.2.2. Spatialization of CO_2 Emissions

The CO_2 emissions of the Guizhou Province were spatially mapped out using a downscaling method and auxiliary data for the years 2009 and 2019. First, this paper established a relationship between the CO_2 emissions of different sectors and their land-use type; then, the CO_2 emissions of different sectors were allocated a space according to their corresponding land-use type. The emissions were allocated a pixel with a resolution of 30 m, and these allocations were based on the corresponding year's auxiliary spatial data for each land-use type [18,33]. The land-use data resolution was 30 m for 2009 and 2019. Land-use types include industrial land, mining land, urban residential land, rural residential land, road traffic land, traffic service facility land, commercial service industry and other service industry land, agricultural facility and hydraulic construction land, woodland, and other lands which produce no carbon emissions. Forty-seven economic sectors were merged into seven sectors, including the sector which controls the production and supply of electric power, the mining sector, transportation service sector, manufacturing industries, the wholesale, retail trade, catering, and other service sectors, the urban residents' energy usage sector, and rural residents' energy usage sector.

CO_2 emissions from different industries were allocated a pixel according to their corresponding land-use types, as specified by the land-use classification system for 2019. Regarding point source data, CO_2 emissions generated by power plants were considered to correspond with the industrial land-use type, and thus, they were allocated as such, in accordance with its power plant coordinates. Data on power plants were obtained from the world power plant database (https://www.wri.org/research/global-database-power-plants (accessed on 13 April 2021)). CO_2 emissions generated by manufacturing processes were considered to correspond with the industrial land-use type, and thus, they were allocated as such; however, this excludes emissions generated from power plant locations. Emissions generated by the combustion of oil fuels in the transportation, storage, post, and telecommunication service sectors were considered to correspond with the road land-use type, and emissions generated by the combustion of non-oil fuels were considered to correspond with the transportation site land-use type; both sets of emissions were allocated accordingly. CO_2 emissions generated by the mining sector were considered to correspond with the mining land-use type, and they were allocated accordingly. Emissions generated by the energy use of urban and rural residents were considered to correspond with urban and rural residential land-use types, respectively; both sets of emissions were allocated accordingly. Emissions generated by the wholesale, retail trade, catering service, and other service sectors were allocated to the commercial land-use type, and were allocated accordingly.

After the emissions generated by different sectors were matched with their corresponding land-use type, the emissions were then allocated to a pixel with a resolution of 30 m, based on the corresponding year's auxiliary data, and measured as a weight for each land-use type [18,33].

$$CE_i^t = \sum_{s=1}^{k} C_{s,j}^t \times \frac{A_i^t}{\sum_{i=1}^{n} A_{i,j}^t} \quad (3)$$

where CE_i are the CO_2 emissions at spatial grid location i in year t, and $\sum_{s=1}^{k} C_{s,j}^t$ is the sum of CO_2 emissions for all sectors s in land class j in the study area. A_i^t is the auxiliary data value for location i in year t, and $\sum_{i=1}^{n} A_{i,j}^t$ is the sum of the auxiliary data for all pixels i in land class j. In this study, the auxiliary data are the corrected global Defense Meteorological Program—Operational Line-Scan System (DMSP-OLS) Nighttime Lights time (NTL) series data [34]. The larger the light value of a pixel, the greater the number of emissions that are allocated to that pixel. To be consistent with the land-use data, the night light data are resampled to 30 m.

3.3. Impact of Urbanization on CO_2 Emissions from 2009 to 2019

Based on the obtained spatial distribution of CO_2 emissions, the CO_2 emissions generated by the urban land in each county (district) of the study area were extracted, and the impact of urbanization on CO_2 emissions was explored. In this study, urbanization is mainly characterized by two dimensions: urban scale and urban land-use intensity. These dimensions are expressed by the urban area itself and the proportion of urban area to total land area, respectively [35,36]. CO_2 emissions are mainly considered in two ways: in terms of total emissions and CO_2 emissions per unit of urban land area.

For each county, the relationship between urbanization and CO_2 emissions was constructed using statistical models that were mainly based on the spatial distribution of CO_2 emissions and land-use acquisition in 2019. Logarithmic, exponential, primary polynomial, quadratic polynomial, and power models were used in this study [37]. The best model was chosen based on its R-squared (R^2) value and Akaike Information Criterion (AIC) [38]. The smaller the AIC value and the higher the R^2 value, the better the model.

3.4. Urban Expansion Simulation and CO_2 Prediction

3.4.1. Cellular Automaton (CA) Model

The cellular automaton (CA) model has been proven to be an effective method for urban spatial simulations of the future [39,40]. It can incorporate the natural and socioeconomic characteristics of an urban system to obtain a more reasonable urban simulation. The CA model can simulate different spatial patterns of future urban expansion by changing a few key parameters, such as the distance from towns or big cities. Thus, by using the CA model, it is feasible to perform urban simulations with the goal of simulating different spatial patterns that account for the next 15 years. This study used a CA model to simulate urbanization expansion.

The CA model comprises five parts: cellular, cellular state, transformation rule function, neighborhood, and cell time [39]. The cell is the basic unit of the CA, which is used to describe the attributes of a variable and is represented in a binary form. The neighborhood refers to the surrounding cells of the target cell, and its value is obtained by setting a fixed cell radius. The rule function notes whether the target cell can be expanded into urban land.

In reference to previous studies [27,39] and regional development requirements, the probability (P^{t+1}) of conversion from non-urban cells to urban cells depends on the influence of the following comprehensive factors: the suitability of urban growth, limiting factors, neighborhood influence, and other interferences.

$$P^{t+1}\left(S_{i,j}^{t} \rightarrow urban\right) = D_{i,j}^{t} * N_{i,j}^{t} * L_{i,j}^{t} * \varepsilon_{i,j}^{t} \quad (4)$$

Here, $S_{i,j}^{t}$ is the state of cellular at location (i, j) and time (t). $D_{i,j}^{t}$ is the suitability of urban growth for pixel (i, j) in year t, which refers to the accessibility of roads, towns, and cities in this study. The higher the accessibility, the higher the suitability for urban growth. $N_{i,j}^{t}$ is the neighborhood index, which refers to the proportion of urban or town pixels in the neighborhood. The higher the proportion of urban land in the neighborhood around the pixel, the higher the possibility of converting the pixel into urban land. The radius is set to 3 in this study. $L_{i,j}^{t}$ represent the factors that limit the expansion of urban land, including areas containing water and topographic conditions; the pixels with a water land-use type will not be converted into urban land, and moreover, the greater the size of a slope, the lower the possibility of converting pixels into urban land—pixels with a slope that is greater than 15 degrees will not be converted into urban land. The $\varepsilon_{i,j}^{t}$ term represents random interference.

The threshold for the probability (P^{t+1}) of urban expansion was calculated based on the urban expansion rate of the study area from 2009 to 2019. When the probability of a non-urban cell is greater than the threshold, the cell is converted to urban land. The CA model was constructed using MATLAB 2016a software. The simulation period was from 2019 to 2035.

3.4.2. Scenario Setting

The spatial agglomeration and diffusion of urban space manifests in the different trends of the spatial distribution of the economy and population. The former concerns an agglomeration shifting from a widely spaced area to a relatively narrow, regional space, and the latter concerns the diffusion of a densely packed unit into widely spaced area [16,41]. This study uses four scenarios to simulate the future, with each using a different urban expansion pattern: spatial agglomeration, spatial dispersion, a synergistic combination of agglomeration and dispersion, and a benchmark scenario. Scenario 1 simulates urban spatial agglomeration. In this scenario, new urban land is mainly concentrated around big cities, and these new urban areas are generated by 'filling in' space or 'spreading out'. Scenario 2 simulates urban spatial dispersion. In this scenario, new urban land is mainly concentrated around small towns in different regions, and these new areas are generated by urban spreading. Scenario 3 simulates a synergistic combination of urban spatial agglomeration and dispersion. In this scenario, new urban lands are generated in a relatively balanced manner, via both spatial agglomeration and dispersion. Scenario 4 simulates a benchmark scenario. In this scenario, new urban lands are generated based on urban expansion pattern trends in Guizhou over the past 10 years (2009–2019). According to scenario 4, spatial expansion patterns in the future would emulate how they have existed for the past 10 years.

The different scenarios are realized by changing the suitability parameter in the CA model [40,42]. Scenario 1 is characterized by spatial aggregation, which means that urban growth is more suited to large cities than small towns. In this scenario, the suitability of a cell near a town is one-fifth as suitable as a cell near a city. Scenario 2 is characterized by dispersed urban expansion, meaning that urban growth is less suited to big cities than towns. In this scenario, the CA model demonstrates that the suitability of a cell near a town is five times as suitable as a cell near a city. Scenario 3 is characterized by the balanced development of urban growth, which means that the suitability of areas surrounding small towns is equal to the suitability of areas surrounding big cities. Scenario 4 is a benchmark scenario. In this scenario, the suitability parameters of the CA model are the same as the parameters used for the urbanization expansion that occurred from 2009 to 2019.

3.4.3. Predicted CO_2 Emissions under Different Scenarios

The relationship between urbanization and CO_2 emissions forms the basis for the prediction of CO_2 emissions in different urbanization expansion scenarios [25,35]. In this study, we mainly considered the relationship between the urban area and the CO_2 emissions generated per urban land unit. The main reason for this is that the expansion of urbanization leads directly to an increase in urban land area, which affects the land-use intensity, thus finally affecting the efficiency of CO_2 emissions per unit of land. The efficiency of CO_2 emissions per unit of land ultimately affects the total CO_2 emissions produced by differently sized cities.

For the year 2035, the urban area of each county (district) in the study area, in each of the different scenarios, was calculated using the urban expansion results. Then, using the relationship (as it was in 2019) between the urban area and CO_2 emissions per urban land unit for different counties, the CO_2 emissions per urban land unit for each county were predicted for the next 15 years; the total CO_2 emissions generated by urban land use for the whole study area were also calculated [25,43]. The CO_2 emissions' characteristics and the emission trends of the study area, in each of the different scenarios for the next 15 years, were then analyzed.

4. Results

4.1. CO_2 Emissions of the Study Area

The spatial distributions of the CO_2 emissions in the study area, shown at a resolution of 30 m, indicated that the emissions in 2009 were concentrated in the center of the urban areas of each city (Figure S1). In 2019, carbon emission areas showed characteristics of diffusion and dispersion. High carbon emission areas reduced in size, whereas areas that generated a medium amount of carbon emissions increased from 2009 to 2019. As they were affected by urban expansion, many areas changed from being areas that produced no carbon emissions to areas that did produce carbon emissions; this shows how, in recent years, the trend of industrial development and urbanization in the Central Guizhou urban agglomeration has been characterized by a synergistic combination of agglomeration and diffusion.

Carbon dioxide emissions generated by urban land use were calculated based on the spatial distributions of the CO_2 emissions. From 2009 to 2019, Guizhou gradually entered a stage of rapid economic development. This period of urbanization mainly centered on the city, and it expanded to the surrounding areas, notably Guiyang, Zunyi, and Anshun (Figure S2). Due to the expansion of urban areas, carbon emissions increased significantly in Central Guizhou. In 2009, the urban built-up area containing the urban agglomeration was 493.74 km^2, and produced 101.67 million tons of CO_2 emissions, which accounted for 80.9% of total emissions. By 2019, the urban area increased to 937.65 km^2, and CO_2 emissions increased to 133.14 million tons. The carbon emissions of urban areas accounted for 85.4% of total carbon emissions; therefore, controlling CO_2 emissions in urban areas is key to achieving carbon neutralization.

4.2. Impact of Urbanization on CO_2 Emissions from 2009 to 2019

The relationship between urbanization and CO_2 emissions in each county (district) of the study area is shown in Figure 3, and the statistical parameters for each model are shown in Table S1. Results show that urbanization, which is expressed by the proportion of the urban area in relation to the total land area, had a significant effect on CO_2 emissions. The CO_2 emissions per land unit show a significant decreasing logarithmic trend as the urban area increases (Figure 3a). When the urban land area is small, increased urbanization leads to a rapid decline in CO_2 emissions per unit; however, when the city grows larger, with the further expansion of the city, the rate of decline for CO_2 emissions per unit slows down.

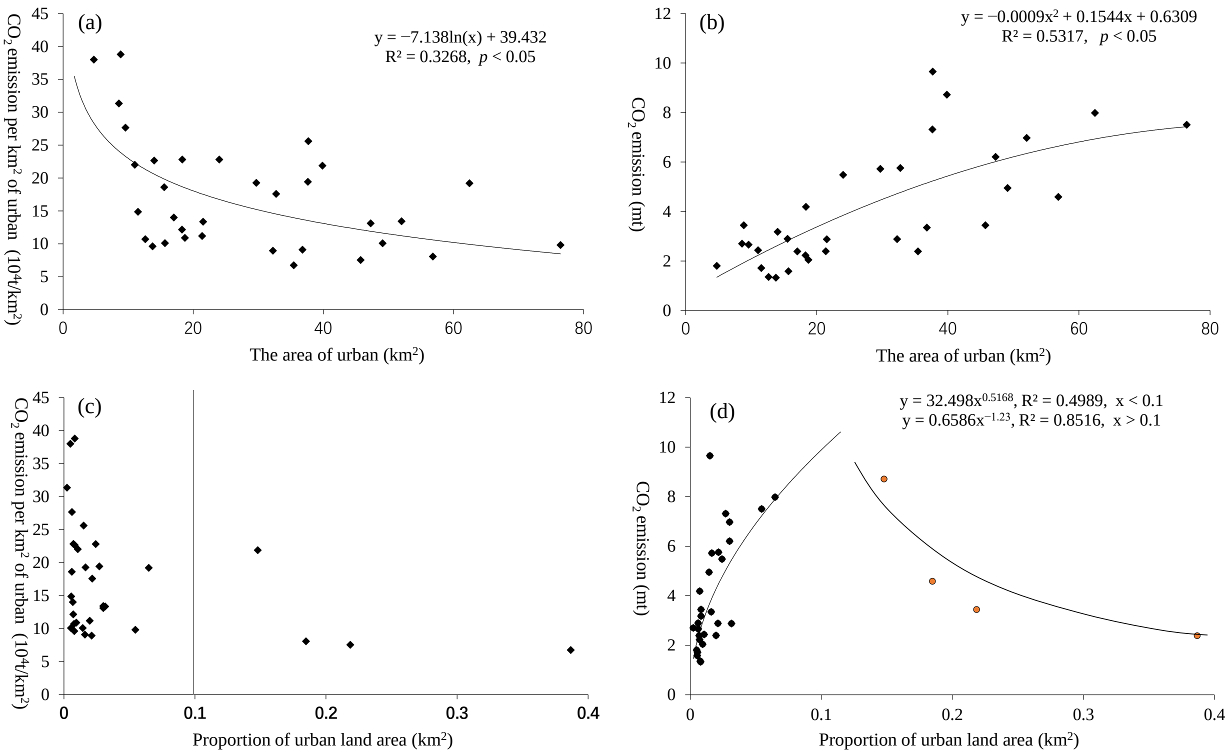

Figure 3. Relationships between CO_2 emissions and urbanization in 2019. Panel (**a**) shows the relationship between the average CO_2 emissions generated by urban land use and the urban area. Panel (**b**) shows the relationship between the total CO_2 emissions generated and the urban area. Panel (**c**) shows the relationship between the average CO_2 emissions generated by urban land use and the proportion of the urban land area. Panel (**d**) shows the relationship between total CO_2 emissions and the proportion of the urban land area.

A scatter diagram of the total CO_2 emissions produced and the area of urban land in each county (district) of the study area is shown in Figure 3b. The results reveal a quadratic relationship between the total urban CO_2 emissions and the urban area—an inverted U-shaped relationship. As the size of the urban area increases, the total amount of urban carbon emissions first increases, then decreases. At present, Guizhou is in the initial stages of urbanization, when CO_2 emissions rapidly increase in accordance with the increasing size of the urban area. Attention should be paid to two key issues in the future: accelerating the development of urbanization and causing CO_2 emissions to peak as soon as possible.

The relationship between the proportion of urban land area and CO_2 emissions are shown in Figure 3c,d. When the urban land-use intensity is relatively low (the proportion of urban land area is less than 10%), the CO_2 emissions show an increasing trend in accordance with the increasing proportion of urban land area. When the proportion of the urban area is greater than 10%, the CO_2 emissions begin to decline exponentially as the proportion of urban area increases. Nevertheless, the rate of decline for CO_2 emissions is slow. The CO_2 emissions per unit of urban land show no obvious trend; however, when the proportion of urban land area is very high (10%), the CO_2 emissions per unit of land are relatively low.

4.3. Urbanization Expansion Results under Different Scenarios

The spatial distribution of urban land in 2035, in accordance with the results of the four scenarios, is shown in Figure 4; all urban land shows a clear expansion over the next 15 years. Moreover, in each different scenario, the distribution of new urban land is significantly different. In scenario 1, new urban land is mainly concentrated around big cities, which emerged due to 'filling' or 'spreading'. In scenario 2, new urban land is mainly concentrated around small towns or cities in different regions, emerging as a result of spreading. In scenario 3, new urban land emerged as a result of the relatively balanced relationship between spatial agglomeration and dispersion; the distribution of new urban land in scenario 4 is similar to scenario 3.

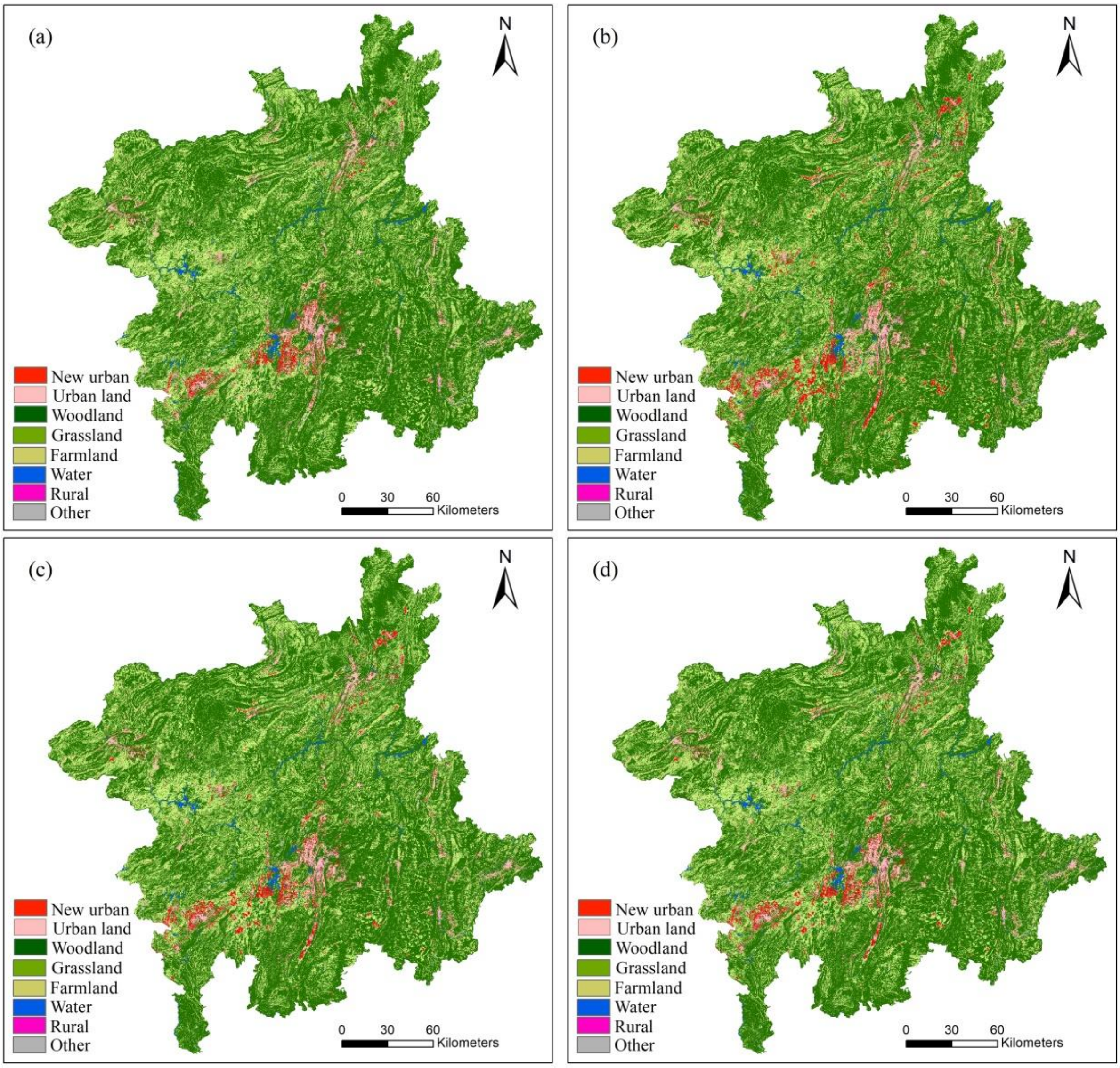

Figure 4. Results of urbanization expansion for 2035, for each different scenario. Panels (**a**–**d**) show the expansion results for scenario 1 to scenario 4, respectively.

For all scenarios, the spatial patterns of urban land have obvious differences to the spatial pattern of 2019. The increased size of the urban areas in scenarios 1 to 4 are 621 km^2, 1350.24 km^2, 911.02 km^2, and 842.35 km^2, respectively. The new urban area of the decentralized mode (scenario 2) is more than twice that of the agglomeration mode (scenario 1), and 1.5 times that of the benchmark scenario (scenario 4). The new urban area in scenario 3 is similar to that of the benchmark scenario. The urban expansion for the agglomeration scenario (1) is characterized by the manner in which it expands (via 'filling'), and its single-center pattern; therefore, in scenario 1, the probability of urban expansion around small towns is relatively low. In this scenario, urban expansion is mainly concentrated in Guiyang city, the provincial capital, as well as Anshun, and Zunyi city.

The urban expansion in scenario 2 has multi-center characteristics. In addition to Guiyang, obvious urbanization expansion occurs in many spaces, such as small towns. Scenario 3 shows that big cities and small towns both expand rapidly. The spatial distribution of urban land for the benchmark scenario (scenario 4) is similar to that of scenario 3. This means that over the past decade, urbanization in Guizhou developed as a result of a combination of agglomeration and decentralization.

The proportion of other land-use types that were converted to urban land in each of the different scenarios for 2035 are significantly different (Figure S3). More than half of new urban land comes from cultivated land in each of the four scenarios. The occupied proportion of cultivated land is highest under the decentralized expansion pattern, accounting for 64.78% of the total occupied land. The occupied proportions of cultivated land in the other scenarios are all greater than 50%. Forest land is also a common land type that is often converted to new urban land; this was especially the case in scenario 1, with forest land conversions accounting for 28.51% of the total occupied land. In scenario 2, a greater proportion of cultivated land is occupied; however, the proportion of occupied forest land was the lowest of the four scenarios. In addition, the proportion of rural residential land that converted to urban land was lower than 10%. The proportion of other land types that converted to urban land was very small.

4.4. CO_2 Emissions under Different Scenarios

Figure 5 shows the predicted CO_2 emissions in 2035, for each different scenario. Scenario 1 (spatial agglomeration pattern) had the lowest predicted emissions, at 156.29 mt; this demonstrates an increase of 23.15 mt when compared with the emissions generated in 2019. Compared with scenario 2 (urban dispersion expansion pattern), scenario 1 shows a reduction in carbon emissions by about 14%. Compared with scenario 3 and scenario 4, scenario 1 shows a reduction in carbon emissions by about 14.81 mt and 10.58 mt, respectively. This means that by 2035, the CO_2 emissions of the study area will experience its greatest ever reduction if the agglomeration development pattern is adopted. In contrast, scenario 2 generated the highest amount of CO_2 emissions, with a value of 181.62 mt. The emissions of the dispersion model are 14.75 mt higher than that of the baseline scenario. The CO_2 emissions of scenario 3 are 171.12 mt, which is about 4.25 mt higher than scenario 4.

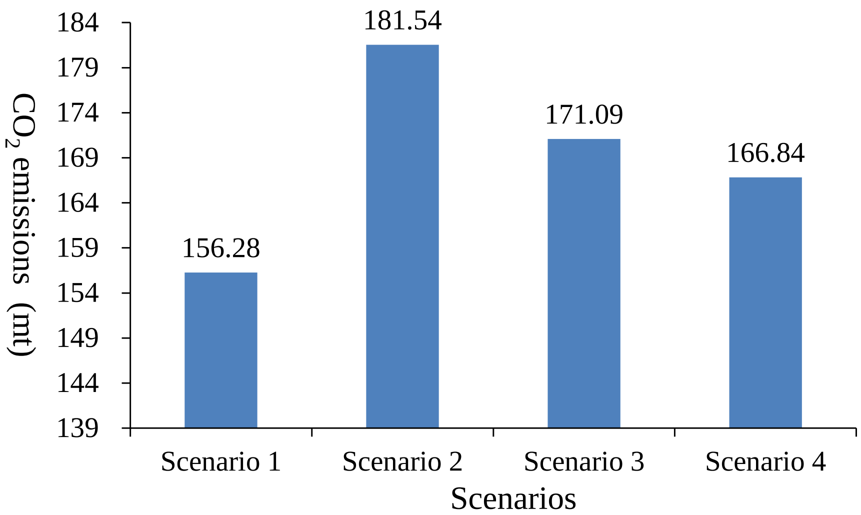

Figure 5. Predicted CO_2 emissions in urban land areas for the year 2035; results from the different scenarios.

When using the CA model to simulate urbanization expansion, the new urban area differs in terms of expansion cycles (years). For each different scenario, the variation in CO_2 emissions, in relation to new urban areas, is shown in Figure 6. The agglomeration pattern is always better than other patterns in terms of emission reduction when the new urban area is the same; however, the decentralized pattern of urbanization is not conducive to reducing carbon emissions, as it persistently produces the highest emissions.

Furthermore, CO_2 emissions and new urban areas have an inverted U-shape relationship in all scenarios; in other words, as the new urban area increases, CO_2 emissions first increase, then decrease. Urban growth, as described by the spatial agglomeration pattern, will reach peak CO_2 emissions earlier than other urban growth patterns. In contrast, the spatial dispersion pattern will be last to reach peak carbon emissions. After urbanization reaches a certain stage, CO_2 emissions show a downward trend in all scenarios. The results indicate that the spatial agglomeration of urban growth is conducive to reaching peak CO_2 emissions early.

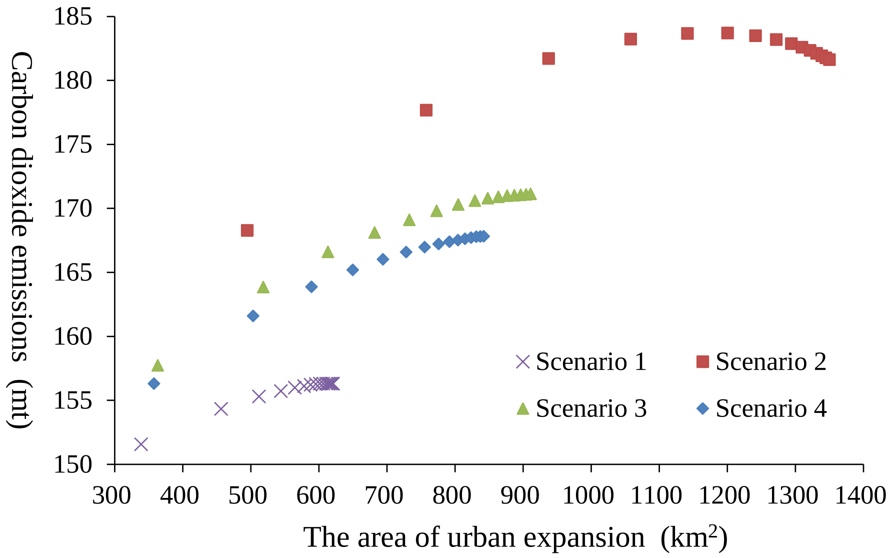

Figure 6. Variation in CO_2 emissions in new urban areas from 2020 to 2035 in each different scenario.

The CO_2 emissions in different regions, using different urbanization expansion scenarios, are shown in Figure 7. Guiyang city, the provincial capital, shows little difference in emissions in each different expansion scenario during the early stages of expansion; however, with regard to the later stages of expansion, scenario 1 is more conducive to reducing carbon emissions, whereas scenario 2 generates the highest amount of emissions. Zunyi is the second largest city in the Guizhou Province. In contrast to Guiyang, the urban expansion in scenario 2, in the Zunyi region, produces a low amount of CO_2 emissions, and the CO_2 emissions in scenario 1 are the highest. In the early stages of urban expansion in Anshun, scenario 1 is more conducive to reducing CO_2 emissions compared with the other scenarios. In the later stages of expansion, as the city expands further, the CO_2 emissions in all scenarios decrease rapidly. Bijie, Qiannan, and Qiandongnan all have the lowest emissions in scenario 1, followed by scenario 3 and scenario 4. The CO_2 emissions in scenario 2 are the highest.

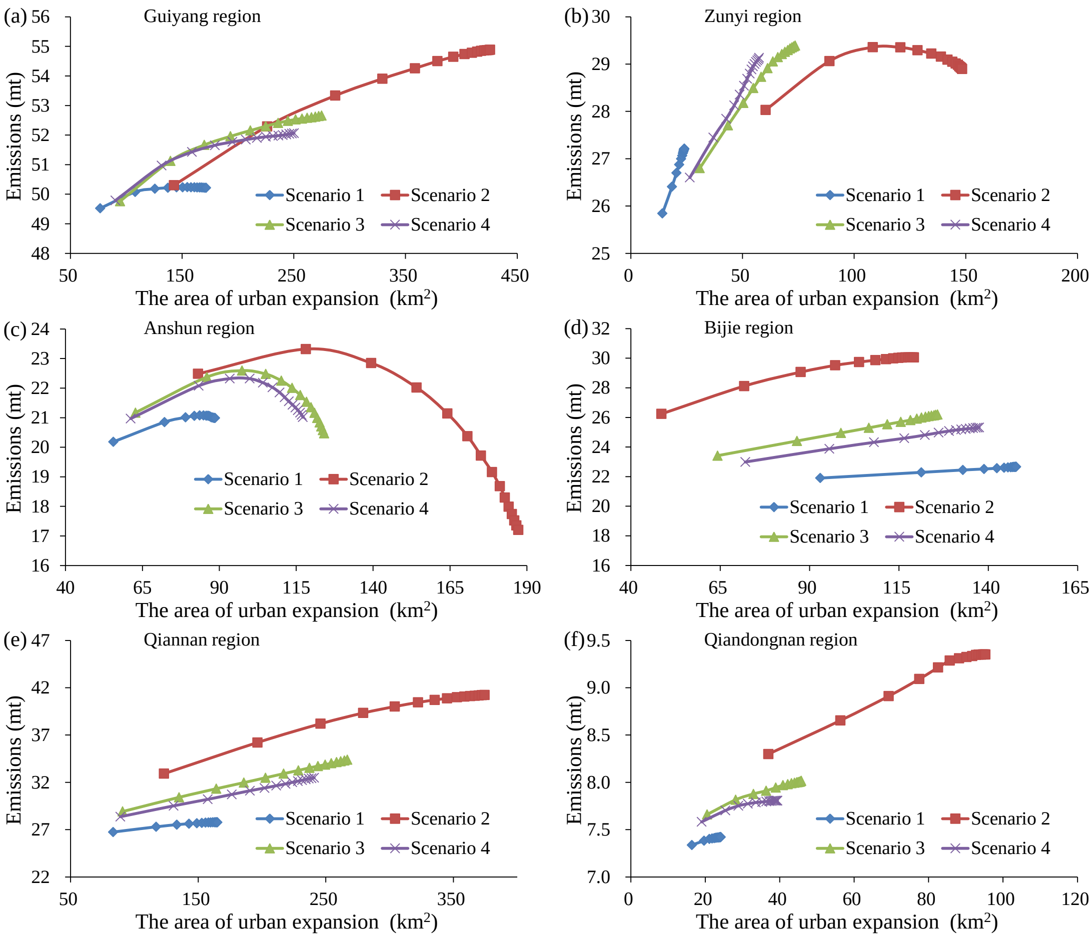

Figure 7. Comparison of CO_2 emissions in different regions for each of the different scenarios from 2020 to 2035. Panel (**a**) is for Guiyang region, panel (**b**) is for Zunyi region, panel (**c**) is for Anshun region, panel (**d**) is for Bijie region, panel (**e**) is for Qiannan region, panel (**f**) is for Qiandongnan region.

5. Discussions and Implications

The world is undergoing a process of rapid urbanization, and people are increasingly concerned about the impact of future urban expansion on carbon emissions. Some studies use different policy interventions to simulate future urban expansion, in order to obtain urban expansion schemes that are more conducive to the reduction of CO_2 emissions [20–24]. Compared with our research, these studies explored urban expansion from a pre-policy intervention perspective. In addition, some studies evaluated the consequences of carbon emissions using future projections of urban expansion, which comprise ex post assessment research [12,44,45]. These studies mainly explored the impact of land-use changes, caused by urban expansion, on CO_2 emissions. Our research focuses on the future impact of different urban spatial expansion patterns on CO_2 emissions based on the existing urban spatial expansion pattern. Different spatial patterns of urban areas mean different layouts of industrial, housing, and transportation networks, thus resulting in different levels of energy consumption and energy efficiency [19]. This study answers the question of which urban expansion pattern should be adopted by the different cities in the study area in order to reduce carbon emissions.

Some existing studies have paid attention to the impact of urban expansion patterns on CO_2 emissions [11,12,27]; however, these studies mainly offer relevant recommendations after assessing the impact of historical urban expansion patterns on CO_2 emissions. First, our study discusses the relationship between regional urbanization and CO_2 emissions based on historical data; then, it explores which future spatial expansion pattern will be more conducive to reducing carbon emissions based on the existing urban pattern. Previous findings indicated that the increased fragmentation of urban forms could result in more carbon emissions, and an agglomeration development pattern of urban land would help reduce carbon emissions [46]. Some other studies also pointed out that greater levels of urban expansion should be encouraged in the developed cities of developing countries to achieve low-carbon development [47]. This is partly similar to our research results. Regarding future scenarios, our results showed that in the study area, the agglomeration pattern of urban land is more conducive to reducing carbon emissions, but different cities in the study area need to adopt different expansion patterns.

This study can provide policy implications for future urban expansion; indeed, this study used four scenarios that included different cities, and it took carbon emission characteristics into account. The results indicated that further agglomeration does not produce a rapid increase in carbon emissions in regions where a certain level of urbanization has been reached, such as in Guiyang city. For medium-sized cities with characteristic industries, such as in Zunyi, urbanization expansion should be guided by industrial agglomeration, rather than urban spatial location agglomeration. Cities with low urbanization levels, such as Bijie, Qiannan, and Qiandongnan city, should expand with an aim to achieve spatial agglomeration; however, due to the fact that these cities have the best capacity for carbon storage, emphasizing ecological governance and the development of eco-tourism products may be a better choice for economic development in these cities.

The spatial agglomeration of urban land reduces the need for low-level repeated infrastructure construction, which disrupts residents' lives. This will improve the level of resource sharing and energy efficiency [19]; however, the spatial agglomeration of cities will also increase the traffic pressure and pressures related to resource supplies [47]. Therefore, in urban planning, more attention should be paid to the reasonable adjustment of traffic land to alleviate traffic congestion. In urban planning, the regional area balance between working place and residence, as well as catering space and residence, should be fully considered to reduce the long distances that residents are required to travel in their daily lives; this should improve people's happiness. In addition, urban planning also plays an auxiliary role in assisting other means of carbon emission control, such as the implementation of a fee charged on vehicles that are driven within a particular urban area; such schemes should ensure that there is a reasonable alternative for new energy vehicles. Urban agglomeration maximizes the use of these facilities. When an area of new urban land remains the same, the development of urban spatial agglomeration often increases peak CO_2 emissions; however, it is difficult to considerably reduce carbon emissions through urban planning only. Controlling the consumption of fossil energy and increasing the utilization of non-fossil energy through various means are prerequisites to carbon neutralization in the future.

In the future, land-use change during urban expansion ought to be a factor that is considered in the urban planning process. Most areas in the Guizhou Province are mountainous; these are known as "eight mountains, one source of water, and one field" areas. Indeed, 80% of the land is mountainous, 10% of the area is water, and 10% of the land is farmland. Due to the peculiar terrain of Guizhou, the amount of land available for urban growth is limited. Most rural settlements are scattered in mountainous areas, which are far larger than urban land areas, and are far away from cities. Here, the land that experiences urban growth is mainly composed of agricultural land and forest land. Compared with forest land, Guizhou's agricultural land is limited in terms of helping to facilitate urban growth. Urban expansion agglomeration (Scenario 1) occupies more forest land than the decentralized pattern (Scenario 2), and thus, it is more conducive to maintaining cultivated land areas and securing the food supply for local residents. Spatially dispersed urban growth takes up more cultivated land than woodland, which is conducive to maintaining forests and increasing carbon sequestration in Guizhou. Different regions can choose suitable urban growth modes according to their regional characteristics.

In addition, nighttime light data has been widely used as a proxy for urban issues. For example, it has been used for spatial–temporal dynamic analysis of urban expansion, defining urban boundaries, and estimating the spatial distribution of CO_2 emissions [18,26,33,48]. This paper uses nighttime light data to obtain CO_2 emissions on a pixel scale, and to extract CO_2 emission measurements in urban land areas [18,26]. Based on the CO_2 emissions generated by urban land use in the study area, we explored the relationship between urbanization and CO_2 emissions. The research results show that the relationship between city scale and CO_2 emissions forms an inverted U-shape, which is similar to previous research results [10,11]; however, the relationship between urban land-use intensity and CO_2 emissions is not a strictly inverted U-shaped or linear relationship. With regard to urban land-use intensity, CO_2 emissions increase rapidly when urban land-use intensity is low. After reaching its peak, as urban land-use intensity increases, CO_2 emissions begin to decrease, but the rate of reduction is far slower than the rate of increase. The relationship between urban land-use intensity and CO_2 emissions may therefore be accurately described as erratic, especially when land-use intensity reaches a certain level.

The urban boundary predictions are difficult to directly verify. Although subjective judgment exists, no relevant research has proposed a direct method to verify the rationality of the simulations' boundaries; however, the effectiveness of the parameters of the CA model for the benchmark scenario had been validated. We obtained the optimum parameters for the benchmark scenario by repeatedly simulating urban growth using the 2009 and 2019 land-use data. Other scenarios were implemented by changing the importance of accessibility in towns and cities, and its relation to the suitability of urban growth in the benchmark scenario. Results indicated that the simulated urban spatial distribution conforms to the initial goal of achieving spatial agglomeration or spatial dispersion.

This study aims to explore the impact of future urban spatial expansion patterns on CO_2 emissions. It does not consider whether the spatial agglomeration of different industries will have an important impact on CO_2 emissions. In the future, we could simulate different spatial patterns for the housing, industrial, and commercial sectors, among others; then, the impact of these patterns on CO_2 emissions could be explored. In addition, this study only examines urban agglomeration in Guizhou, an underdeveloped province, as the study area. More studies can be conducted in the future to compare the differences between different urban expansion patterns and their impact on CO_2 emissions in different regions.

6. Conclusions

The spatial patterns of urban expansion have a potentially significant impact on carbon emissions; however, little attention has been paid to the impact of future urban expansion patterns on carbon emissions based on the existing urban expansion pattern. Focusing upon urban agglomeration in Central Guizhou, this study aimed to investigate the impact of urban expansion patterns on the reduction of carbon emissions, and it provided suggestions for low-carbon development. The relationships between regional urbanization and CO_2 emissions in the study area were analyzed based on historical data. Four urban expansion scenarios, including spatial agglomeration, spatial dispersion, a synergistic combination of agglomeration and dispersion, and a benchmark scenario, were simulated; the CO_2 emissions under each scenario were subsequently predicted for the next 15 years.

Regional urbanization had significant effect on CO_2 emissions. The CO_2 emissions per land unit showed a significant decreasing logarithmic trend as the urban area increased; although, the total carbon emissions showed an inverted U-shaped trend as the urban area increased. When the urban land-use intensity was relatively low, CO_2 emissions showed an increasing trend as land-use intensity also increased. When the land-use intensity was greater than 10%, the CO_2 emissions began to decline exponentially with increasing land-use intensity; however, the rate of decline was slow.

In the next 15 years, urban expansion will lead to a significant increase in CO_2 emissions. The CO_2 emissions were lowest in the spatial agglomeration scenario and highest in the spatial dispersion scenario. The spatial agglomeration of urban growth helps to quickly facilitate the peaking of CO_2 emissions in urban areas; however, different cities in the study area can adopt different urban expansion modes. In areas where urbanization has reached a certain level, such as in Guiyang city, further agglomeration did not produce a rapid increase in carbon emissions. For medium-sized cities with characteristic industries, such as in Zunyi, urbanization expansion should be guided by industrial agglomeration, rather than urban spatial agglomeration. The expansion of cities with low urbanization levels, such as Bijie, Qiannan, and Qiandongnan city, should develop with the aim of achieving spatial agglomeration; however, due to the fact that these cities have the best capacity for carbon storage, emphasizing ecological governance and the development of eco-tourism products may be a better choice for economic development.

The spatial agglomeration of cities will also increase the traffic pressure and pressures relating to resource supplies. In urban planning, more attention should be paid to the reasonable adjustment of traffic land to alleviate traffic congestion. In urban planning, the regional area balance between working place and residence, and catering land and residence, should be fully considered to reduce the length of time that residents must travel long distances, thus improving people's happiness. This research provides an important reference guide for urban planning in the Guizhou province and other similar areas. In the future, more studies could be conducted to compare the impact of urban expansion patterns on CO_2 emissions in different regions, with different urbanization degrees. Moreover, the spatial expansion patterns of different industries and their impact on CO_2 emissions also deserves further study.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land11081211/s1, Figure S1: Spatial distribution of CO2 emissions for 2009 (a) and 2019 (b) in the study area; Figure S2: Land use data for 2009 (a) and 2019 (b) in the study area; Figure S3: Proportion of other land-use types converted to urban land in 2035; Table S1: Statistical parameters for each model.

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