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Research on Provincial Carbon Emission Reduction Path Based on LMDI-SD-Tapio Decoupling Model: The Case of Guizhou, China

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Abstract: The successful implementation of the national carbon emissions reduction work necessitates the collaboration of various regions. Carbon emission reduction strategies need to be adjusted according to local circumstances due to the differences in regional development levels. From 2005 to 2020, carbon emissions were measured in Guizhou Province, and the contribution degree and action direction of various influencing factors were analyzed using the LMDI model. Using an SD model, we performed dynamic simulations of carbon emission trends under eight scenarios and calculated the Tapio decoupling relationship between economic growth and CO_2 emissions. According to the study, carbon emissions in Guizhou Province increased from 2005 to 2020, emphasizing the high pressure for carbon emission reduction. The industry sector ranked first in contribution, contributing 62.71% in 2020. Furthermore, this study found a weak decoupling relationship between economic growth and carbon emissions. The economic scale was the key driver driving the increase in carbon emissions, whereas the industrial fossil energy intensity was the main factor inhibiting the growth of carbon emissions. Additionally, it was predicted that carbon emissions would only peak at 277.71 million tons before 2030 if all three measures were implemented simultaneously, and a strong decoupling relationship with economic growth could be achieved as early as possible. These findings provided Guizhou Province with an effective path for reducing carbon emissions.

Keywords: LMDI; system dynamics; scenario simulation; tapio decoupling analysis; the carbon emission reduction path

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Citation: Wang, H.; Xu, W.; Zhang, Y. Research on Provincial Carbon Emission Reduction Path Based on LMDI-SD-Tapio Decoupling Model: The Case of Guizhou, China. *Sustainability* **2023**, *15*, 13215. https://doi.org/10.3390/su151713215

Academic Editors: Fuqiang Wang, Chao Shen, Dong Li and Zhonghao Rao

Received: 24 June 2023
Revised: 24 August 2023
Accepted: 1 September 2023
Published: 3 September 2023

1. Introduction

The greenhouse gas emissions have exacerbated the global greenhouse effect, primarily CO_2, and the resulting climate change issues severely threaten the economy, society, and ecosystem. Reducing carbon emissions has developed into a mutual issue confronting the global community. China, which has the most significant total carbon emissions globally, is still seeing a rise in its carbon emissions, resulting in increased pressure to decrease it. China proposed "dual carbon" goals in September 2020. That is, carbon dioxide emissions aim to peak by 2030, and strive to achieve carbon neutrality by 2060, known as the carbon peak, carbon neutrality '3060' goal. How to implement effective carbon emission reduction measures is an urgent challenge for China today. Due to the variation in the driving mechanisms and peak times of different provinces of CO_2 [1], each region should adopt corresponding emission reduction measures according to its conditions. Thus, exploring the provincial carbon emission reduction path is significant.

To explore the scientific approach to lowering carbon emissions, scholars have continuously proposed new perspectives. Some researchers have investigated from a spatial perspective, such as a regional perspective [2–4] and an industry perspective [5–7], which provides a scientific foundation for formulating effective carbon emission reduction strategies. Some researchers have studied from the perspective of carbon emission responsibility allocation [8,9] and quota allocation [10,11]. Through these studies, governments and policymakers can consider different regions and industries' actual situations and responsibilities more scientifically and comprehensively when formulating carbon emission reduction strategies. Among these, the discussion of carbon emission impact mechanism and peak time is particularly intense in the research of regional carbon emissions. For example, to drive China to achieve its "dual carbon" goals, Guo et al. took the Yangtze River Delta region as an example. They found that the key influencing factors for carbon emissions differ among provinces [12]. Huang et al. analyzed the factors influencing terminal energy consumption in typical urban clusters. The research found that energy intensity and energy consumption structure significantly impact carbon reduction [13]. Yue et al. anticipated China's carbon emission trends from 2020 to 2035 by combining scenario analysis with predictive algorithms, which assisted China in meeting its target for carbon peaks [14].

Several methods are commonly used to study the factors influencing carbon emissions, including the structural decomposition approach (SDA) [15], the logarithmic mean Divisia index (LMDI) model [16,17], the grey relational analysis [18], as well as Stochastic Impacts by Regression on Population, Affluence, and Technology STIRPAT model [19–21]. For its ability to handle zero values with ease and provide an independent analysis path, the LMDI model is frequently employed by academics [22]. For example, using the LMDI model, Xu et al. successfully decomposed the contributing factors of carbon emission. They elucidated the influences of energy intensity, energy structure, industrial structure, and economic growth [23]. Yang et al. found that carbon emissions were predominantly influenced by the significant effects of economic growth and energy intensity [24]. In addition, carbon emission trend prediction is also one of the critical concerns in the academic sphere. In order to investigate the possibility of achieving carbon emission peaks and predict the timing for their occurrence, scholars have used various methods, including the long-term energy alternative planning (LEAP) model [4,25], artificial neural network model [26], STIRPAT model [27,28], system dynamics (SD) model [29,30] and Kuznets curve (EKC) [7] to predict and simulate the future carbon emission scenarios. Among them, system dynamics, as a theory and method to explore the overall system structure, has been widely used in recent years to solve carbon emission reduction problems. Additionally, the model is utilized to explore ways of emission reduction of carbon in both the industrial [31] and residential sectors [32]. For example, a multi-level SD model was developed by Yang et al. to predict China's future carbon emissions levels while also providing suggestions to promote energy low-carbon transformation [33]. Similarly, Du et al. employed a combination of system dynamics modeling and scenario analysis to simulate the trend of carbon emissions [34].

Despite the insightful contributions the LMDI model can offer, it has limitations in directly observing the effectiveness of corresponding measures in reducing emissions. System dynamics modeling proves highly beneficial in dealing with complex issues, but most studies are more subjective in constructing models. Therefore, to avoid the limitations of a single model, some scholars have tried to combine these two models to analyze the interrelationships among various relevant factors and predict carbon emission trends under different scenarios. For example, some scholars combined LMDI models with system dynamics models to explore the crucial factors behind alterations in carbon emissions [35] or predict future carbon emission trends [36]. In summary, national and city levels of carbon emission reduction research are the main subjects of the literature that is now available. However, more attention should be paid to reducing carbon emissions in underdeveloped provinces. Moreover, few studies have simultaneously considered the decoupling relationship between economic growth and carbon emissions across various scenarios. Considering this, this paper introduces the Tapio decoupling index based on previous studies, combines the characteristics of LMDI and SD models, takes Guizhou province as an example, subdivides emission sectors, and explores its carbon emission reduction problem from a more comprehensive perspective.

Guizhou Province possesses the most significant amount of coal resources among the regions in southern China. Over the past decade, its economic growth rate has continuously ranked among the highest in the country. However, as an underdeveloped area in China, Guizhou Province commenced its industrial development comparatively late. Currently, the secondary sector still dominates, and its industrial development highly relies on coal, making it challenging to achieve a carbon emission peak. Nevertheless, existing literature lacks attention to carbon emissions reduction in such regions. Therefore, we chose Guizhou Province as an example in the hope of conducting a more thorough analysis of the carbon emission reduction path at the provincial level.

The paper makes several key contributions. Firstly, the carbon emissions in Guizhou Province are calculated, and the LMDI model is employed to examine the contribution degree and action direction of different influencing factors, thereby identifying crucial driving factors that influence carbon emissions. Secondly, based on the analysis results from the LMDI model, an SD model is constructed to dynamically simulate future carbon emission trends and examine the direct impact of corresponding measures on carbon emissions. Thirdly, by calculating the Tapio decoupling index, this research observes the changing trends in the decoupling relationship between economic growth and carbon emissions under different scenarios. The study's findings provide insights for Guizhou Province in developing strategies to reduce carbon emissions and hold crucial practical significance for achieving national carbon emission reduction goals.

The rest of this paper is structured as follows. The Section 2 is the methodology and data source. The Section 3 presents the results. The Section 4 includes the discussion and policy recommendations. The Section 5 is the conclusions.

2. Methodology and Data Source

2.1. Study Area

Guizhou Province is located in the southeast of southwestern China, between 103°36′ to 109°35′ east longitude and 24°37′ to 29°13′ north latitude. In 2020, the province's gross domestic product (GDP) increased by 4.34 % year-on-year. The primary, secondary, and tertiary industries accounted for 8.70%, 44.16%, and 47.14% of the total output value, respectively. As of 2020, the province's population stood at 35.85 million, with an urban population accounting for 53.16%, an increase of 1.75 percentage points compared to 2019. The total energy consumption amounted to 114.14 million tons of standard coal, indicating an annual decrease of 2.05%. Cement production reached 108.21 million tons, with an annual decrease of 2.17%. Moreover, coal remains the primary energy source in the current energy structure.

2.2. IPCC Carbon Emission Calculation Method

According to data from the International Energy Agency (IEA), carbon emissions from coal in China accounted for 79.61% of the total carbon emissions in 2019. At the same time, global cement production contributes to over 7% of the total carbon emissions annually [37]. Both coal and cement production are core components of economic activities in Guizhou Province, making significant contributions to carbon emissions. Furthermore, Guizhou Province has an annual coal production exceeding 100 million tons and has the richest coal resources in southern China. Currently, it is in a phase of rapid economic growth, with the secondary industry as the dominant sector, heavily reliant on coal for its development. Therefore, considering the scale of carbon emission contributions, regional characteristics, and development conditions of Guizhou Province, as well as the data availability, this study primarily focuses on carbon emissions from energy consumption and cement production.

Carbon emissions from fossil energy consumption were calculated using the Intergovernmental Panel on Climate Change (IPCC) emission factor methodology [38]. Since the carbon emission factors provided in the Guidelines for Provincial Greenhouse Gas Inventory better suit China's national conditions, the carbon content and carbon oxidation rate figures provided by these guidelines were adopted. At the same time, the calorific value was determined using the average low-level heat generation data from the China Energy Statistical Yearbook. The calculation method is shown in Equation (1).

$$C_e = \sum E_k \times NCV_k \times CC_k \times O_k \times \frac{44}{12} \tag{1}$$

where C_e was the energy consumption CO_2 emissions, the subscript k was the subdivided energy type, E_k was the fossil energy consumption, NCV_k was the average low-level heating value of energy source k, CC_k was the carbon content of energy k, O_k was the carbon oxidation rate of energy k, and 44/12 was the conversion coefficient of CO_2 and C. The carbon emission produced by the cement production process can be calculated using Equation (2).

$$C_c = AD \times EF \tag{2}$$

where C_c was the carbon dioxide emissions resulting from cement production, AD was the volume of cement production, and EF was the carbon emission factor associated with cement production, referring to the 0.2906 provided by Shan et al. [39].

2.3. Logarithmic Mean Divisia Index (LMDI)

The logarithmic mean Divisia index decomposition is commonly used to study energy, resources, and the environment [22]. In this paper, we extended the Kaya identity [40] by introducing economic scale, industrial structure, energy intensity, and population structure to analyze the contributions and directions of different influencing factors to CO_2 emissions. We utilized the LMDI-I additive [41] decomposition analysis to decompose carbon emissions from energy consumption and cement production.

We used ES (=1, 2, . . ., 8) to represent the eight major emission sectors, including the primary sector, such as agriculture, forestry, animal husbandry, and fishery, abbreviated as AFAHF; the secondary industry, such as industry and construction; the tertiary sector such as transport, storage, and post, abbreviated as TSP, wholesale, retail trade, hotel, and restaurants, abbreviated as WRTHR, as well as other service industries, abbreviated as OSI, in addition to the above, it also included urban and rural sectors. J (=1, 2, 3) represented coal, petroleum, and natural gas. Equation (3) demonstrates the total CO_2 emissions, Equations (4) and (5) respectively show the carbon emissions from the industrial and residential sectors, and Equation (6) displays the emissions from cement production, while Table 1 defines the variables.

$$C = C_e + C_c = (C_1 + C_2) + C_c = \left(\sum_{ES=1}^{6} \sum_{j=1}^{3} C_{ES,j} + \sum_{ES=7}^{8} \sum_{j=1}^{3} C_{ES,j} \right) + C_c \tag{3}$$

$$C_1 = \sum_{ES=1}^{6} \sum_{ES=1}^{3} \frac{C_{ES,j}}{E_{ES,j}} \times \frac{E_{ES,j}}{E_{ES}} \times \frac{E_{ES}}{G_{ES}} \times \frac{G_{ES}}{G} \times G = \sum_{ES=1}^{6} \sum_{j=1}^{3} b_{ES,j} \times d_{ES,j} \times f_{ES} \times h_{ES} \times G \tag{4}$$

$$C_2 = \sum_{ES=7}^{8} \sum_{j=1}^{3} \frac{C_{ES,j}}{E_{ES,j}} \times \frac{E_{ES,j}}{E_{ES}} \times \frac{E_{ES}}{R_{ES}} \times \frac{R_{ES}}{P_{ES}} \times \frac{P_{ES}}{P} \times P = \sum_{ES=7}^{8} \sum_{j=1}^{3} b_{ES,j} \times d_{ES,j} \times q_{ES} \times r_{ES} \times s_{ES} \times P \tag{5}$$

$$C_c = \frac{C_c}{AD} \times \frac{AD}{G_2} \times \frac{G_2}{P} \times P \tag{6}$$

Table 1. The definition of variables in the equation.

Variable	Meaning	Variable	Meaning
$C_{ES,j}$	Carbon emissions from the consumption of fossil energy j in sector ES	$E_{ES,j}$	Consumption of fossil energy j in sector ES
E_{ES}	The fossil energy consumption of sector ES	G_{ES}	The gross domestic product of sector ES
G	Gross Domestic Product (GDP)	R_{ES}	Household consumption expenditure in department ES
P_{ES}	The number of people in sector ES	P	Total population of the region
$b_{ES,j} = C_{ES,j}/E_{ES,j}$	Carbon emission coefficient of sector ES fossil energy j	$d_{ES,j} = E_{ES,j}/E_{ES}$	Fossil energy structure of sector ES
$f_{ES} = E_{ES}/G_{ES}$	The fossil energy intensity of industrial sector	$h_{ES} = G_{ES}/G$	Industrial structure
$q_{ES} = E_{ES}/R_{ES}$	The fossil energy intensity of residential sector	$r_{ES} = R_{ES}/P_{ES}$	Per capita consumption level
$s_{ES} = P_{ES}/P$	Urban and rural population structure	$m = C_c/AD$	Carbon emission coefficient of cement
$n = AD/G_2$	Cement production intensity	$u = G_2/P$	Industrial sector per capita output value

We assumed that C^t and C^{t-1} denoted the CO_2 emissions for the year t and $t-1$, respectively, and ΔC denoted the year-to-year change influence of carbon emissions. Equation (7) illustrates the calculation method.

$$\Delta C = C^t - C^{t-1} = (\Delta b + \Delta d + \Delta f + \Delta h + \Delta G) + (\Delta b + \Delta d + \Delta q + \Delta r + \Delta s + \Delta P) + (\Delta m + \Delta n + \Delta u + \Delta P) \quad (7)$$

where Δb was the fossil energy carbon emission coefficient influence, Δd was the fossil energy structure influence, Δf was the industrial energy intensity influence, Δh was the industrial structure influence, ΔG was the economic scale influence, Δq was the residential energy intensity influence, Δr was the per capita consumption level influence, Δs was the population structure influence, Δm was the cement carbon emission coefficient influence, Δn was the cement production intensity influence, Δu was the industrial sector per capita output value influence, and ΔP was the population scale influence. Since the cement emission factor is constant, the contribution of Δm is zero. The carbon emission influence of each variable can be calculated by Equation (8).

$$\Delta C_x = \sum_{ES,j} \frac{C^t_{ES,j} \times C^{t-1}_{ES,j}}{\ln\left(C^t_{ES,j}\right) - \ln\left(C^{t-1}_{ES,j}\right)} \times \ln\left(\frac{x^t}{x^{t-1}}\right) \quad (8)$$

where x was any of the 11 influences, we introduced the relative contribution degree δ to represent the proportion of the influence of a specific impact factor at a certain stage in the total influence of all impact factors at that stage. The calculation method is shown in Equation (9).

$$\delta = \frac{\Delta C_x}{\left|\sum_x \Delta C_x\right|} \quad (9)$$

where, if $\delta > 0$, the factor had a positive impact on carbon emissions; otherwise, if $\delta < 0$, the factor had an adverse effect, with the absolute value of δ reflecting the degree of contribution.

2.4. Construction of Carbon Emission System Dynamics Model

2.4.1. System Boundary and Research Hypothesis

System dynamics (SD) possesses inherent advantages in addressing complex nonlinear problems. Combining system dynamics and scenario analysis methods can dynamically simulate future trends. The study took the administrative boundary of Guizhou province as the spatial boundary of the system, and we used the overall interaction of the influencing factors obtained through the LMDI model decomposition as the system's behavioral boundary. The time span of analysis was set as 2005–2040, with forecast years ranging from 2021 to 2040, and the model was run using a time step of 1 year for the simulation.

2.4.2. Subsystem Division and System Model Establishment

Based on the decomposition results of the LMDI model, the carbon emission system in Guizhou Province was divided into four subsystems: population, economy, energy, and environment. By analyzing the interaction between variables, we have successfully established a CO_2 emission system for Guizhou province using the Vensim PLE software. Figure 1 displays the stock-flow diagram.

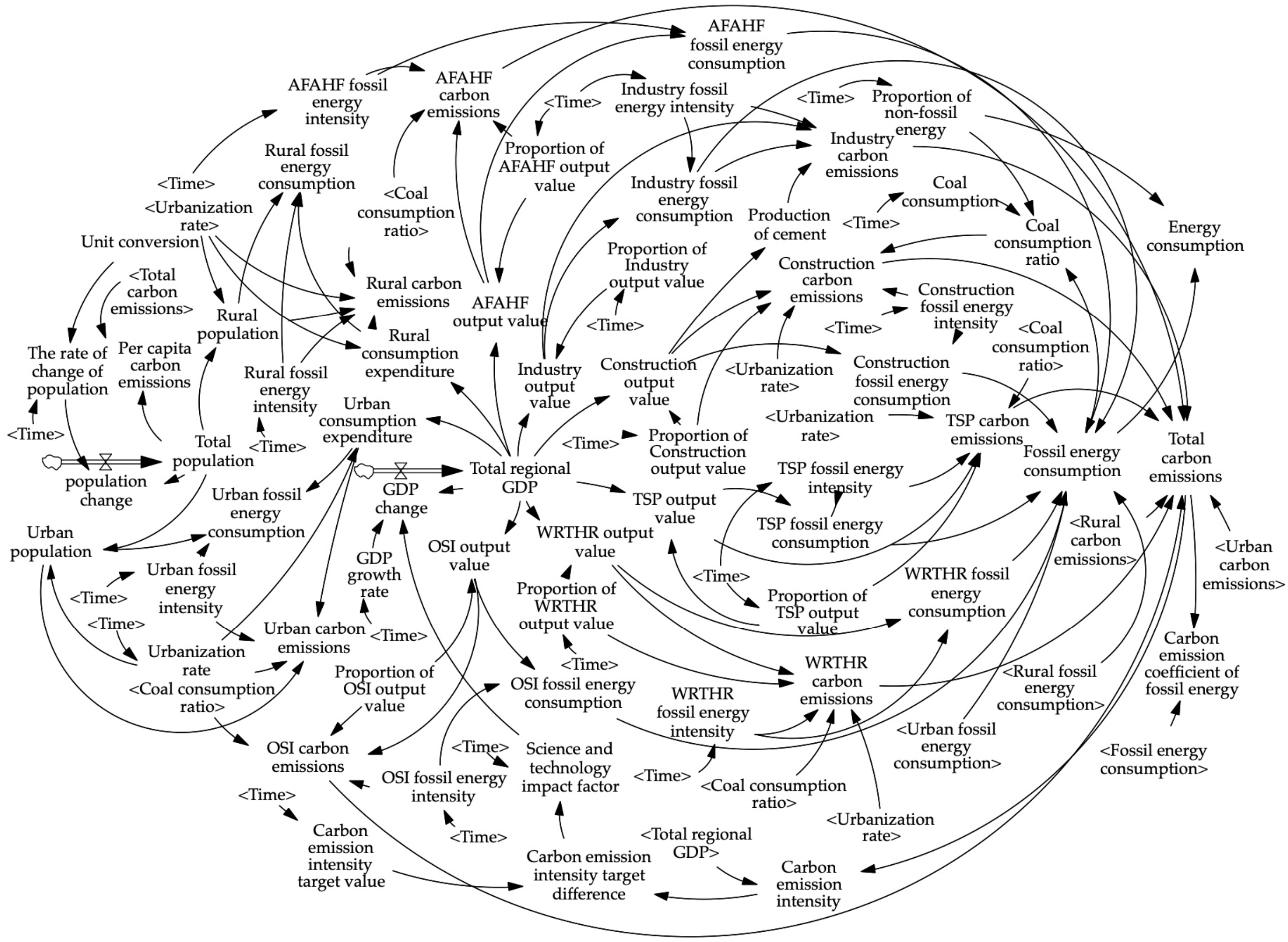


Figure 1. Stock-flow diagram of the carbon emission system.

The population subsystem primarily influenced the other three subsystems through the total population, household consumption expenditure, and urbanization. As urbanization levels increased, residential consumption expenditure and carbon emissions tended to change. The intensity of fossil energy, residential consumption expenditure, and population size determined the amount of residential energy consumption, affecting the total carbon emissions. The economic subsystem mainly influenced the other three through total regional GDP and industrial structure. Changes in GDP played a significant role in influencing consumption expenditure levels, while GDP growth was closely linked to the development and use of fossil energy. Industrial structure changes directly affected fossil energy utilization across different industrial sectors, influencing the environmental subsystem. The energy subsystem is the core system that influences carbon emissions, and most carbon emissions from human activities come from fossil fuel combustion [42]. By improving technology, decreasing the intensity of fossil fuel usage and increasing the percentage of non-fossil energy sources could lead to lowered fossil fuel consumption and optimized energy consumption structure, ultimately affecting carbon emissions in Guizhou Province. The environmental subsystem included carbon emissions from energy consumption and cement production, influencing carbon emission intensity and the total regional GDP.

The relationship functions among the variables were constructed by employing the direct assignment method, regression analysis method, mean value method, ratio analysis method, and table function method. Table 2 lists the relationship equations between some critical variables.

Table 2. The specific relationship equations between variables.

Variables	Equation
Total carbon emissions	TSP carbon emissions + OSI carbon emissions + Rural carbon emissions + AFAHF carbon emissions + Urban carbon emissions + Industry carbon emissions + Construction carbon emissions + WRTHR carbon emissions
AFAHF carbon emissions	EXP (LN (Coal consumption ratio × 100) × (−0.365647) + LN (AFAHF fossil energy intensity) × 0.955531 + LN (AFAHF output value) × 0.50745 + LN (Proportion of AFAHF output value) × (−0.174425) + 5.15538)
Construction carbon emissions	EXP (LN (Coal consumption ratio × 100) × 0.502325 + LN (Construction fossil energy intensity) × 1.11191 + LN (Construction output value) × 0.59081 + LN (Proportion of Construction output value) × 0.33328 + LN (Urbanization rate × 100) × 1.08194 − 1.82582)
Industry carbon emissions	EXP (LN (Industry fossil energy intensity) × 0.0237222 + 0.0136943 × LN (Industry output value) +0.0552457 × LN (Production of cement) +0.00684715 × LN (Industry output value × Industry output value) + 0.894751 × LN (Industry fossil energy consumption) + 1.25979)
OSI carbon emissions	EXP (LN (Coal consumption ratio × 100) × 0.649347 + LN (OSI fossil energy intensity) × 1.02937 + LN (OSI output value) × 1.02964 + LN (Proportion of OSI output value) × 0.262082 − 1.76103)
Rural carbon emissions	EXP (LN (Coal consumption ratio × 100) × 0.234948 + 1.01362 × LN (Rural fossil energy intensity × 100) +LN (Rural consumption expenditure) × 1.10321 + 0.292281 × LN ((1 − Urbanization rate) × 100) + LN (Rural population) × 0.77769−14.1891)
TSP carbon emissions	EXP (LN (Coal consumption ratio × 100) × 0.154314 + LN (TSP fossil energy intensity) × 1.02946 + LN (TSP output value) × 1.12309 + LN (Proportion of TSP output value) × (−0.279472) + LN (Urbanization rate × 100) × (−0.212805) − 0.633044)
Urban carbon emissions	EXP (LN (Urban consumption expenditure) × 0.844486 + LN (Urbanization rate × 100) × 0.470785 + LN (Urban population) × 0.22218 + LN (Urban fossil energy intensity) × 1.01239 − 3.05799)
WRTHR carbon emissions	EXP (LN (Coal consumption ratio × 100) × (0.497733) + LN (WRTHR fossil energy intensity) × 1.06022 + LN (WRTHR output value) × 0.410425 + LN (WRTHR output value × WRTHR output value) × 0.205212 + LN (Proportion of WRTHR output value) × 0.553747 + (Urbanization rate × 100) × 0.0119902 + 0.690354)
Rural consumption expenditure	EXP (−0.692313 × LN (Urbanization rate) + LN (Total regional GDP) × 0.543471 + 2.24237)
Urban consumption expenditure	EXP (−0.29377 × LN (Urbanization rate) + 0.372021 × LN (Total regional GDP) + 5.43239)
Production of cement	1.024/(1 + 19.531 × EXP (−9.754 × Construction output value/866.365)) × 10820.9
Proportion of non-fossil energy	IF THEN ELSE (Time < 2021, -8×10^{-6} × (Time-2004) × (Time-2004) × (Time-2004) × (Time-2004) + 0.0003 × (Time-2004) × (Time-2004) × (Time-2004) − 0.0035 × (Time-2004) × (Time-2004) + 0.0187 × (Time-2004) + 0.0861, 0.0002 × (Time-2004) × (Time-2004) + 0.0007 × (Time-2004) + 0.1125)

2.4.3. Validity Test of SD Model

Historical data testing and sensitivity analysis are essential evaluation methods to validate the SD model. Generally, a model has good prediction accuracy and can be used for simulation and model tuning when the simulation results compared with the historical data have an error of no more than 15%. The model test years were from 2005 to 2020. Following persistent debugging of the model, the relative discrepancy between the simulation outcomes and historical data did not exceed 9%, so the model passed the historical data test and can accurately simulate the future carbon emission trend of Guizhou province.

Sensitivity analysis examines the impact of important parameters on system output results by varying the magnitude of their values [43]. In general, the greater the system's sensitivity to the parameter, the more likely the parameter is the critical factor influencing the system. The study selected six parameters: urbanization rate, GDP growth rate, energy intensity, non-fossil energy proportion, industrial structure, and coal consumption, to test the sensitivity of the system variables. The absolute values of the sensitivity of the model parameters range from 0% to 13.51%, indicating that the model was robust and sensitive. At the same time, there was no over-sensitivity observed. Therefore, the model passed the sensitivity test.

2.5. Scenario Settings

By setting different scenarios, using a system dynamics model can further test the influence of relevant factors' changes on carbon emission reduction. This paper combined LMDI decomposition results and SD model sensitivity analysis while also considering the structural characteristics of the system dynamics model to select the regulatory variables for scenario analysis. These variables were the average annual GDP growth rate, the proportion of tertiary industry output value, and the cumulative decline in fossil energy intensity.

2.5.1. Variable Assumptions

We assumed two scenarios for three variables. Table 3 displays the assumptions made for specific variables. The first variable was the average annual GDP growth rate. We assumed that under the baseline scenario, the average annual GDP growth rate was set at 7% during 2021–2025 with reference to the Guizhou Province's 14th Five-Year Plan. Then the average annual growth rate gradually slowed down over time, which was consistent with the actual economic development of Guizhou Province, and the variable was at a high level of development in this scenario. Under the scenario of emission reduction measures, we assumed that Guizhou Province focused on high-quality economic development and avoided the crude economic development model, and the economic growth rate slowed down. From 2021 to 2025, the average annual GDP growth rate maintained the growth rate of the last five years, which was set at 5.69%, then decreased year by year, and the variable under this scenario was at a medium level of development.

The second variable was the proportion of tertiary industry output value. In the baseline scenario, we assumed that Guizhou Province gradually increased the importance of the tertiary sector's development in accelerating economic restructuring. Still, this transformation took time, so the proportion of tertiary industry output value was expected to increase slowly. At that time, according to the curve-fitting prediction, it was set that the proportion of tertiary industry output value reached 48.37%, 48.84%, 49.23%, and 49.56% in 2025, 2030, 2035, and 2040, respectively, and the variable was at a medium level of development under this scenario. Under the scenario of emission reduction measures, Guizhou Province accelerated the development of the tertiary sector, especially the development of the service industry and the enhancement of technological innovation capacity, to promote the optimization, transformation, and upgrading of the economic structure. It was promoting emission reduction measures provided good opportunities for the development of the tertiary sector, which was expected to increase its share of output value gradually. The proportion of tertiary industry output value in 2025, 2030, 2035, and 2040 was set to be 49.02%, 51.35%, 54.51%, and 57.86%, respectively, and the variable was at a high development level in this scenario.

The third variable was the cumulative decline in fossil energy intensity. Under the baseline scenario, with reference to the Guizhou "14th Five-Year Plan" Comprehensive

Work Program for Energy Conservation and Emission Reduction, the cumulative decline in fossil energy intensity was set to be 13% from 2021 to 2025, and considering the gradual improvement of environmental protection requirements, it increased year by year. The variable under this scenario was at a medium development level. Under the emission reduction measures scenario, to cope with climate change and environmental pollution, we assumed that Guizhou Province would accelerate the reduction of fossil energy intensity and improve the efficiency of energy utilization, and the reduction rate of fossil energy intensity was expected to increase year by year under the impetus of emission reduction measures. The cumulative decline in fossil energy intensity from 2020 to 2040 was set to be 15%, 17%, 19%, and 21%, respectively, and the variables in this scenario were at a high level of development.

Table 3. Variables assumptions.

Regulatory Variables	Years	Average Annual GDP Growth Rate	The Proportion of Tertiary Industry Output Value	Cumulative Decline in Fossil Energy Intensity
High	2021–2025	7.00%	49.02%	15%
	2026–2030	6.00%	51.35%	17%
	2031–2035	5.00%	54.51%	19%
	2036–2040	4.50%	57.86%	21%
Medium	2021–2025	5.69%	48.37%	13%
	2026–2030	5.29%	48.84%	15%
	2031–2035	4.49%	49.23%	17%
	2036–2040	3.99%	49.56%	19%

2.5.2. Scenario Assumptions

Three variables, with six states, were set to the following eight scenarios. Table 4 displays the simulation assumptions.

1. Baseline Scenario (Scenario I) assumed a continuation of the current development trend without implementing additional mitigation measures. The average annual GDP growth rate was set at a high level of development. The proportion of tertiary industry output value and the cumulative decline in fossil energy intensity was set at a medium level of development, which provided a reference for setting the other scenarios.
2. High-quality Economic Development Scenario (Scenario II) assumed that economic development was able to avoid "high consumption" and "high emissions" and focus on high-quality economic development and that the average annual GDP growth rate slowed down to a medium development level. Other indicators were consistent with the baseline scenario.
3. Industrial Structure Optimization Scenario (Scenario III) assumed that Guizhou Province would accelerate the transformation from a "2-3-1" industrial structure, where the secondary sector dominated, to a "3-2-1" structure, where the tertiary sector took the lead, aiming to achieve a reduction in carbon emissions by adjusting the ratio of outputs in Guizhou Province. The proportion of tertiary industry output value was set to be at a high level of development, and other indicators were consistent with the baseline scenario.
4. Fossil Energy Intensity Adjustment Scenario (Scenario IV) assumed that Guizhou Province accelerated the formation of an energy-efficient society and consumed the same amount of fossil energy to generate more GDP than in the baseline scenario. This scenario aimed to reduce carbon emissions by adjusting the cumulative decline in fossil energy intensity in eight sectors, setting it at a high level of development while keeping the other indicators consistent with the baseline scenario.
5. Take Any Two Measures Combination Scenario (Scenarios V, VI, and VII) assumed that the average annual GDP growth rate slowed down under Scenario V while

accelerating the increase in the proportion of tertiary industry output value. Under Scenario VI, the average annual GDP growth rate slowed while the cumulative decline in fossil energy intensity increased. Under Scenario VII, the increase in the proportion of tertiary industry output value accelerated while increasing the cumulative decline in fossil energy intensity.

6. The Combined Scenario (Scenario VIII) assumed that the government took three measures simultaneously to achieve carbon emission reductions. Specifically, this included maintaining the current GDP growth rate while emphasizing high-quality economic development, accelerating the development of the tertiary sector, optimizing the industrial structure, reducing fossil energy intensity, and improving energy use efficiency. The average annual GDP growth rate was set at a medium development level, and the proportion of tertiary industry output value and cumulative decline in fossil energy intensity was set to be at a high development level.

Table 4. Scenario assumptions.

Scenario	Average Annual GDP Growth Rate	The Proportion of Tertiary Industry Output Value	Cumulative Decline in Fossil Energy Intensity
Scenario I	High	Medium	Medium
Scenario II	Medium	Medium	Medium
Scenario III	High	High	Medium
Scenario IV	High	Medium	High
Scenario V	Medium	High	Medium
Scenario VI	Medium	Medium	High
Scenario VII	High	High	High
Scenario VIII	Medium	High	High

2.6. Tapio Decoupling Index

The Tapio decoupling model is an extension of the model proposed by the Organization for Economic Cooperation and Development (OECD). The decoupling index constructed by Tapio can describe the status of the association between economic growth and carbon emissions. The calculation method is shown in Equation (10).

$$\varepsilon = \frac{(\Delta C/C_0)}{(\Delta G/G_0)} \tag{10}$$

where $\Delta C/C_0$ was the carbon emission growth rate, $\Delta G/G_0$ was the GDP growth rate. The ε was the decoupling index and the decoupling index status classification criterion is shown in Figure 2 [44].

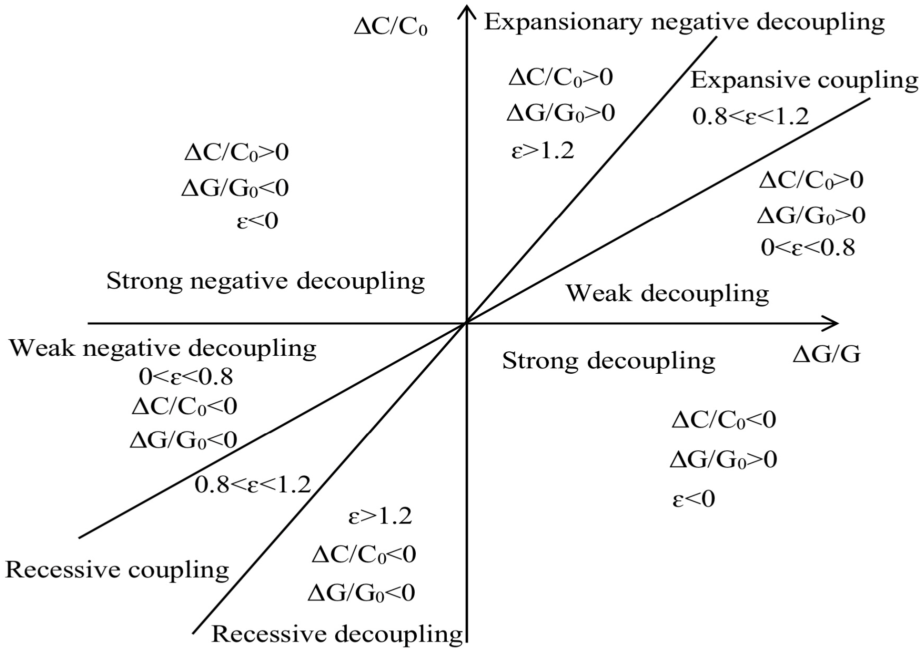


Figure 2. Decoupling index status classification and evaluation criterion.

2.7. Data Source

Considering the data's reliability and accessibility, the study selected 2005–2020 as the study interval and 2021–2040 as the forecast interval. To conduct price deflation on the price-related data using constant prices based on the year 2004 to eliminate the impact of inflation. The energy consumption and standard coal coefficients for the industrial and residential sectors were determined by consulting the China Energy Statistical Yearbook. Cement production, regional GDP, per capita consumption level, consumer price index, regional GDP index, and population numbers were obtained from the annual data of Guizhou Province from China's National Bureau of Statistics.

3. Results

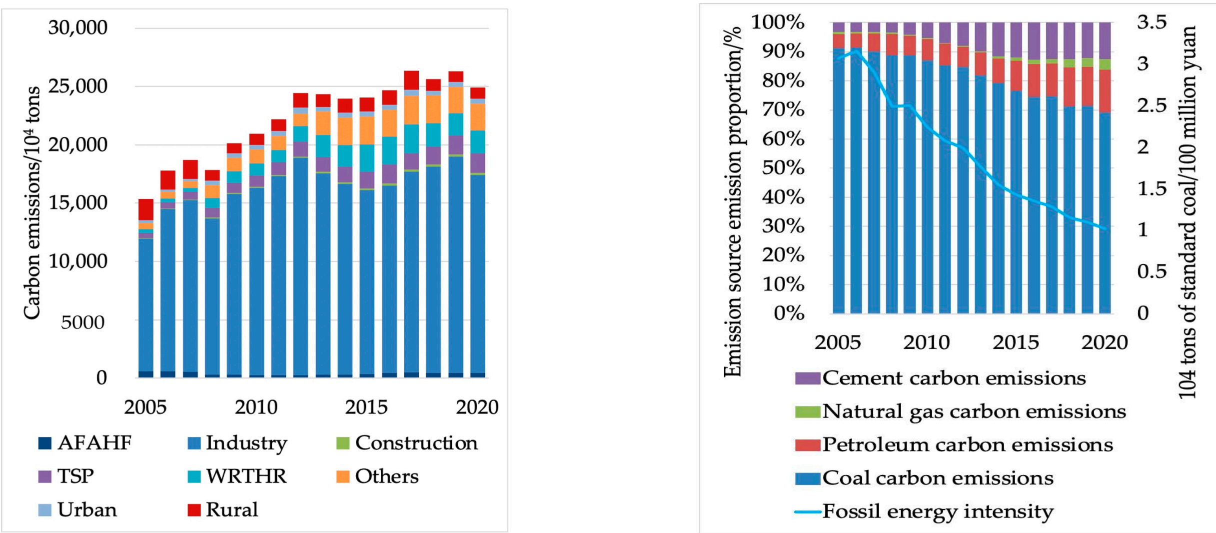
3.1. Analysis of Carbon Emission Trend and Historical Decoupling Status

3.1.1. Carbon Emissions Trend Analysis

The carbon emission status of Guizhou Province from 2005 to 2020 is shown in Figure 3. Generally, carbon emissions in Guizhou province have been rising since 2005, with a faster growth rate from 2005 to 2012 and a slower growth rate after that, but still no downward trend. At that time, carbon dioxide was mainly emitted through coal consumption, but the proportion of carbon emissions from petroleum and natural gas gradually increased. This indicated that the energy consumption structure of Guizhou Province had been gradually improving.

In terms of carbon emission sectors, the industrial structure of Guizhou province was dominated by the secondary sector from 2005 to 2020. The industry has consistently ranked first in carbon emissions since 2005, accounting for 78.68% of 2007 and 62.71% in 2020. Therefore, this industry is crucial for Guizhou Province to achieve low carbon transformation. Over the study period, it became clear that CO_2 emissions from various tertiary industry sectors, including transportation, storage and post, wholesale, retail trade, hotel, restaurants, and other service industries, rapidly increased due to the rising share of tertiary industry output value. In addition, despite the continuous improvement in urbanization and living standards in Guizhou province, the carbon emission proportion of urban residents' lifestyles remained low and unchanged due to the ongoing reduction in energy intensity, resulting in limited room for carbon reduction. Furthermore, the rural sector's carbon emissions have also been on a downward trend due to the decreasing population, improving energy structure, and decreasing energy intensity.

Even though the fossil energy intensity in Guizhou Province was declining, most sectors still heavily relied on coal, resulting in a continuous increase in carbon emissions. Economic growth accompanied by massive CO_2 emissions makes it challenging to achieve decarbonization, and the current carbon emission situation is far from optimistic. Therefore, it is imperative to promptly explore effective carbon emission reduction strategies to advance the national "dual carbon" goal and enable Guizhou Province to achieve a carbon emission peak as soon as possible.



(**a**) (**b**)

Figure 3. Carbon emission status of Guizhou province from 2005 to 2020: (**a**) Carbon emissions in various sectors; (**b**) Carbon emission proportion and energy intensity, illustrating the relative contributions of carbon emissions from coal, petroleum, natural gas, and cement production.

3.1.2. Historical Decoupling Status Analysis

The decoupling status of various sectors in Guizhou Province from 2005 to 2020 is shown in Table 5. Overall, the decoupling index of economic growth and carbon emissions was getting smaller and smaller. This phenomenon indicated that the green development model is gradually gaining importance as society develops. However, a strong decoupling of these two variables was not achieved during the study period. This illustrated the continued dependence of economic growth on fossil energy consumption. In terms of sectoral classification, the decoupling index gradually decreased in all sectors except agriculture, forestry, animal husbandry, and fishery, as well as industry. Especially in the wholesale, retail trade, hotel, restaurants, and other service industries, they achieved strong decoupling during the study period. Since the industrial sector plays a critical role in reducing carbon emissions, it should strive to achieve decoupling of economic growth and carbon emissions at the earliest.

Table 5. Decoupling of historical relationships.

Sector	2005–2010		2010–2015		2015–2020	
	ε	Decoupling State	ε	Decoupling State	ε	Decoupling State
Total carbon emissions	0.45	WD	0.19	WD	0.07	WD
AFAHF	−2.14	SD	0.70	WD	0.72	WD
Industry	0.51	WD	−0.02	SD	0.17	WD

Table 5. *Cont.*

Sector	2005–2010		2010–2015		2015–2020	
	ε	Decoupling State	ε	Decoupling State	ε	Decoupling State
Construction	2.09	END	0.37	WD	0.25	WD
TSP	1.18	EC	0.64	WD	0.25	WD
WRTHR	1.90	END	1.61	END	−0.29	SD
OSI	1.07	EC	1.31	END	−0.08	SD

Note: The WD was the weak decoupling, the SD was the strong decoupling, the END was the expansionary negative decoupling, and the EC was the expansive coupling.

3.2. LMDI Factor Decomposition Results Analysis

The LMDI decomposition findings are illustrated in Figure 4. The research indicated two key factors contribute to the growth of carbon emissions in Guizhou Province: economic scale and fossil energy intensity in industrial sectors. The dominant factor that curbed carbon emissions growth was the intensity of fossil energy usage, while the chief driver behind their growth was the economic scale. They were also pivotal in designing carbon emission reduction paths. Therefore, in formulating policies to reduce carbon emissions, it is crucial to focus on promoting clean energy, optimizing industrial production processes, and improving energy efficiency. These measures aim to achieve an effective reduction in carbon emissions. In addition, the per capita output value of the industrial sector promoted the growth of carbon emissions in Guizhou Province. In contrast, cement production intensity, fossil energy structure, energy carbon emission coefficients, and industrial structure inhibited carbon emissions.

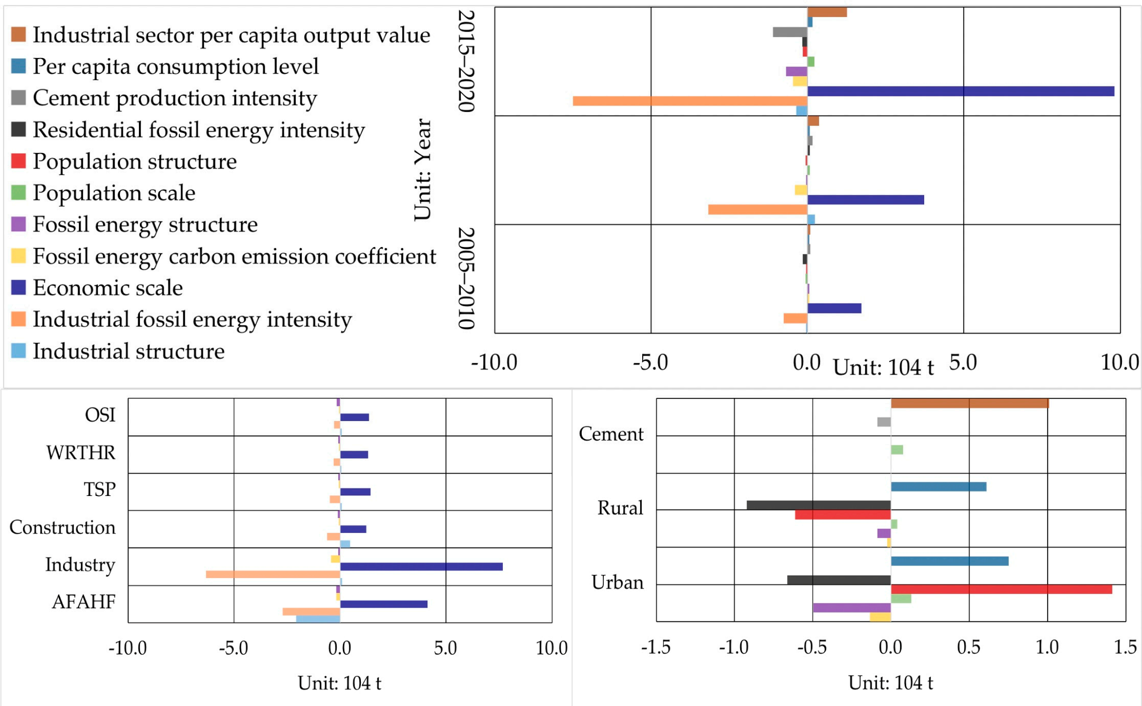


Figure 4. The contribution of influencing factors.

Looking at it from an industrial sector perspective, the economic scale and the fossil energy intensity of the industrial sector were the most significant influencing factors. Different industrial sectors were affected differently by the industrial structure. It promoted carbon emissions in other sectors except for the primary industrial output value. This is because the share of the output value of the primary industry in Guizhou province continues to decline while secondary and tertiary industries flourish. In terms of residential sectors, the three main factors influencing carbon emissions were per capita consumption level, the fossil energy intensity of residential sectors, and population structure. Per capita consumption level led to increased carbon emissions, whereas residential sectors' energy intensity helped reduce them. In addition, the population structure was also a critical contributing factor, which promoted carbon emissions from urban residents and suppressed carbon emissions from rural residents, a phenomenon consistent with the characteristics of urban-rural population mobility in Guizhou Province.

3.3. Simulation Analysis

Eight scenarios were simulated separately using the debugged model. The simulation results are shown in Figure 5.

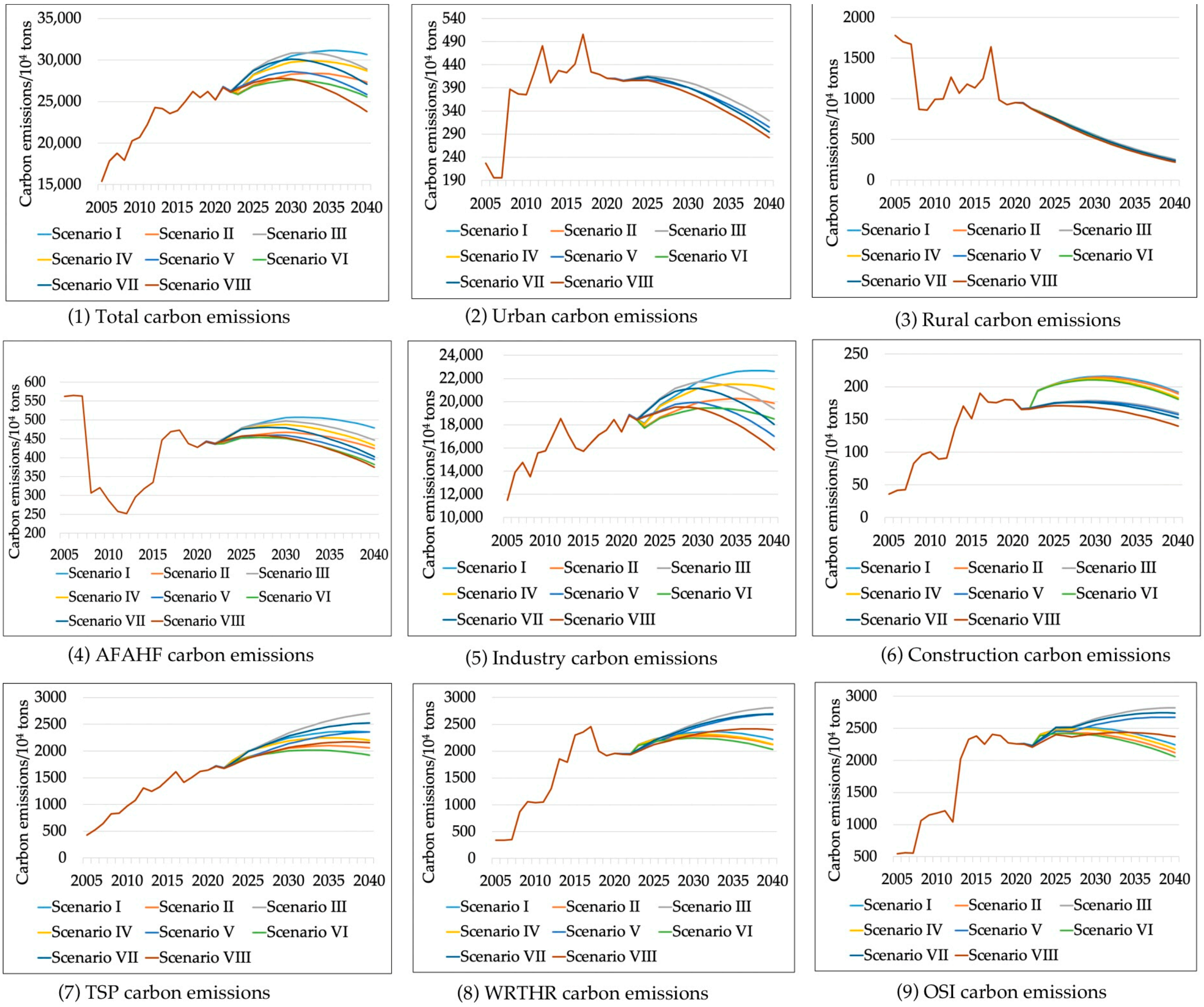


Figure 5. Trend prediction of carbon emission scenarios under eight scenarios.

3.3.1. Baseline Scenario

In this scenario, it was predicted that Guizhou Province would attain its highest level of carbon emissions among all eight scenarios, reaching a peak of 311.48 million tons in 2035. From the perspective of emission sectors, the industry remained the main contributor to carbon emissions. Industry, transport, storage, and post peaked in 2038, with 226.89 million tons and 23.66 million tons, respectively. Construction reached its peak of 2.16 million tons in 2031. Projections indicated that most sectors would not reach their peak emissions before 2030. Overall, under the scenario, this was disadvantageous to attaining Guizhou Province's carbon emission reduction goals, and carbon emission pressure was expected to continue increasing.

3.3.2. High-Quality Economic Development Scenario

The scenario reached a peak of 283.94 million tons in 2033. Compared with the baseline scenario, the peak was achieved two years in advance and reduced by 8.84 %. In terms of emission sectors, apart from the construction sector, the rest of the sectors had a significant influence in reducing carbon emissions, particularly the transport, storage, and post and industry sectors, which saw reductions of 8.25% and 7.74%, respectively, compared to the base scenario, and both reached their peaks in 2035. The peak for other service industries occurred in 2027, reaching 24.30 million tons, two years earlier than the baseline scenario. This indicated that carbon emissions in most sectors were more sensitive to adjusting the economic growth rate. Therefore, increased economic growth would result in higher carbon emissions, aligning with the LMDI model's decomposition analysis findings. Therefore, promoting high-quality economic development without sacrificing the environment was conducive to reducing carbon emissions.

3.3.3. Industrial Structure Optimization Scenario

Under this scenario, it was predicted that the peak carbon emissions of 30.88 million tons would be reached in 2032, years ahead of the baseline scenario, but with just a 0.85% reduction from the peak value. After reaching its peak, the rapid decrease in carbon emissions in Guizhou Province suggests that efforts to optimize the industrial structure could have helped the province achieve its carbon emission peak earlier. However, it is important to note that the initial decrease in emissions was relatively small. In terms of emission sectors, the industry was expected to peak in 2030, eight years ahead of the baseline scenario. In contrast, this measure led to an increase in carbon emissions from the tertiary sector, making it challenging for the industry to reach its peak by 2040. However, due to the relatively small contribution of the tertiary sector to carbon emissions, the general reduction in carbon emissions during the later period was more significant than that of the baseline scenario. Therefore, on the whole, industrial structure optimization helped achieve long-term carbon emission reduction goals.

3.3.4. Fossil Energy Intensity Adjustment Scenario

Under this scenario, it was predicted that carbon emissions would peak at 298.93 million tons in 2033, two years earlier than the baseline scenario, resulting in a reduction of 4.03% compared to the peak value. When examining the emissions sector, the decline in fossil energy intensity had an inhibitory influence on carbon emissions across all sectors, consistent with the conclusions drawn from the decomposition analysis of the LMDI model. Among them, the reductions in agriculture, forestry, animal husbandry, and fishery and urban residents showed more significant decreases, with an average decline of 4.28% and 3.07% during the forecast period compared to the baseline scenario. The industry and the transport, storage, and post peaked in 2035 at 215.05 million tons and 22.47 million tons, respectively. On the other hand, the wholesale, retail trade, hotel, and restaurants peaked in 2017 at 24.60 million tons, and other service industries peaked at 24.89 million tons in 2028.

3.3.5. Take Any Two Measures Scenario

Under Scenario V, Scenario VI, and Scenario VII, carbon emissions were projected to peak in 2030 at 286.23 million tons, 276.10 million tons, and 301.07 million tons, respectively. The respective reductions compared to the baseline scenario were 8.11%, 11.36%, and 3.34%, which indicated that the combined effect of two measures on emission reduction was more significant than that of a single measure. Among them, adjustments to the

GDP growth rate and the intensity of fossil energy had demonstrated a more significant influence on emission reduction. In terms of emission sectors, except for the tertiary sector, the impact of carbon emission reduction in other sectors was more significant than in single measures. In the combined scenario of industrial structure optimization and any other single measure, carbon emissions in the tertiary sector were projected to increase faster than in the baseline scenario but slower than in the industrial structure optimization scenario. This indicated that any other measure could offset the negative influence of industrial structure optimization on tertiary sector carbon emissions. Furthermore, it emphasizes the significance of implementing overlapping measures to achieve carbon emission reduction goals.

3.3.6. The Combined Scenarios

Under this scenario, carbon emissions were predicted to peak at 277.71 million tons in 2029, six years ahead of the baseline scenario, resulting in a 10.84% reduction in peak emissions. From the carbon emission sector perspective, all other sectors exhibited the lowest emission levels except for the tertiary sector. Furthermore, except for transport, storage, and post and other service industries, all other sectors were projected to reach their carbon emission peaks before 2030. Among them, the industry sector with the highest carbon emission contribution peaked in 2027, 11 years earlier than the baseline scenario, resulting in 195.45 million tons of carbon emissions and a reduction of 13.86%. In the combined scenario, although the carbon emissions of the tertiary sector were not at the lowest level, the overall decline rate of carbon emissions was still faster than in other scenarios due to the significant proportion of industrial carbon emissions, surpassing the tertiary sector. Therefore, overall, the combined scenario had the most notable impact on reducing carbon emissions, facilitating Guizhou Province to reach its peak emissions as soon as possible.

3.4. Analysis of Decoupling States under Eight Scenarios

The primary driver of carbon emissions in Guizhou Province is economic growth. A strong decoupling relationship between economic growth and carbon emissions has yet to be established. Therefore, early conversion to achieving strong decoupling becomes pivotal in attaining coordinated development between the economy and low-carbon. Consequently, conducting a comprehensive examination of the decoupling status between economic growth and carbon emissions under different scenarios can test measures to achieve strong decoupling as soon as possible.

The decoupling index results under eight scenarios are shown in Figure 6. When the GDP change is positive, if $0 < \varepsilon < 0.8$, it shows a weak decoupling state; if it is less than 0, it shows a strong decoupling state [44]. In the baseline scenario, a shift from weak to strong decoupling between economic growth and carbon emissions was projected to occur during 2036–2038, and the decoupling index would slowly decrease. In taking a single measure, the strong decoupling between economic growth and carbon emissions would be achieved between 2032 and 2034, indicating that any single measure could promote the early achievement of strong decoupling. Notably, industrial structure optimization exerted the most significant influence. In scenarios combining any two measures, three scenarios would achieve strong decoupling between 2030 and 2032, which was more evident than any single measure. Furthermore, implementing three emissions reduction measures led to a shift from weak to strong decoupling between 2028 and 2030, demonstrating the earliest achievement of strong decoupling and the fastest decline in the decoupling index. This indicated that the time required for strong decoupling between the variables progressively reduced with each additional emission reduction measure introduced.

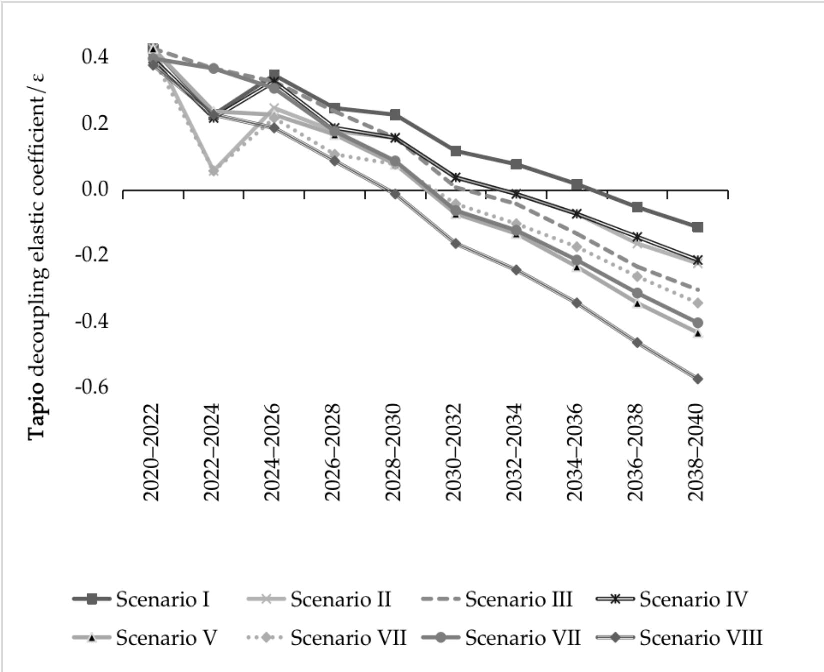


Figure 6. Prediction decoupling between economic growth and carbon emission.

When the above evidence is combined, it is discovered that each emission reduction measure can effectively reduce carbon emissions in Guizhou Province compared to the baseline scenario. Moreover, combining any two measures was more effective than a single measure. Nevertheless, it was difficult to achieve the peak before 2030, and the strong decoupling could only be achieved after 2030, which was not conducive to China's "3060" dual carbon goal. However, only in the combined scenario, where all three emission reduction measures were taken simultaneously, could Guizhou Province achieve the emission peak by 2030. A strong decoupling between economic growth and carbon emissions would be realized during the period spanning from 2028 to 2030. This scenario's carbon emission intensity and fossil energy consumption were all at low levels. In conclusion, the combination scenario with multiple emission reduction measures emerged as the most influential approach for curbing carbon emissions in Guizhou Province, providing an effective path towards achieving significant reduction.

4. Discussion and Policy Recommendations

4.1. Policy Recommendations

Based on the research, Guizhou Province can effectively achieve its carbon reduction goals by simultaneously implementing measures of high-quality economic development, industrial structure optimization, and energy intensity reduction. First, under the high-quality economic development scenario, carbon emissions peaked two years earlier than the baseline scenario, with a peak decline of 8.84%. Therefore, abandoning the unsustainable traditional growth model, transforming the economic growth model, and promoting high-quality economic development are crucial measures to curb carbon emissions in Guizhou Province. Second, under the industrial structure optimization scenario, carbon emissions peaked three years earlier than the baseline scenario. This indicates that substantial reductions in carbon emissions can be achieved by promoting industrial upgrading. Finally, accelerating the decline of fossil energy intensity had an emission reduction influence on all sectors. Consequently, enhancing the efficiency of fossil energy consumption, reducing the intensity of fossil energy, fostering the development of high-tech industries, and accelerating efforts to build an energy-saving society will aid in the earlier attainment of the carbon emission reduction goal.

4.2. Limitations

The following three aspects can be used to widen the scope of the study: First, the study only considers two emission sources. However, more emission sources, such as agriculture and waste disposal, can be considered when data is available. At the same time, carbon emission absorption can also be considered. Second, the model construction is constructed primarily on assumptions. Because of the different boundary settings, the prediction results will vary. As a result, it is difficult to compute an accurate value; more is to test the influence of carbon emission reduction measures. In the future, with more time, we can increase the model variables and expand the model boundaries to simulate reality more accurately and assist policymakers in making more reliable policy recommendations. Third, this research only constructs the model using provincial regions as the research object. In the future, the model has the potential to be applied to other areas of carbon emission reduction research.

5. Conclusions

This study takes Guizhou province, a less developed region in southwest China, as a representative case study to conduct a more comprehensive analysis of the carbon emission reduction path at the provincial level. The goal is to tackle the provincial carbon emission reduction challenge by merging three models of the LMDI, SD, and Tapio decoupling model. The LMDI model assists policymakers in understanding the key factors influencing carbon emissions. Based on this, a system dynamics model is constructed, and different scenarios are set to assess the future carbon emission trends under various emission reduction measures. Additionally, the Tapio decoupling index tests which scenario can achieve a strong decoupling relationship between economic growth and carbon emissions as early as possible to support policymakers in making decisions. The findings demonstrate that, firstly, carbon emissions in Guizhou province increased from 2005 to 2020, with the industrial sector contributing the most carbon emissions. Although the decoupling index is declining, it is still in a weak decoupling state. Secondly, economic scale and industrial fossil energy intensity are the primary driving and hindering factors in Guizhou Province's carbon emissions, respectively. Finally, only a combination of three measures simultaneously can Guizhou Province reach the peak carbon emission of 277.71 million tons in 2029, and a strong decoupling of economic growth and carbon emissions can be achieved early. This research framework also applies to studying other regions' carbon reduction issues.

Author Contributions: Conceptualization, H.W.; project administration, H.W.; funding acquisition, H.W.; investigation, W.X.; resources, W.X.; methodology, W.X.; writing—original draft, W.X.; validation, W.X.; writing—review & editing, W.X.; data curation, W.X.; visualization W.X.; Supervision, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Humanities and Social Sciences of Ministry of Education Planning Fund of China, grant number 22YJA630096.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data can be found here: http://stjj.guizhou.gov.cn/, https://data.stats.gov.cn/, https://data.cnki.net/yearBook (accessed on 1 September 2022).

Acknowledgments: Thanks to the anonymous reviewers and all the editors in the process of revision.

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

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