

Article

Dual Substitution of Rural Energy Structure in China: Its Evolutionary Characteristics and Carbon Decoupling Effects

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Abstract: Accelerating the transformation of the rural energy structure is an indispensable part of energy transformation in developing countries. In this novel study, the transformation effect of China's rural energy structure from 2001 to 2020 was evaluated. Further, this paper also identified the decoupling state between the rural energy structure transition and carbon emissions, and decomposed the spatial-temporal effects of rural carbon decoupling through efficiency measures. According to the survey, the dual substitution index of the rural energy structure in China increased from 0.466 to 1.828, and showed a decreasing trend in spatial distribution from the east to the central and western regions. Economic development and climate characteristics have become important influencing factors for the dual substitution of the rural energy structure. The decoupling relationship between the dual substitution of the rural energy structure and carbon emissions was mainly characterized in the strong decoupling, expansion negative decoupling, and strong negative decoupling states. Regional imbalances have deepened as the efficiency of rural energy carbon decoupling has gradually increased. The annual average efficiency of rural energy carbon decoupling in a dynamic perspective has increased by 10.579%, and the dual substitution of the energy structure has a significant driving effect on rural carbon reduction.

Keywords: rural areas; dual substitution of energy structure; carbon decoupling; evolutionary characteristics; energy transformation



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1. Introduction

Energy and environmental sustainability have become major challenges for today's society, and governments are trying to optimize and adjust the intensity of energy consumption and the structure of energy consumption [1]. Under the pressure of global climate change, energy conservation and emission reduction have become a consensus in various countries and regions [2]. Large energy-consuming countries often take accelerating the energy structure transformation as an important starting point of the energy revolution. How to accelerate the transition to a cleaner energy structure has become one of the focus points for realizing low-carbon development as early as possible. In developing countries, there is a close correlation between energy consumption, carbon emissions, and rapid regional economic growth [3,4]. This also requires developing countries to pay more attention to energy conservation and emission reduction while emphasizing economic development. As the world's largest greenhouse gas emitter, China's coal consumption increased by 5.6% in 2023, and the problem of a carbon-heavy energy structure still exists. In particular, coal-heavy energy consumption preferences are not likely to change completely in the short term [5]. Compared to carbon control entities such as cities and industries, energy and carbon emission issues in rural areas also deserve attention. At this stage, China's rural energy consumption structure is gradually diversifying, including coal, electricity, gas, and

biomass energy. As the rural energy structure gradually enters the modern energy stage, renewable energy industries such as wind, solar, and biomass are gradually emerging in rural areas. However, the proportion of primary electricity, natural gas, and renewable energy, and other clean energy consumption in the rural end-use energy consumption structure is still low, and there is an urgent need to build a multi-energy complementary energy supply system. What is the progress of China's rural energy substitution? How effective is the decoupling of carbon in the process of replacing China's rural energy structure? There is still room for research and practical value in exploring these issues.

Attention to energy structure transformation has been more abundant at the urban and regional levels, while less attention has been paid to energy transformation in rural areas. The energy structure refers to the proportional relationship between various energy sources in the production or consumption process. Firstly, there is currently no recognized academic method for measuring the energy structure. The general thinking is mainly from the following perspectives: On the one hand, the energy structure is measured by adopting the proportion of end-use consumption of a certain single fossil energy source [6–8]. On the other hand, the energy structure is measured comprehensively by multiple energy consumption or constructing an energy structure index [9–11]. Secondly, in the evaluation of the energy structure transformation, the effectiveness of the transition, clean energy application, regional differences, and consumption forecasts are often explored [12–14]. Thirdly, in the analysis of the drivers of the energy structure, existing studies have paid attention to the driving effects of industrial transformation, digital facilities, financial openness, and environmental regulation [15–18]. Previous studies have provided a reference for the study of the rural energy structure substitution index. However, it has to be noted that there are significant differences in the transformation of the rural energy structure compared to cities and regions.

Achieving carbon decoupling is one of the important goals for accelerating the transformation of the energy structure. Carbon decoupling usually reflects the relationship between changes in carbon emissions and economic growth, mainly used to measure the regional low-carbon status. The decoupling subject generally refers to the environmental factors wanting to disengage from economic activities [19]. The research on carbon decoupling in regional economic development has always been paid attention to by academics. Zhang and Da used the Logarithmic Mean Divisia Index (LMDI) model to examine the main pathways of carbon decoupling in China, pointing out that, in addition to the impact of economic growth, a decrease in energy intensity and a clean energy structure also have significant impacts [20]. Madaleno and Mouthinho focused on the carbon decoupling efforts of 15 European Union (EU) countries, pointing out that decoupling efforts are not influenced by internal CO₂ driving factors [21]. In addition to carbon decoupling studies at the regional level, carbon decoupling studies involved in industrial development are also relatively abundant, mainly involving industry, manufacturing, transportation, and tourism [22–24]. Obviously, there are fewer studies on carbon decoupling involving rural areas. In particular, the subject of carbon decoupling is not limited to economic behavior, and the scope of carbon decoupling application has been gradually expanded. For example, Li et al. examined the decoupling effect of carbon emissions and the human development index using panel data from 189 countries around the world [25]. Liu et al. examined the decoupling relationship between electricity consumption and carbon emissions and found that the decoupling of electricity consumption in poor areas is better than that in non-poor areas [26].

The literature review shows that previous studies have mostly considered the proportion of single or multiple energy sources in measuring the energy structure, while ignoring the structural relationships between different energy categories. Fossil energy is gradually being replaced by non-fossil energy, and this reality and future trend should also be considered in the measurement of the energy structure [27–29]. Based on the reality of the rural energy transformation, this study attempted to construct a dual substitution index for the rural energy structure. On the one hand, it identified the changing character-

istics of the main energy sources in rural energy structure substitution, and, on the other hand, it explored the carbon decoupling effects in the process of rural energy structure transformation.

Regarding the contributions of this paper, it is mainly reflected in the following three aspects: First, this paper constructed a new rural energy structure substitution index to more accurately characterize the transformation process between rural energy categories. Second, the evolution characteristics of carbon decoupling in the dual substitution of the rural energy structure were revealed, providing valuable references for formulating rural carbon reduction strategies. Third, the carbon decoupling efficiency based on the dual substitution of the rural energy structure was measured, and the contribution factors of the carbon decoupling efficiency from a technical perspective were decomposed.

The remainder of this study is structured as follows: Section 2 explains the research data and measurement methodology. Section 3 demonstrates the evolution of the dual substitution of the rural energy structure and carbon decoupling effects. Section 4 provides further discussion. Section 5 gives the conclusion.

2. Materials and Methods

2.1. Research Subjects and Data Sources

This study identified new trends in rural energy structure by constructing a double substitution index for rural energy structure, and explored the decoupling effect of carbon emissions under the perspective of structural substitution. Since the 21st century, China's rural development has entered a new stage, and the categories of rural energy consumption have become more diversified. Considering the completeness of the data within the study period, we set the period of study for the impact of carbon emissions from changes in the rural energy structure to be from 2000 to 2020. This study involved rural data from 30 Chinese provinces (excluding Hong Kong, Macao, Taiwan, and Tibet) from 2000 to 2020. The data sources mainly include two types: one type is rural energy data, taken from the China Energy Statistical Yearbook [30]; another type is rural economic data, including rural population, total output value of agriculture, forestry, animal husbandry, and fishery, total planting area of crops, and total power of agricultural machinery, taken from the China Rural Statistical Yearbook [31].

2.2. Methodology for Measuring the Dual Substitution Index of Energy Structure

A newly characterized double substitution index for the energy structure was constructed. In contrast to previous studies, we started from the background of rural energy transformation and comprehensively considered the substitution process of rural energy structure. Previous single-structure measurements of the energy structure do not provide a good representation of the process of rural energy modernization [32,33]. Further, we created a comprehensive index of multi-trend energy substitution directions, which systematically considers the degree of substitution of coal and fossil energy by electricity and non-fossil energy, and provides a new interpretation of the transformation process of rural energy structure from the perspective of dual substitution. With the gradual modernization of China's rural areas, the energy consumption pattern of "electricity replacing coal and non-fossil energy replacing fossil energy" is gradually emerging. In order to more closely match the changes in rural energy structure, this article constructed a dual substitution index for rural energy structure based on the characteristics of rural energy structure transformation. The mathematical logic of index construction is as follows: Due to differences in the units of the energy categories involved, this paper converted the various types of energy into standard coal quantities based on the conversion coefficients for each energy category (coefficients factor from China Energy Statistics Yearbook), and unified the energy measurement unit to 10,000 tons of standard coal. E_c , E_p , E_n , and E_f denote rural coal, oil, natural gas, and the remaining fossil energy categories; E_e denotes rural electricity

consumption; E_t denotes total rural energy consumption; and E_m indicates the share of rural fossil energy consumption (Unit: %), set as follows:

$$E_m = \frac{E_c + E_p + E_n + E_f}{E_t} \quad (1)$$

The dual substitution of rural energy structure consists of two main components, one from the rural electricity substitution for coal index (ETC) and the other from the non-fossil energy substitution for fossil energy index (ETM):

$$ETC = E_e/E_c \quad ETM = \frac{1 - E_m}{E_m}, \quad (2)$$

ETC reflects the structural changes in the proportion of electricity consumption to coal consumption; and ETM reflects the structural changes in the proportion of non-fossil energy consumption to fossil energy consumption. Further, a dual substitution index of energy structure was measured based on the geometric mean of the two substitution indices:

$$RDS = \sqrt{ETC \times ETM} = \sqrt{\frac{E_e \times (1 - E_m)}{E_c \times E_m}} \quad (3)$$

In the formula, RDS represents the dual substitution index of rural energy structure. The larger the RDS, the higher the degree of substitution for high-quality energy in rural areas, and the more significant the effect of rural energy structure transformation.

2.3. Energy Structure–Carbon Decoupling Model

Decoupling models have been widely applied to the study of the relationship between economic growth and carbon emissions, but there are few studies based on the decoupling model to investigate the changes between rural energy structure and carbon emissions. On the basis of decoupling theory, the measurement of decoupling coefficient generally comes from the change relationship between two variables. In this study, the decoupling coefficient was expressed as follows:

$$\delta_t = \frac{\Delta RCE_t}{\Delta RDS_t} = \frac{(RCE_T - RCE_{T-1})/RCE_{T-1}}{(RDS_T - RDS_{T-1})/RDS_{T-1}} \quad (4)$$

where δ_t denotes the decoupling coefficient; ΔRCE_t denotes the elasticity coefficient of the change in rural carbon emissions in period t ; RCE_T and RCE_{T-1} represent the rural carbon emissions in years T and $T - 1$; ΔRDS_t denotes the elasticity coefficient of the dual substitution of rural energy structure in period t ; and RDS_T and RDS_{T-1} represent the indices of dual substitution of rural energy structure in years T and $T - 1$, respectively. Drawing on Tapio' extended model for the division of decoupled states [34], with $\delta = 0.8$ and $\delta = 1.2$ as the dividing line, the decoupled states were divided into eight types, as shown in Figure 1.

Among them, the strong decoupling type refers to the case where RCE goes down as RDS goes up; the weak decoupling type refers to the case where RCE grows in parallel with the development of RDS, but their growth rate is less than the rate of RDS; the expansion connection type refers to the simultaneous growth of RCE and RDS at roughly the same rate of growth; the expansion negative decoupling type refers to the simultaneous growth of RCE and RDS, but their growth rate is greater than the rate of RDS; the recession decoupling type refers to the case where both RCE and RDS are decaying and RCE is decaying at a relatively large rate; the recession connection type refers to the case where RCE and RDS all decay and decrease at approximately the same rate; the weak negative decoupling type refers to the case where RCE falls in tandem with RDS, but RCE falls at a relatively small rate; and the strong negative decoupling type refers to the growth of RCE with the decline in the level of RDS.

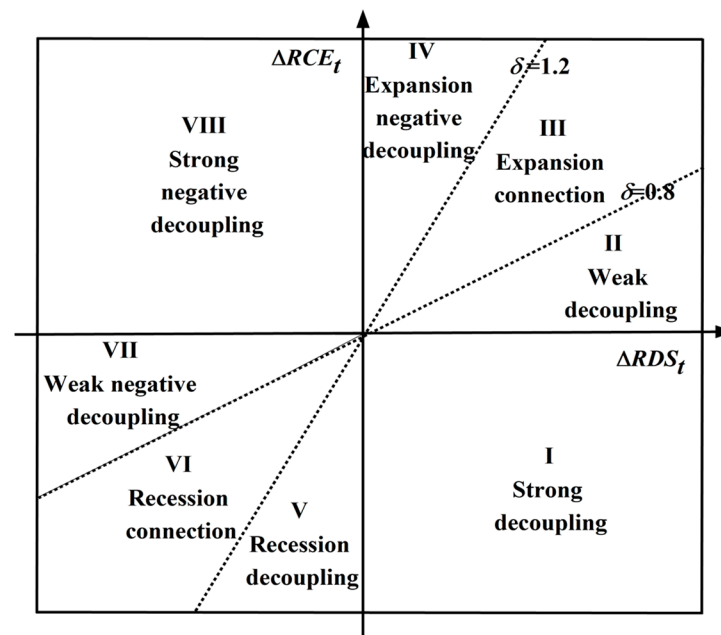


Figure 1. Determination of decoupling types.

2.4. Rural Carbon Decoupling Efficiency Measurement and Decomposition Modeling

2.4.1. Estimation of Carbon Emissions

A carbon emission measurement method that considers multiple energy categories in rural areas was adopted. Drawing on Zhang and Li's approach to calculating rural carbon emissions [35], this study estimated carbon emissions from different energy sources through the carbon emission coefficient method based on 21 energy categories in rural areas, with the following formula:

$$RC = \sum_{m=1}^{21} R_m \times A_m \times F_m \times O_m \times \frac{44}{12} \quad (5)$$

where RC represents carbon emissions from rural energy consumption; m characterizes different energy categories; R_m represents rural energy consumption; A_m , F_m , and O_m represent the average lower heating value, carbon content per unit heating value, and oxidation rate; and $44/12$ is the coefficient of conversion from C to CO_2 , and the coefficients were taken from the General Principles for the Calculation of Comprehensive Energy Consumption (GB/T 2589-2020) [36], Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (for trial use), and IPCC reference values.

2.4.2. Efficiency Measurement and Decomposition Modeling

A decoupling efficiency model that takes into account the negative outputs of carbon emissions was constructed. Tone incorporated the undesired outputs into the slacks-based measure (SBM) model to facilitate the consideration of the efficiency measurement problem in the case of concomitant output shortfalls [37]. In the process of efficiency measurement may occur in the case where the efficiency value is greater than 1, and, then, on the basis of the SBM model, Tone has proposed the super-efficiency SBM model, which comprehensively considers the effective differentiation of efficiency values and the problem of unexpected output [38]. In order to more systematically measure the dynamic effects of carbon decoupling in the process of rural energy structure transition, we comprehensively considered the input and output factors of rural carbon decoupling efficiency measurement. In terms of input factors, on the basis of considering the dual substitution of energy structure, the impact of rural production and population was also taken into account, especially including factors such as crop planting area and agricultural

machinery power. In terms of output factors, rural economic output was taken as the expected output, and rural carbon emissions were taken as the unexpected output. Based on the above input and output factors, this article adopted the super-efficiency SBM model for measurement. Assuming that there are n decision units with input elements (x), desired and undesired output elements (y and a), and N , M , and L represent the number of x , y , and a , respectively, the main form of the model is as follows:

$$\min \rho = \frac{1 - \frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{x_{kn}^t}}{1 + \frac{1}{M+L} \left(\sum_{m=1}^M \frac{s_m^y}{y_{km}^t} + \sum_{l=1}^L \frac{s_l^a}{a_{kl}^t} \right)} \quad (6)$$

Among them, k represents the province, t represents the time variable, and s represents the slack variable. The slack variable for the n -th input, m -th, and l -th outputs was $\{s_n^x, s_m^y, s_l^a\}$, and the input–output vector for the k -th region in year t was $\{x_{kn}^t, y_{km}^t, a_{kl}^t\}$. The relationship between the slack and intensity variables of carbon decoupling efficiency input factors was constrained as follows:

$$s.t. \sum_{t=1}^T \sum_{j=1, j \neq k}^n z_j^t x_{jn}^t + s_n^x = x_{kn}^t, n = 1, \dots, N \quad (7)$$

In the formula, $j = 1, 2, \dots, n$; z represents the intensity variable, and the other variables are the same as in Equation (6). The values of the slack and intensity variables are greater than or equal to 0. In this paper, in the process of carbon decoupling efficiency measurement, with carbon emissions as a non-desired output, reflecting the existence of the negative effect of carbon emissions in the process of rural energy structure transformation, its desired output elements and non-desired output elements slack variables and intensity variables relationship constraints are as follows:

$$\sum_{t=1}^T \sum_{j=1, j \neq k}^n z_j^t y_{jm}^t + s_m^y = y_{km}^t, m = 1, \dots, M \quad (8)$$

$$\sum_{t=1}^T \sum_{j=1, j \neq k}^n z_j^t a_{jl}^t + s_l^a = a_{kl}^t, l = 1, \dots, L \quad (9)$$

The variable symbols involved in the above equation are the same as those in Equations (6) and (7).

Further, this paper employs the Malmquist index (ML) to decompose the efficiency of rural energy carbon decoupling from the technical efficiency (TE) and technical progress (TP) perspectives. ML is proposed based on the data envelopment analysis (DEA) model, which uses the ratio of distance functions to calculate input–output efficiency, and is gradually being applied in the field of environmental sustainability evaluation [39]. ML can also be further decomposed into changes in technical efficiency and technical progress. In this study, changes in the technical efficiency of carbon decoupling for rural energy reflect the effects of matching energy structure with carbon emissions. Changes in rural energy carbon decoupling technical progress reflect changes in the contribution of rural carbon decoupling input factors to output factors. Compare the efficiency value change with 1 to reflect the magnitude of the change. The main manifestations were as follows:

$$TE = D^{t+1}(x_n^{t+1}, y_n^{t+1}) / D^t(x_n^t, y_n^t) \quad (10)$$

$$TP = \left[D^t(x_n^{t+1}, y_n^{t+1}) / D^{t+1}(x_n^{t+1}, y_n^{t+1}) \times D^t(x_n^t, y_n^t) / D^{t+1}(x_n^t, y_n^t) \right]^{\frac{1}{2}} \quad (11)$$

$$M(x_n^{t+1}, y_n^{t+1}, x_n^t, y_n^t) = \frac{D^{t+1}(x_n^{t+1}, y_n^{t+1})}{D^t(x_n^t, y_n^t)} \times \left[\frac{D^t(x_n^{t+1}, y_n^{t+1})}{D^{t+1}(x_n^{t+1}, y_n^{t+1})} \times \frac{D^t(x_n^t, y_n^t)}{D^{t+1}(x_n^t, y_n^t)} \right]^{\frac{1}{2}} \quad (12)$$

where x and y represent the input and output variables, t is the time variable, and D is the distance function for measuring efficiency.

3. Results

3.1. Evolution and Distribution of Dual Substitution of Rural Energy Structure

The evolution of the dual substitution index of the rural energy structure in China from 2001 to 2020 is shown in Figure 2. The dual substitution index of the rural energy structure showed an overall upward trend, and the growth rate was relatively significant. From 2001 to 2020, the regional average of the dual substitution index of the rural energy structure increased from 0.466 to 1.828, especially in Fujian, Jiangsu, and Zhejiang. The rise in the dual substitution index of the rural energy structure also showed regional differences. In terms of provincial differences in the growth of the rural energy structure substitution index, Guangxi had the fastest growth rate, while Heilongjiang showed negative growth. The growth rate in rural areas in the north was overall lower than in the south. Due to the large geographical span between the northern and southern regions, there are also significant differences in heating methods between the northern and southern regions in winter [40]. Southern regions do not require heating for warmth in winter, while winter heating in northern regions increases the reliance on lower-order energy sources and makes coal consumption in northern regions a higher proportion of the energy structure.

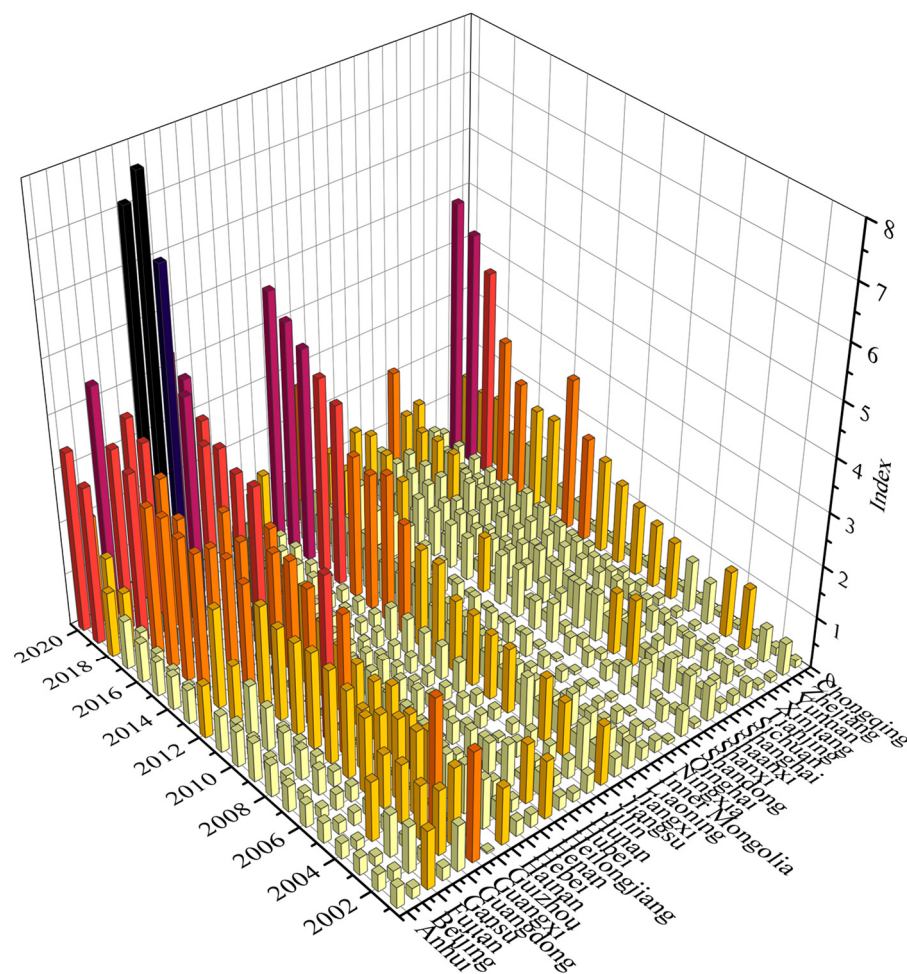


Figure 2. Dynamic evolution of dual substitution of rural energy structure.

From the integer breakpoints of the index distribution, the dual substitution index of the rural energy structure in China presented three echelons as a whole. The first echelon, represented by Zhejiang, Jiangsu, and other places, had an annual average index greater than 2, and showed yearly growth. The second echelon, represented by places such as Anhui and Liaoning, had an annual average index between 1 and 2. The third echelon, as represented by Ningxia and Shaanxi, had an annual average index between 0 and 1, and the index growth of this tier was relatively slow. Among them, most rural areas in provinces were located in the third echelon. This indicates that the dual transformation of China's rural energy structure is relatively slow, and there is still much room for progress in improving the effectiveness of the energy transformation.

In order to further investigate the regional differences in the evolution of the dual substitution index of the rural energy structure in China, Figure 3 shows the distribution of the dual substitution index of the rural energy structure at different time points. The dual substitution index of the rural energy structure in 2020 showed a significant increase compared to 2001, but regional distribution differences still exist. Firstly, the spatial distribution of the rural energy structure substitution index showed a stepped pattern, with a gradually decreasing trend in the eastern, central, and western regions. The economic development level in the eastern region is better than that in the central and western regions. The economic development level in rural areas helps to promote the revolution of the rural energy structure and accelerate the application and popularization of high-quality energy in rural areas. Secondly, the overall dual substitution index of the rural energy structure was highest in the southeastern coastal region, while it was relatively low in the northeastern region. This indicates that regional climate characteristics are one of the important factors affecting the transformation of the rural energy structure. Thirdly, in areas with abundant energy resources such as Heilongjiang, Sichuan, and Shanxi, the dual substitution index of the rural energy structure was at the lower middle level of the country. This indicates that the level of energy endowment does not directly affect the effectiveness of the energy transformation in rural areas. On the contrary, the influence of regional energy use preferences often constrains the energy consumption behavior of farmers, thereby affecting the process of energy substitution in rural areas.

3.2. Carbon Decoupling Performance of Dual Substitution of Rural Energy Structure

The streamline diagram in Figure 4 shows the changes in rural energy carbon emissions. In 2001, the average annual energy carbon emissions in rural areas reached 7.892 million tons of standard coal, with most areas concentrated in 5–8 million tons of standard coal. The differences in energy carbon emissions between regions were relatively small. However, in 2020, the average annual energy carbon emissions in rural areas reached 12.477 million tons of standard coal, and the regional emission gap gradually widened. In terms of regional differences in average annual emissions, Hainan had the lowest rural energy carbon emissions, with 1.814 million tons of standard coal in 2020; and Hebei had the highest rural energy carbon emissions, with 46.876 million tons of standard coal in 2020. Rural energy carbon emissions mainly come from two main sources—rural production and residential life—and rural life is still gradually becoming the main contribution to carbon emissions in rural areas [41]. From 2001 to 2020, the overall carbon emissions from rural energy showed a fluctuating growth trend, with a sharp increase in the growth rate in some areas. Rural areas are gradually comprehensively lifted out of poverty, and regional economic development continues to stimulate modern energy consumption, accelerating the growth of energy carbon emissions. As the consumption of commodity energy in rural areas gradually exceeds that of non-commodity energy, the consumption of coal, natural gas, and electricity in rural areas has been increasing. In addition, agricultural production methods tend to be more mechanized, and the use of agricultural machinery has also increased the carbon emissions of diesel and gasoline in rural areas.

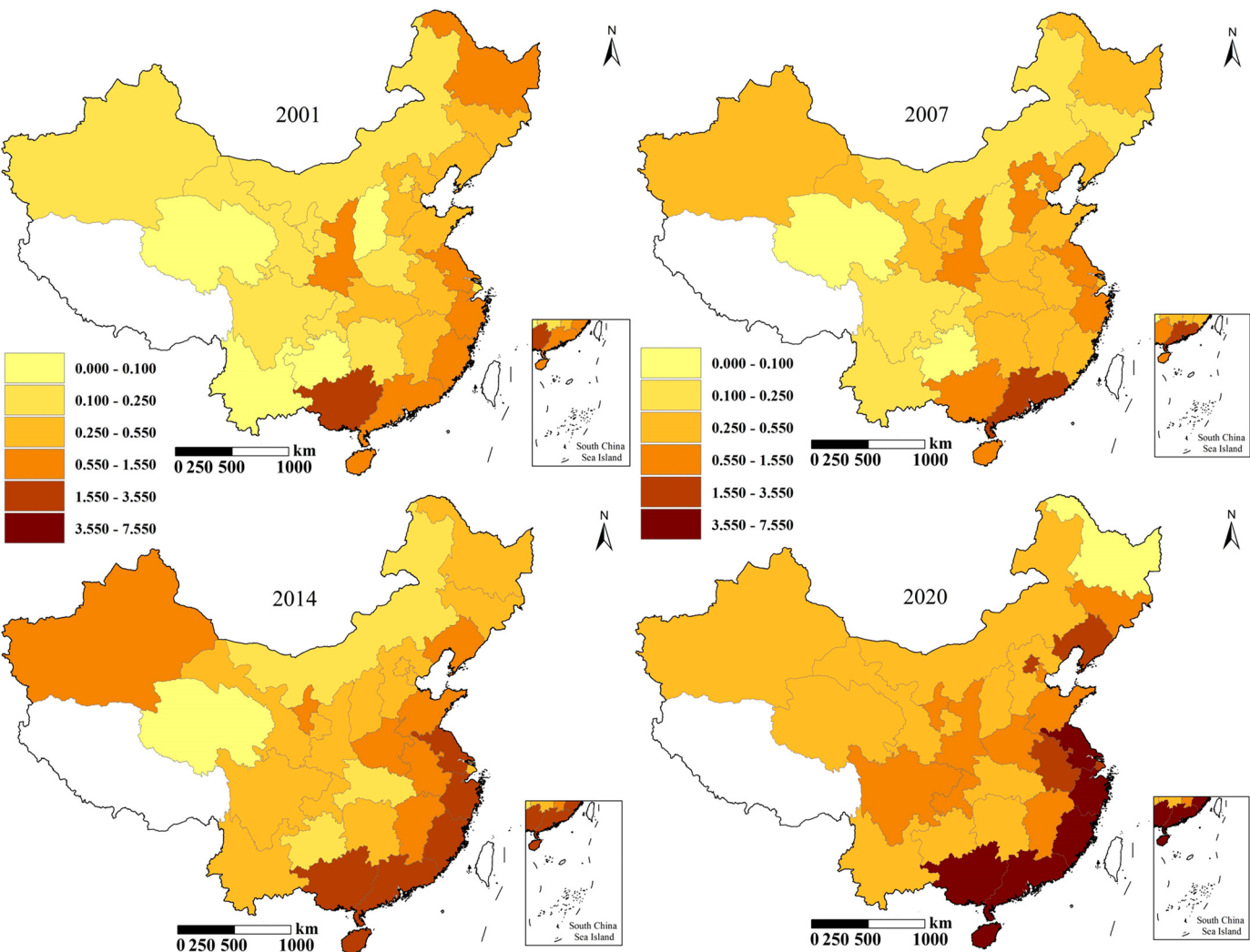


Figure 3. Spatial–temporal distribution of dual substitution of rural energy structure. Note: Blank provinces are regions without data.

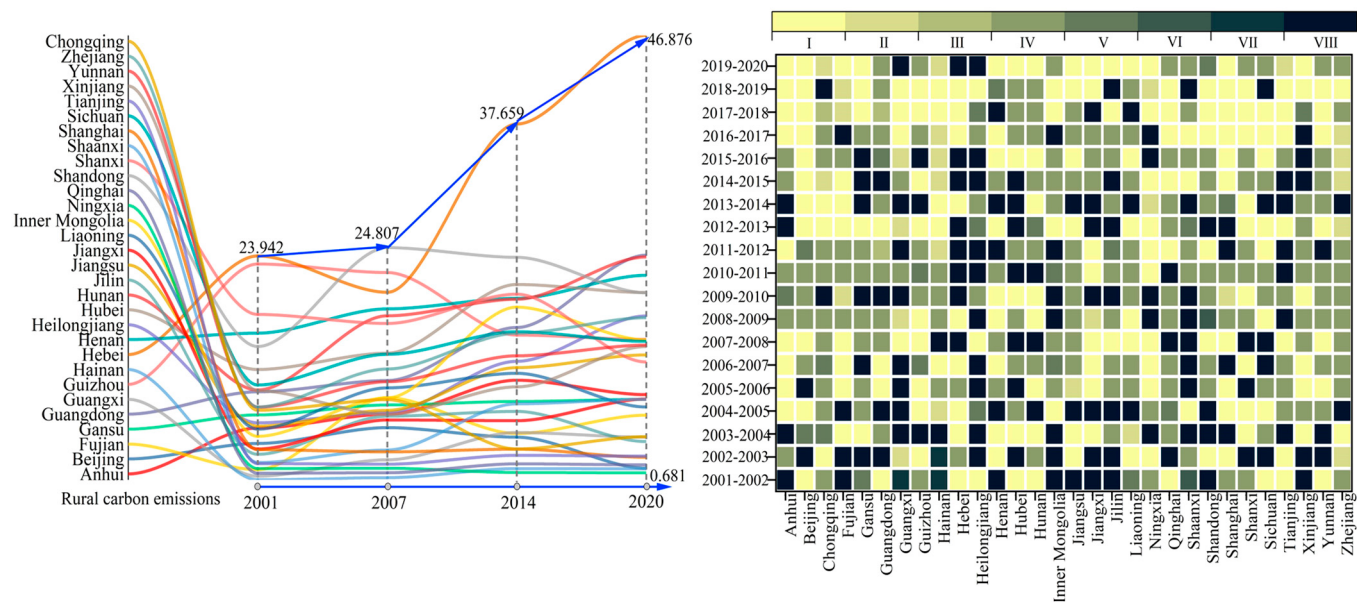


Figure 4. Rural carbon evolution and decoupling changes.

The grid diagram in Figure 4 shows the decoupling state between the dual substitution of the rural energy structure and carbon emissions. From 2001 to 2020, there were multiple states between the dual substitution of the rural energy structure and carbon emissions in 30 provinces, including strong decoupling, weak decoupling, expansion coupling, expansion negative decoupling, recession decoupling, and strong negative decoupling. However, in most regions, strong decoupling, expansion negative decoupling, and strong negative decoupling were the main types of decoupling. In 2019–2020, the decoupling status between regions was dominated by strong decoupling, reflecting that the dual substitution index of the rural energy structure rises while carbon emissions are effectively controlled. This indicates that a low-carbon energy structure has initially emerged in some regions. During the period of 2001–2007, the decoupling status of many regions varied between strong decoupling and strong negative decoupling. Due to the low level of the dual substitution of the energy structure, the consumption of low-quality energy, such as coal, has slowed down the process of substitution in the energy structure and exacerbated the carbon emissions from the energy consumption at the same time. During the period of 2008–2012, many regions experienced expansion negative decoupling as the main decoupling state. This indicates that both the dual substitution of the rural energy structure and carbon emissions have increased, but the growth rate of carbon emissions is higher than that of the dual substitution of the rural energy structure. Carbon emissions have not been reduced as a result of structural adjustment due to a carbon-heavy energy structure.

From the regional differences in decoupling status, Heilongjiang, Jiangxi, Shaanxi, and other regions have shown a strong negative decoupling state over the years, which is the least ideal decoupling state. The above regions have experienced a slow transformation of the rural energy structure and an increase in carbon emissions over the years, indicating that the energy structure in these regions is relatively unreasonable. Coal-heavy energy consumption preferences add to the burden of the energy transition in these regions. Guangdong, Beijing, Shanghai, and other places have shown a strong decoupling state in most years, which is the most ideal state. This indicates that the carbon emissions of rural energy in the above-mentioned areas have been effectively controlled, and the transformation of rural energy has achieved partial results. However, the decoupling status between regions is not singular, and the decoupling relationship between the dual substitution of the rural energy structure and carbon emission is differentiated in the time change and spatial change.

3.3. Carbon Decoupling Effects of Dual Substitution of Rural Energy Structure

3.3.1. Changes in Carbon Decoupling Efficiency

Based on the dual substitution of the rural energy structure, the carbon decoupling efficiency of rural energy considering an unexpected carbon emissions output is shown in Figure 5. Figure 5 shows the carbon decoupling efficiency of rural areas for four time periods between 2001 and 2020. The regional average of rural energy carbon decoupling efficiency in 2001 was 0.115, and, by 2020, the rural energy carbon decoupling efficiency had increased to 0.369. The areas with high carbon decoupling efficiency in rural energy were mainly located along the southeast coast, northeast region, and some central regions. In 2020, the carbon decoupling efficiency in Guangdong, Tianjin, Jiangsu, and other regions exceeded 1, while the carbon decoupling efficiency in Xinjiang, Hebei, Guizhou, and other regions was below 0.1, reflecting a regional imbalance in the carbon decoupling efficiency of rural energy.

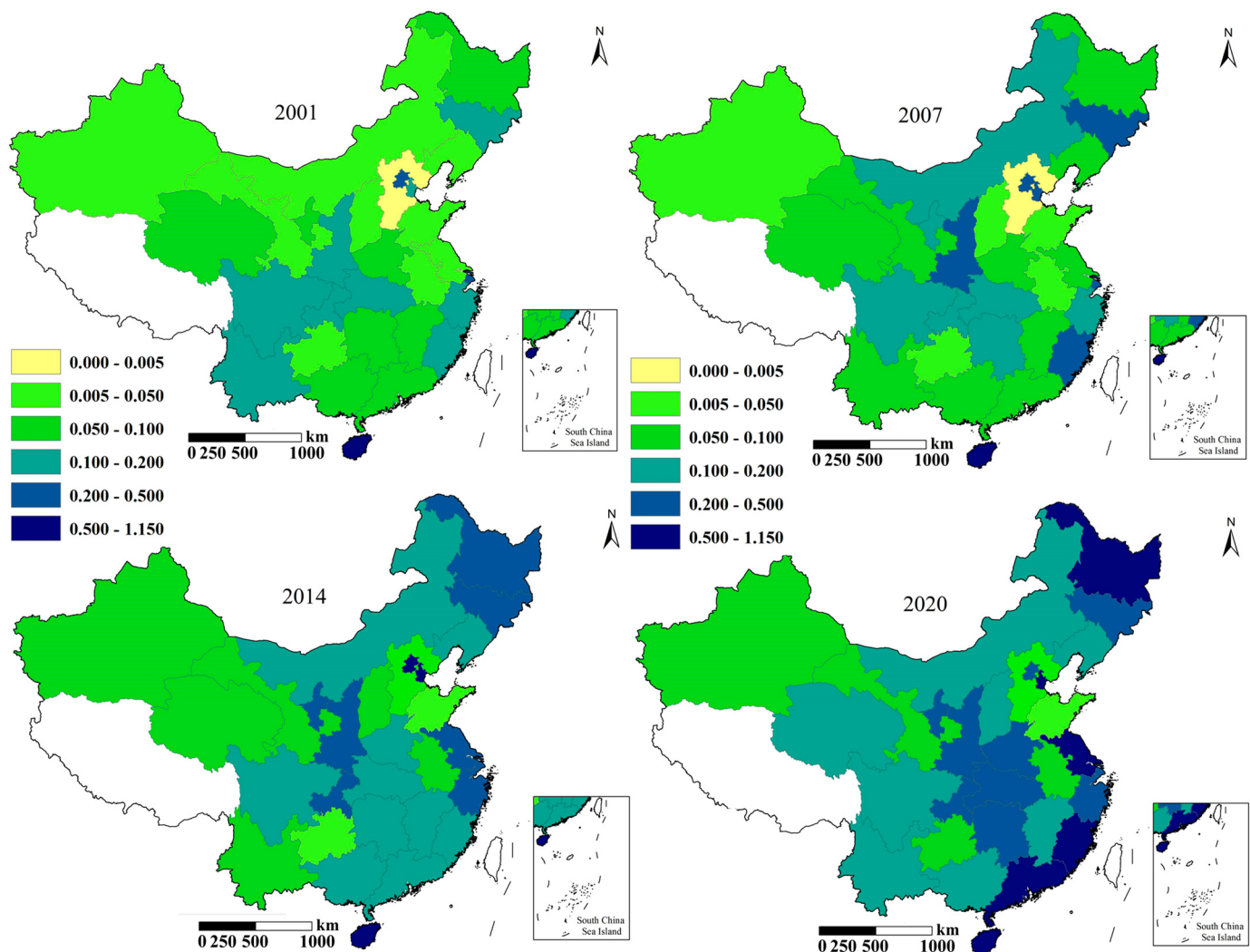


Figure 5. Spatial-temporal changes in carbon decoupling efficiency.

The provincial differences in the efficiency of rural energy carbon decoupling are mainly reflected in the following aspects. First, the carbon decoupling efficiency of rural energy in Fujian, Guangdong, Jiangsu, and other regions has shown the most significant growth. These regions have a lower dependence on low-quality energy such as coal, making it easier to promote and popularize cleaner energy in the process of accelerating the energy structure adjustment. Second, the growth rate of the rural energy carbon decoupling efficiency in Ningxia, Jilin, Chongqing, and other regions was around 0.1–0.2, with a slowdown in the growth rate. Third, Yunnan, Sichuan, Hainan, and other regions have experienced a negative or stable growth in some years. The process of urbanization is constantly accelerating, with a large amount of rural labor flowing to cities, and rural industries are mainly labor-intensive, which will weaken the scale effect of input factors for efficiency allocation. In some economically underdeveloped rural areas, the urgency of improving the efficiency of rural energy carbon decoupling may be higher than in economically developed areas.

3.3.2. Regional Comparisons and Differences

Figure 6 shows the regional differences in rural energy carbon decoupling efficiency at different time points. In 2020, the efficiency of rural energy carbon decoupling between regions showed a spatial pattern of differentiation as follows: the eastern region > the northeastern region > the central region > the western region. In terms of the growth rate between regions, the rural energy carbon decoupling efficiency in northeast and eastern

regions has a higher growth rate than that in central and western regions. The average annual rural energy carbon decoupling efficiency in the northeast region was 0.203, and the overall trend was increasing from year to year. The improvement of rural energy carbon decoupling efficiency in Heilongjiang and Jilin had a greater impact on the northeast region. The average annual rural energy carbon decoupling efficiency in the eastern region was 0.342, and the overall growth trend was more stable than that in the northeastern region. In the eastern region, Tianjin and Guangdong were located at a high level within the region, but there were also differences within the region. The average annual rural energy carbon decoupling efficiencies in the central and western regions were 0.119 and 0.125, respectively, but, in recent years, the efficiency values in the central region have gradually exceeded those in the western region. This indicates that inter-regional differences in rural energy carbon decoupling efficiency are a major factor contributing to the overall regional imbalance.

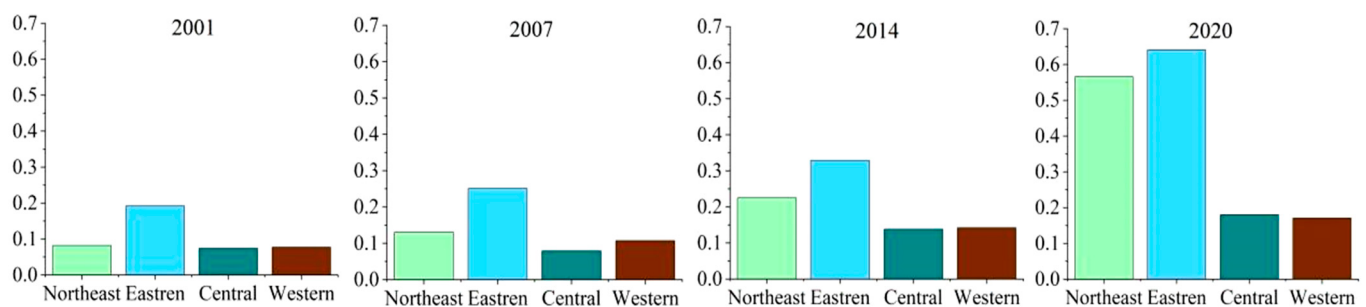


Figure 6. Regional comparison of carbon decoupling efficiency.

To further understand the contribution of regional differences, this paper also investigated the efficiency differences within regions from an intra-regional perspective, which will contribute to regional harmonization. In this paper, the efficiency differences in rural energy carbon decoupling between provinces within the region were measured by the coefficient of variation, as shown in Figure 7. The internal differences in the northeast and eastern regions were higher than those in the central and western regions, with an annual average coefficient of variation of 0.895 in the northeast region and 1.103 in the eastern region. It is worth noting that the coefficient of variation of rural energy carbon decoupling efficiency in the eastern region showed significant fluctuations, indicating that the differences among provinces within the region are more prominent. This suggests that differentiated rural carbon control policies are more effective than those in the eastern and northeastern regions.

3.3.3. Decomposition of Carbon Decoupling Efficiency from a Dynamic Perspective

The carbon decoupling efficiency value analyzed by the super-efficiency SBM model belongs to static values. In order to deeply analyze the dynamic changes of carbon decoupling based on the dual substitution of the rural energy structure, this paper used the Malmquist index (ML) to dynamically analyze the carbon decoupling efficiency of rural energy from 2001 to 2020. Table 1 shows the dynamic inter-annual changes in the carbon decoupling efficiency of rural energy. From 2001 to 2020, the ML values of the rural energy carbon decoupling efficiency were all greater than 1, indicating a positive change in efficiency. In terms of the time effect of the rural energy carbon decoupling efficiency, the overall ML value in rural areas was in a fluctuating trend of rising and falling, with more significant fluctuations before 2005. The ML value increased by 35.5% from 2004 to 2005, which was the peak of inter-annual growth. In contrast, from 2019 to 2020, the ML value only increased by 1%, with a relatively small growth rate. When the energy structure in rural areas tends to be relatively stable, the resulting welfare effect of carbon emission reduction will also decrease.

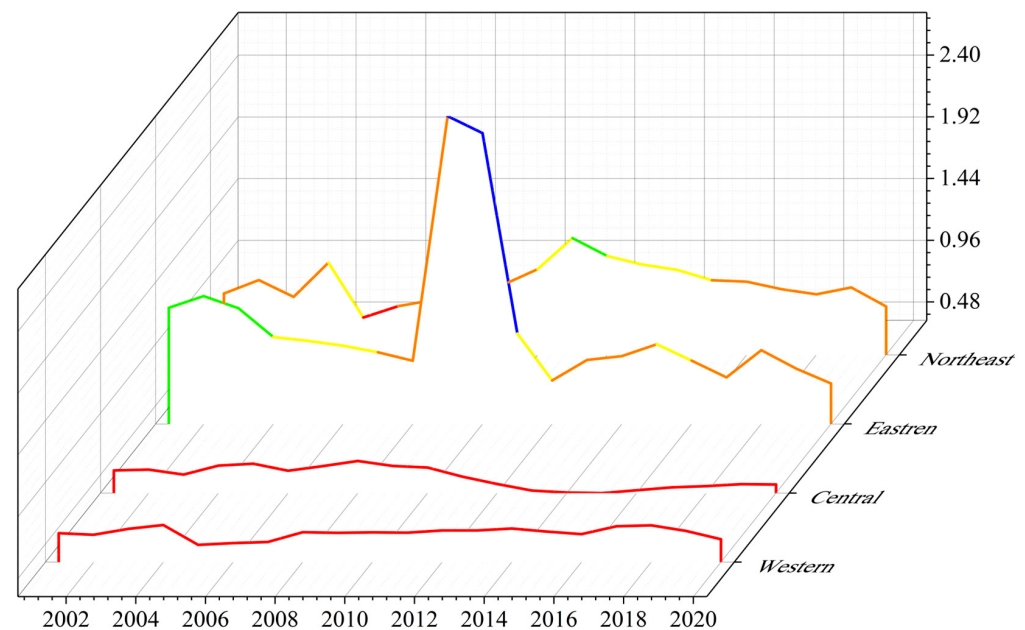


Figure 7. Regional differences in carbon decoupling efficiency.

Table 1. Time effects of carbon decoupling efficiency decomposition.

Year	TE			TP			ML		
	Average Value		Standard Deviation	Average Value		Standard Deviation	Average Value		Standard Deviation
2001–2002	0.972	↓	0.191	1.191	↑	0.791	1.043	↑	0.14
2002–2003	1.199	↑	0.893	1.089	↑	0.193	1.298	↑	0.937
2003–2004	0.984	↓	0.121	1.160	↑	0.185	1.142	↑	0.238
2004–2005	1.147	↑	0.432	1.255	↑	0.524	1.355	↑	0.658
2005–2006	0.998	↓	0.109	1.122	↑	0.131	1.115	↑	0.16
2006–2007	1.047	↑	0.137	1.029	↑	0.065	1.070	↑	0.078
2007–2008	1.001	↑	0.153	1.032	↑	0.162	1.023	↑	0.169
2008–2009	1.048	↑	0.102	1.156	↑	0.186	1.212	↑	0.23
2009–2010	1.019	↑	0.113	1.088	↑	0.091	1.111	↑	0.186
2010–2011	1.039	↑	0.111	1.139	↑	0.114	1.188	↑	0.215
2011–2012	0.967	↓	0.095	1.133	↑	0.165	1.087	↑	0.12
2012–2013	1.108	↑	0.188	0.990	↓	0.093	1.097	↑	0.23
2013–2014	0.997	↓	0.073	1.036	↑	0.062	1.032	↑	0.09
2014–2015	1.000	-	0.034	1.051	↑	0.053	1.051	↑	0.056
2015–2016	1.006	↑	0.164	1.082	↑	0.092	1.078	↑	0.122
2016–2017	1.116	↑	0.893	1.053	↑	0.152	1.065	↑	0.267
2017–2018	1.114	↑	0.318	0.918	↓	0.084	1.014	↑	0.272
2018–2019	0.995	↓	0.064	1.025	↑	0.054	1.019	↑	0.074
2019–2020	0.969	↓	0.143	1.054	↑	0.164	1.010	↑	0.169

The TE values reflect changes in the proportional effectiveness of the input and output factors of rural energy carbon decoupling, while the TP values reflect the changes in the contribution of the dual substitution of the energy structure, agricultural production, and rural life input factors to carbon decoupling. From 2001 to 2020, the TE value showed a decrease of less than 1 over many years, which indicates that there is a decline in the proportional validity of inputs and outputs in some years. Except for 2012–2013 and 2017–2018, the TP values of the remaining years were all greater than 1, indicating that

the input factors represented by the energy structure can always play a role in carbon emission reduction. From 2018 to 2020, the changes in ML values were mainly affected by the decrease in TE, and the validity of the ratio of input and output for rural energy carbon decoupling decreased, weakening the positive effect of TP on ML. Based on the standard deviation of the array, TE had a higher degree of dispersion than TP, which indicates that there are obvious regional differences in the proportional validity of the effectiveness of rural energy structural transformation and carbon emission reduction.

To further identify the characteristics of regional contributions to the carbon decoupling efficiency of rural energy, this study investigated the changes in regional efficiency elements separately from the regional perspective; see Figure 8. There were significant differences in the changes in the ML values between regions, but the overall ML values were in the range of positive changes from 0% to 30%. In Shaanxi, Chongqing, Guizhou, and other regions, ML value changes were mainly influenced by TE changes. This indicates that the above-mentioned regions belong to the TE-dominated type and have a good factor ratio in the process of rural energy transformation and carbon reduction. In Hebei, Liaoning, Qinghai, and other regions, changes in ML values were mainly influenced by changes in TP. This indicates that the above-mentioned regions belong to the TP-dominated and can regulate carbon emissions from the perspective of input factors, and the rural energy structure transformation has a strong pulling effect on carbon emission reduction in the above areas. Differences in the variation of regional ML values are also related to the economic development attributes, resource endowment, and rural population size of the region. The designed model logic of the dual substitution–carbon decoupling of rural energy structure helps to identify the interaction between the energy structure transformation and carbon emission reduction in rural areas.

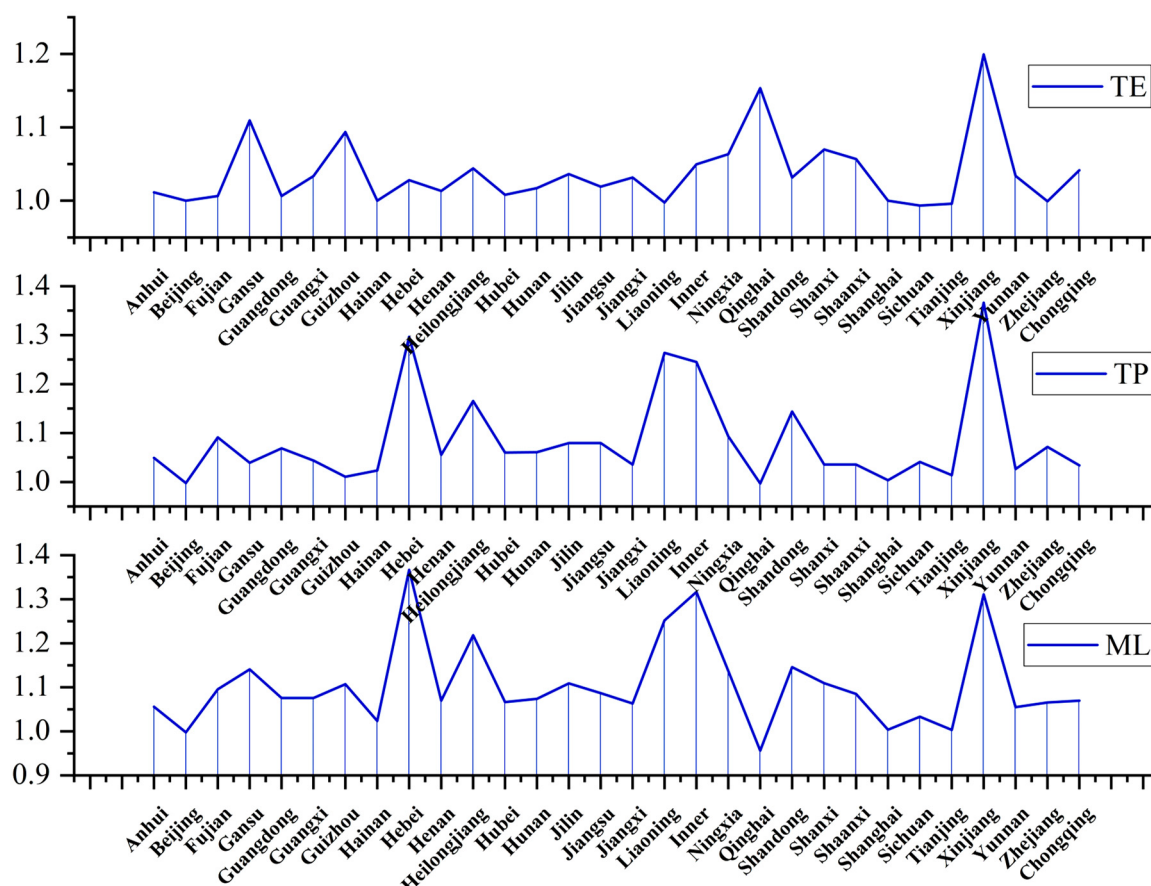


Figure 8. Spatial effects of carbon decoupling efficiency decomposition.

4. Discussion

The process of dual substitution in China's rural energy structure is one of the realistic portraits of the rural energy revolution. Compared with the existing research, focusing on modern energy consumption categories can provide a new research perspective for the transformation of the rural energy structure. The dual substitution index of the rural energy structure in China showed an overall upward trend from 2001 to 2020, but this trend showed significant spatial differences among regions. Rural areas in some provinces of China were still in the third tier of the energy structure transformation, and the process of modernization energy transformation was still relatively lagging behind. The western region may become a weak link in the transformation of the rural energy structure from the perspective of regional synergy. Regions with a low energy transition efficiency are usually not guided by alleviating greenhouse effect pressures [42]. Based on the regional distribution characteristics of the dual substitution index of the rural energy structure, it is found that the level of economic development and climate characteristics have become important factors in the transformation of China's rural energy structure.

Distinguishing from the traditional rational economic man hypothesis in the past, energy-consuming subjects at this stage prefer the ecological economic man hypothesis [43]. Restricted by governmental environmental regulations such as banning straw burning and private logging, the carbon emissions contribution of rural energy categories in China mainly comes from modern energy sources such as coal and electricity [44]. China's rural energy carbon emissions in 2001–2020 showed an overall fluctuating growth trend, which makes the carbon decoupling based on the dual substitution of the rural energy structure reflect a variety of decoupling states. From 2019 to 2020, rural areas in 30 provinces were mainly in a strong decoupling state, and carbon reduction achieved partial results in the transformation of the rural energy structure. However, a heavily carbonized energy structure still exists in some rural areas, which is the main reason for the unsatisfactory carbon decoupling status in such areas.

The carbon decoupling efficiency model based on the dual substitution of the rural energy structure helps to identify the rationing relationship of input and output factors between regions and to grasp the contribution characteristics of rural carbon reduction factors. From 2001 to 2020, the carbon decoupling efficiency of rural energy in China has increased by more than twice, especially in the southeastern coastal areas. The process of the differentiated rural energy structure transformation also leads to a regional imbalance in the distribution of carbon decoupling efficiency in rural energy. The spatial characteristics of the carbon decoupling efficiency of rural energy in China showed the following relationship: eastern region > northeastern region > central region > western region. The decomposition results of the Malmquist index model of carbon decoupling efficiency under the dynamic perspective showed that the ML value was in the trend of upward-declining repeated changes, and the annual average value of the ML value rose by 10.579% from 2001 to 2020, but there were fluctuations in the growth amplitude of upward-declining repeated fluctuations. The results of the regional ML value decomposition showed that TE-dominated regions were mainly represented by Shaanxi and Chongqing, and TP-dominated regions were mainly represented by Hebei and Liaoning. There are regional differences in the degree of coupling between the rural energy structure transformation and carbon reduction effectiveness. This also indicates that developing differentiated governance strategies is the correct approach for the government to promote rural energy transformation and carbon reduction between regions.

The dual substitution evaluation of the rural energy structure can provide theoretical value for regional governments to promote rural energy revolution. In the process of dual substitution, one is to achieve the effective substitution of electricity for coal, and the other is to achieve the substitution and supplementation of non-fossil energy for fossil energy. Accelerating rural electricity consumption to replace coal is a guarantee for promoting the development of modern energy in rural areas and connecting with the transformation of development modes. Local governments should accelerate the construction of an electricity

infrastructure in rural areas, and enhance the capacity of distributed power sources to consume and maintain supply locally. Steadily increasing the proportion of non-fossil energy to replace fossil energy is also an inevitable requirement for building a new energy system in rural areas. Local governments should pay more attention to the application of solar energy, wind energy, and biomass energy in rural areas, and prepare for the layout of distributed energy in advance. Based on the decomposition results of rural energy carbon decoupling efficiency, the regional imbalance is also an obstacle to rural energy transformation. This requires rural energy transformation measures to vary from region to region and targeted policy instruments to be selected, taking into account regionally differentiated energy consumption preferences and emission reduction characteristics. However, it has to be recognized that the rural energy transition is also a long-term and complex process, the use of policy tools needs to be adjusted in the feedback, and the formulation of regional emission reduction policies needs to be tailored.

5. Conclusions

Based on the categories of modern energy in rural China from 2001 to 2020, this study measured the dual substitution index of the rural energy structure from a new perspective, identified the spatial–temporal evolution characteristics of the rural energy transformation, and further explored the carbon decoupling effects of the rural energy structure transformation. The carbon decoupling efficiency model for the rural energy structure substitution is constructed to better reflect the driving effect of the rural energy structure transformation on carbon reduction. The main conclusions of this study are as follows:

First, the dual substitution index of the rural energy structure in China showed an upward change from 0.466 to 1.828 from 2001 to 2020. The index growth rate in southern rural areas is higher than that in northern areas, and climate conditions are one of the factors influencing the substitution of the rural energy structure. Two-thirds of the provinces are in the third tier of the rural energy dual substitution process, and, overall, China's rural energy transformation process is relatively slow.

Second, strong decoupling, expansive negative decoupling, and strong negative decoupling are the main state manifestations of carbon decoupling from rural energy in China. However, the decoupling relationship between the rural energy structure substitution and carbon emissions is heterogeneous in terms of temporal and spatial changes. The energy structure of heavy carbonization remains the key to carbon decoupling in some rural areas.

Third, the carbon decoupling efficiency of rural energy increased by nearly twice from 2000 to 2020, with high-efficiency areas mainly distributed in the southeast coastal areas, northeast regions, and some central regions. The inter-regional rural energy carbon decoupling efficiency shows the following relationship: eastern region > northeastern region > central region > western region. Differences in the carbon decoupling efficiency of rural energy between regions are the main factor contributing to the overall regional imbalance.

Fourth, from a dynamic perspective, the average annual growth rate of the rural energy carbon decoupling efficiency was 10.579%, and the dual substitution of the energy structure has a significant driving effect on rural carbon reduction. There are dynamic differences in the performance of TE-dominant and TP-dominant types, which will better co-ordinate the ratio relationship between the input–output factors of carbon decoupling efficiency. However, when the energy structure tends to stabilize, the welfare effect of the carbon emission reduction from the rural energy structure substitution is also limited.

This study attempts to find a more accurate measure of the rural energy structure substitution, with a view to exploring the interactive effects of the rural energy structure transformation and carbon emission reduction. On the one hand, this study provides some valuable references for the formulation of rural energy structure transformation policies. The rural energy structure substitution index is more biased towards modernized rural energy sources, which also coincides with the current situation of the modern transformation of rural energy, and helps to provide policymakers with sample ideas for a rural

energy transition evaluation, and a more comprehensive understanding of rural energy structure changes from a dual substitution perspective. The differentiated performance of the rural energy structure substitution between regions can also provide a reference for government departments to formulate differentiated energy management policies. On the other hand, this study provides the management direction and tools for energy carbon reduction efforts in rural areas. The rural energy carbon decoupling efficiency quantifies to a certain extent the ratio relationship between the input and output factors of rural carbon reduction. Policymakers can grasp the resource allocation status of rural carbon emission reduction by the rural energy carbon decoupling efficiency, and then improve the regulatory efficiency of rural carbon emission reduction.

However, this study also has several limitations. First, from the perspective of the energy structure substitution, only the application of modern energy in rural areas was considered, limited by the availability of data, and the impact of rural straw and firewood was not considered in the energy category. Future research can focus on more granular data units of rural energy, such as rural households or farmers, and biomass preferences can also be considered into the rural energy structure substitution process. Second, changes in the carbon decoupling efficiency of rural energy may be influenced by many factors, and this study only investigated the carbon reduction effects brought about by the substitution of the rural energy structure. Future research can continue to delve deeper into the environmental impact of rural energy structure substitution, including deepening the research on its carbon reduction from the perspective of the impact channels and mechanisms. These limitations may provide an inspiration and a direction for future research.

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References

1. Steinacher, M.; Joos, F.; Stocker, T.F. Allowable carbon emissions lowered by multiple climate targets. *Nature* **2013**, *499*, 197–201. [[CrossRef](#)] [[PubMed](#)]
2. Xu, T.; Kang, C.; Zhang, H. China's efforts towards carbon neutrality: Does energy-saving and emission-reduction policy mitigate carbon emissions? *J. Environ. Manag.* **2022**, *316*, 115286. [[CrossRef](#)] [[PubMed](#)]
3. Keho, Y. What drives energy consumption in developing countries? The experience of selected African countries. *Energy Policy* **2016**, *91*, 233–246. [[CrossRef](#)]
4. Amri, F. Intercourse across economic growth, trade and renewable energy consumption in developing and developed countries. *Renew. Sustain. Energy Rev.* **2017**, *69*, 527–534. [[CrossRef](#)]
5. Yunrui, W.; Yao, W.; Jinghui, Z.; Juan, L.; Yue, W. Research on the decision-making method of coal order price and coal purchase quantity based on prediction. *Comput. Ind. Eng.* **2024**, *188*, 109885. [[CrossRef](#)]
6. Feng, T.; Sun, L.; Zhang, Y. The relationship between energy consumption structure, economic structure and energy intensity in China. *Energy Policy* **2009**, *37*, 5475–5483. [[CrossRef](#)]
7. Ji, Q.; Zhang, D. How much does financial development contribute to renewable energy growth and upgrading of energy structure in China? *Energy Policy* **2019**, *128*, 114–124. [[CrossRef](#)]

8. Hou, S.; Yu, K.; Fei, R. How does environmental regulation affect carbon productivity? The role of green technology progress and pollution transfer. *J. Environ. Manag.* **2023**, *345*, 118587. [[CrossRef](#)] [[PubMed](#)]
9. He, Y.; Lin, B. Forecasting China's total energy demand and its structure using ADL-MIDAS model. *Energy* **2018**, *151*, 420–429. [[CrossRef](#)]
10. Zeng, S.; Su, B.; Zhang, M.; Gao, Y.; Liu, J.; Luo, S.; Tao, Q. Analysis and forecast of China's energy consumption structure. *Energy Policy* **2021**, *159*, 112630. [[CrossRef](#)]
11. Fang, G.; Chen, G.; Yang, K.; Yin, W.; Tian, L. Can green tax policy promote China's energy transformation?—A nonlinear analysis from production and consumption perspectives. *Energy* **2023**, *269*, 126818. [[CrossRef](#)]
12. Li, Y.; He, Y.; Zhang, M. Prediction of Chinese energy structure based on Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM). *Energy Sci. Eng.* **2020**, *8*, 2680–2689. [[CrossRef](#)]
13. Liang, X.; Shi, Y.; Li, Y. Research on the Yellow River Basin Energy Structure Transformation Path under the “Double Carbon” Goal. *Sustainability* **2023**, *15*, 9695. [[CrossRef](#)]
14. Xu, C.; Xiao, X.; Chen, H. A novel method for forecasting renewable energy consumption structure based on compositional data: Evidence from China, the USA, and Canada. *Environ. Dev. Sustain.* **2024**, *26*, 5299–5333. [[CrossRef](#)]
15. Fan, L.; Zhang, Y.; Jin, M.; Ma, Q.; Zhao, J. Does New Digital Infrastructure Promote the Transformation of the Energy Structure? The Perspective of China's Energy Industry Chain. *Energies* **2022**, *15*, 8784. [[CrossRef](#)]
16. Chen, F.; Shao, M.; Chen, W.; Wang, F. Environmental regulation, energy consumption structure, and industrial pollution emissions. *Environ. Res. Commun.* **2024**, *6*, 015011. [[CrossRef](#)]
17. Jia, X.; Xu, W.; Wang, K. Financial openness and energy structure transformation. *Front. Environ. Sci.* **2024**, *11*, 1346594. [[CrossRef](#)]
18. Wu, B.; Wang, Z.; Tian, Y.; Zheng, S. The impact of industrial transformation and upgrading on fossil energy elasticity in China. *J. Clean. Prod.* **2024**, *434*, 140287. [[CrossRef](#)]
19. Grand, M.C. Carbon emission targets and decoupling indicators. *Ecol. Indic.* **2016**, *67*, 649–656. [[CrossRef](#)]
20. Zhang, Y.-J.; Da, Y.-B. The decomposition of energy-related carbon emission and its decoupling with economic growth in China. *Renew. Sustain. Energy Rev.* **2015**, *41*, 1255–1266. [[CrossRef](#)]
21. Madaleno, M.; Moutinho, V. Effects decomposition: Separation of carbon emissions decoupling and decoupling effort in aggregated EU-15. *Environ. Dev. Sustain.* **2018**, *20* (Suppl. S1), 181–198. [[CrossRef](#)]
22. Wang, Q.; Hang, Y.; Zhou, P.; Wang, Y. Decoupling and attribution analysis of industrial carbon emissions in Taiwan. *Energy* **2016**, *113*, 728–738. [[CrossRef](#)]
23. Han, X.; Xu, Y.; Kumar, A.; Lu, X. Decoupling analysis of transportation carbon emissions and economic growth in China. *Environ. Prog. Sustain. Energy* **2018**, *37*, 1696–1704. [[CrossRef](#)]
24. Huang, Q.; Xia, X.; Liang, X.; Liu, Y.; Li, Y. Is China's Equipment Manufacturing Export Carbon Emissions Decoupled from Export Growth? *Pol. J. Environ. Stud.* **2022**, *31*, 85–97. [[CrossRef](#)] [[PubMed](#)]
25. Li, D.; Shen, T.; Wei, X.; Li, J. Decomposition and Decoupling Analysis between HDI and Carbon Emissions. *Atmosphere* **2022**, *13*, 584. [[CrossRef](#)]
26. Liu, F.; Kang, Y.; Guo, K. Is electricity consumption of Chinese counties decoupled from carbon emissions? A study based on Tapio decoupling index. *Energy* **2022**, *251*, 123879. [[CrossRef](#)]
27. Yao, C.; Chen, C.; Li, M. Analysis of rural residential energy consumption and corresponding carbon emissions in China. *Energy Policy* **2012**, *41*, 445–450. [[CrossRef](#)]
28. Ding, W.; Wang, L.; Chen, B.; Xu, L.; Li, H. Impacts of renewable energy on gender in rural communities of north-west China. *Renew. Energy* **2014**, *69*, 180–189. [[CrossRef](#)]
29. Wang, J.; Liu, M. Supply-demand bilateral energy structure optimization and carbon emission reduction in Shandong rural areas based on long-range energy alternatives planning model. *Front. Environ. Sci.* **2022**, *10*, 1009276. [[CrossRef](#)]
30. Energy Department of the National Bureau of Statistics. *China Rural Statistical Yearbook*; China Statistics Press: Beijing, China, 2022.
31. Rural Social and Economic Survey Department of the National Bureau of Statistics. *China Energy Statistical Yearbook*; China Statistics Press: Beijing, China, 2022.
32. Li, Y.; Yang, X.; Ran, Q.; Wu, H.; Irfan, M.; Ahmad, M. Energy structure, digital economy, and carbon emissions: Evidence from China. *Environ. Sci. Pollut. Res.* **2021**, *28*, 64606–64629. [[CrossRef](#)] [[PubMed](#)]
33. Liang, L.; Wu, W.; Lal, R.; Guo, Y. Structural change and carbon emission of rural household energy consumption in Huantai, northern China. *Renew. Sustain. Energy Rev.* **2013**, *28*, 767–776. [[CrossRef](#)]
34. Tapio, P. Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp. Policy* **2005**, *12*, 137–151. [[CrossRef](#)]
35. Zhang, H.; Li, S. Carbon emissions' spatial-temporal heterogeneity and identification from rural energy consumption in China. *J. Environ. Manag.* **2022**, *304*, 114286. [[CrossRef](#)] [[PubMed](#)]
36. GB/T 2589-2020; General Principles for the Calculation of Comprehensive Energy Consumption. China Standard Publishing House: Beijing, China, 2020.
37. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [[CrossRef](#)]
38. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [[CrossRef](#)]

39. Kortelainen, M. Dynamic environmental performance analysis: A Malmquist index approach. *Ecol. Econ.* **2008**, *64*, 701–715. [[CrossRef](#)]
40. Guo, J.; Huang, Y.; Wei, C. North–South debate on district heating: Evidence from a household survey. *Energy Policy* **2015**, *86*, 295–302. [[CrossRef](#)]
41. Zhou, Q.; Liu, Y.; Qu, S. Emission effects of China’s rural revitalization: The nexus of infrastructure investment, household income, and direct residential CO₂ emissions. *Renew. Sustain. Energy Rev.* **2022**, *167*, 112829. [[CrossRef](#)]
42. Ruíz-Carmona, O.; Islas-Samperio, J.M.; Larrondo-Posadas, L.; Manzini, F.; Grande-Acosta, G.K.; Álvarez-Escobedo, C. Solid Biofuels Scenarios from Rural Agricultural and Forestry Residues for Mexican Industrial SMEs. *Energies* **2021**, *14*, 6560. [[CrossRef](#)]
43. Merk, C.; Rehdanz, K.; Schröder, C. How consumers trade off supply security and green electricity: Evidence from Germany and Great Britain. *Energy Econ.* **2019**, *84*, 104528. [[CrossRef](#)]
44. Wang, Y.; Zhang, L.; Zhang, Y.; Zhong, W.; Pei, K.; Qiao, W.; Jiao, Q.; Cao, W. Evolution Characteristics of Rural Carbon Emissions in Northwest China from 2006 to 2019. *Environ. Res. Commun.* **2023**, *5*, 105002. [[CrossRef](#)]

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