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Study on the Measurement and Influencing Factors of Rural Energy Carbon Emission Efficiency in China: Evidence Using the Provincial Panel Data

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Abstract: This paper summarizes the spatial–temporal characteristics of China's rural energy carbon emission efficiency and then uses the Tobit model to explore its influencing factors. The results show that the rural energy carbon emission efficiency had experienced a growing trend in China during 2005 and 2020, with an annual growth rate of 4.82%. The growth is more affected by technological changes than by improvements in technical efficiency. Although all 30 provinces were in a state of improvement in rural energy carbon productivity during the period under review, there were significant differences between them. Technological change played a significant important role in promoting rural energy carbon productivity in the majority of Chinese provinces, while technical efficiency not only played a slightly less important role but also deteriorated in many provinces. Rural energy carbon emission efficiency is positively influenced by the level of agricultural development, the structure of rural labor force, and the urbanization level. However, it is negatively affected by the structure of cultivated land use, the rural human capital and rural residents' consumption level. As such, policy formulation should support and promote the overall improvement of rural energy carbon emission efficiency.

Keywords: rural energy carbon emissions; agricultural carbon emissions; carbon emission efficiency; influencing factors

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1. Introduction

The rapid increase of carbon emissions poses significant threats to the ecosystem; hence, there is an increased emphasis on climate change. Countries have considered various legally binding agreements to combat global climate change, including the United Nations Framework Convention on Climate Change (UNFCCC), the Kyoto Protocol, and the Paris Agreement. The agreements proposed binding targets and emission-reduction methods for significant greenhouse gases. Despite efforts to curb carbon emission reduction, global greenhouse gas emissions continue to increase. According to the United Nations Environment Program's (UNEP) statistics report, global carbon dioxide emissions peaked at 59.1 billion tons in 2019 but slightly declined in 2020 due to the COVID-19 epidemic rather than emission-reduction efforts.

As one of the first parties to the United Nations Framework Convention on Climate Change, China has been an active participant and supporter of global climate governance. For instance, in 2009 and 2015, it committed itself to achieving its independent emission-reduction targets. In 2020, the "double carbon" target was explicitly proposed, implying that China would commit to achieving peak carbon emissions by 2030 and carbon neutrality by 2060. According to the *Government Work Report* released by China's State Council [1] in March 2021, "Do a good job in carbon peaking and carbon neutrality" was one of the government's critical tasks. Similarly, in March 2022, the *Government Work Report* released by China's State Council (data sources: http://fgw.guizhou.gov.cn/fggz/ywdt/202203

/t20220315_72995030.html; accessed on 15 March 2022) further proposed that they were to orderly promote the work of achieving the carbon peak and carbon neutrality. As such, the Chinese government shows commitment to the phased reduction target as a responsible superpower. While promoting carbon emission reduction and focusing on densely populated urban centers, emphasis should be directed toward agricultural carbon emissions in rural areas.

Agricultural carbon emissions attract the attention of scholars. Initially, some scholars constructed and measured the agricultural carbon emission measurement index system from different perspectives. For example, West and Marland measured the carbon emissions of crop production from the perspective of agricultural resource inputs [1]. Johnson included rice cultivation, livestock and poultry breeding, and crop straw burning into the measurement system and then calculated agricultural carbon emissions in the United States [2]. Yadav and Wang constructed an agricultural soil carbon emission model and estimated the carbon emissions in Canada [3]. Early studies mainly focused on greenhouse gas emissions from rice cultivation and livestock and poultry farming [4]. After that, some scholars measured and analyzed the carbon emissions from farmland utilization [5–7], from the input of agricultural materials [8,9], and from fishery production [10,11]. Meanwhile, other scholars have systematically and comprehensively measured China's agricultural carbon emissions from multidimensional perspectives, such as agricultural resource utilization, the input of agricultural production materials, rice cultivation, and livestock and poultry breeding [12–15]. Moreover, scholars have successively analyzed the characteristics and drivers of agricultural carbon emissions [13,16], measured agricultural carbon emission efficiency and assessed emission reduction potential [17], and explored the interactions between the external environment and agricultural carbon emissions [18,19].

In addition, since the number of energy inputs in agricultural production has increased, some scholars have conducted studies on agricultural energy carbon emissions. Early scholars mainly measured agricultural energy carbon emissions and explored the influencing factors. Their studies indicated that economic growth, trade terms, and the industry scale were the key factors leading to the quantitative growth of agricultural energy carbon emissions [20,21]. In recent years, scholars mainly compared rural energy carbon emissions among different regions [22] and explored the interrelationships between technological progress and agricultural energy carbon emissions [23,24]. These studies concluded that energy carbon emissions were distinct in rural parts of China and that technological progress harmed rural energy carbon emissions to some extent. Moreover, some other scholars discussed carbon emissions from energy consumption by rural residents. For example, Wei measured carbon emissions from end-use energy consumption in rural China [25]. Chen and Zhu assessed carbon emissions from the consumption of straw, fuelwood, and other commercial renewable energy sources [26]. Some other scholars found that the carbon emissions from rural energy consumption were on an upward trend, and the differences among different parts of China were narrowed in carbon emissions from rural energy consumption [27–29]. Furthermore, Liu and Zhang found that carbon emissions from rural energy consumption were significantly influenced by rural production and living factor investment, rural population size, rural living quality, and changes in the structure of rural residents' domestic consumption expenditure [30,31].

Despite these more nuanced analyses of the measurement and comparison of agricultural and rural carbon emissions in different regions and the influencing factors, economists have arguably performed a poor job in two respects. First, they should have analyzed the distinctions between climate-neutral and climate-disastrous carbon when examining agricultural carbon emissions. In definition, climate-neutral carbon mainly refers to the carbon cycle in natural ecosystems and soils, such as carbon emissions from rice cultivation and livestock and poultry breeding [32]. These carbon emissions have a neutral impact on the whole climate system [32]. Climate-disastrous carbon mainly refers to carbon emissions caused by fossil energy use or artificial production activities, including all types of carbon emissions from energy consumption. These fossil energies are stored initially under the ground but excavated and released into the atmosphere by modern processes, thus resulting in surface warming and climate catastrophe [32]. Second, only some scholars have examined carbon emissions from agricultural production and rural residents' energy consumption. Meanwhile, only some scholars have measured and analyzed the spatial–temporal energy carbon emission efficiency patterns.

The current initiatives are positive, although deficiencies exist. First, the distinction between climate-neutral and climate-disastrous carbon is ignored when investigating agricultural carbon emissions. For climate-neutral carbon, while inconsistencies within the natural ecosystem and soil are inconsistent under certain circumstances, the impact is relatively low. This includes emissions from rice plantations, livestock, and poultry. Climate-disaster carbon comes from fossil energy or production activities [32]. All kinds of energy-consumption carbon emissions belong to this category. Second, few scholars have calculated the carbon emissions and efficiency of agricultural production energy consumption and rural residents' domestic energy consumption.

The paper seeks to provide a viable approach to measuring rural energy carbon productivity that serves as a point of reference for future research. It also explores the spatial patterns of rural energy carbon emission efficiency and its impacts within China's provinces.

2. Materials and Methods

2.1. Methodology

2.1.1. Measurement of Carbon Emissions from Rural Energy

Unlike previous studies measuring carbon emissions from rural energy from a single perspective, this paper systematically examines it from two dimensions: agricultural production and rural residents' living. In the agricultural-production dimension, we mainly study the carbon emissions caused by the direct use of raw coal, other washed coal, briquette coal, coke, gasoline, diesel oil, fuel oil, liquefied petroleum gas, natural gas, heat, and electricity in agriculture. We also study the indirect carbon emissions caused by energy consumption in producing chemical fertilizers, pesticides, and agricultural films. In the rural residents' living dimension, we only focus on the carbon emissions caused by the direct use of the above 11 types of energy in rural living. Accordingly, the formula for measuring carbon emissions from rural energy is given as follows:

$$C = C_1 + C_2 \tag{1}$$

$$C_1 = \sum C_{1c} = \sum T_{1c} \times \delta_{1c} \tag{2}$$

$$C_2 = \sum C_{2c} = \sum T_{2c} \times \delta_{2c} \tag{3}$$

where C, C_1, and C_2 denote the total carbon emissions from rural energy, energy consumption of agricultural production, and energy consumption of rural residents' living, respectively; C_{1c} and C_{2c} denote the carbon emissions caused by energy consumption of agricultural production and of rural residents' living, respectively; T_{1c} and T_{2c} indicate the real quantity of various carbon sources; δ_{1c} and δ_{2c} denote the carbon emission coefficients corresponding to each type of carbon source; and c denotes the category of carbon source. The relevant carbon emission coefficients are from the studies of Tian [13], Jiang [33], and Tian and Yin [34].

2.1.2. Measurement Method of Rural Energy Carbon Emission Efficiency and the Selection of Input–Output Indicators

This paper's rural energy carbon emission efficiency differs from traditional agricultural productivity in that the output indicators include undesirable output. The traditional Shephard distance function must consider the unexpected output when measuring carbon productivity. The undesirable SBM (slacks-based measurement) model makes up for this defect. (The SBM direction distance function is a weighted additive model that can consider input elements, expected outputs, and undesired outputs. Färe and Grosskopf [35] proposed a deformation expression of a simple additive model, which is essentially a weighted additive model with a weight value of 1). It is one of the DEA (Data Envelopment Analysis) derivative models. Compared with the traditional DEA model, the non-expected output SBM model avoids the deviation caused by radial and angular measurement and considers the impact of the non-expected output factors in the production process, which can better reflect the essence of efficiency evaluation. As a result, the Malmquist productivity index based on the SBM directional distance function is constructed to measure the carbon productivity of rural energy in China. First, the input–output set would be defined, and then the undesirable output SBM directional distance function would be determined. Finally, the Malmquist–Luenberger index model is constructed.

(1) ***Input–output set***. In this paper, DMU (production decision-making unit) includes 30 provinces in China, which involves multiple input indicators, as well as expected output and undesirable output. Accordingly, the input–output set can be expressed by the following:

$$p^t(x) = \left\{ (x^t, y^t, z^t) : \sum_{k=1}^{k} \lambda_k^t y_k^t \geq y_k^t, \sum_{k=1}^{k} \lambda_k^t x_{kn}^t \leq x_{kn}^t, \forall N, \sum_{k=1}^{k} \lambda_k^t z_k^t = z_k^t, \sum_{k=1}^{k} \lambda_k^t = 1, \lambda_k^t \geq 0, \forall k \right\} \tag{4}$$

where $p^t(x)$ denotes the input–output set in period t, x is each input factor ($x = x_1, \cdots, x_n$), y denotes the desired output, z denotes the undesirable output, $t = 1, 2, \cdots, T$, $k = 1, 2, \cdots, K$ ($K = 30$, denotes each province), and λ_k^t is the weight of DMU cross-sectional observation values. Under the condition that the weight is non-negative, if the sum of weights is equal to 1, it indicates the variable return to scale. Otherwise, it means the constant return to scale.

Selecting appropriate input–output indicators is crucial for accurately measuring the carbon productivity of rural energy. In order to ensure the scientificity and rationality of indicators selection, this paper reviewed relevant studies and found that the input indicators mainly include agricultural labor, total power of agricultural machinery, cropland area, chemical fertilizers, and pesticides [36,37] and that expected output indicators mainly include agricultural added value. In contrast, undesirable output indicators mainly include agricultural surface source pollution and agricultural carbon emissions [17,38]. Based on these studies and the data available, the input–output indicators selected in this paper are as follows.

Input indicators include agricultural labor force, farmland, chemical fertilizer, pesticides, agricultural film, agricultural machinery power, and agricultural capital stock. More precisely, the agricultural labor force is measured by the number of primary industry employees in each province at the end of the year, and the unit is 10,000 persons, which reflects the input of human capital. Farmland is the material basis for agricultural production activities, and it is measured by the cropland area at each province's year-end. The unit is 1000 hm^2. Fertilizer, pesticide, and agricultural film are necessary agricultural production materials that profoundly impact agricultural production, especially planting production. The actual usage of each province measures these materials over the years, and the unit is 10,000 tons. The wide use of agricultural machinery is an essential means to promote the improvement of agricultural productivity. In this paper, agricultural machinery power is also taken as an input indicator and the total power measures in each province over the years. The unit is 10,000 kW. In addition, agricultural production activities involve tangible fixed assets that can be reused or purchased, i.e., agricultural capital stock. It is also used as a vital input indicator in this study. Specifically, agricultural capital stock refers to the proportion of agricultural fixed asset investment in total social fixed asset investment multiplied by total social fixed capital formation, and the unit is 1 billion RMB. The annual value is calculated by the perpetual inventory method, in which the base period capital stock, depreciation rate, and investment price index are drawn from the study of Li [39].

Output indicators consist of the desired agricultural gross output value and the undesired rural energy carbon emissions. The former is measured by the total agricultural output value of each province over the years, and the unit is 1 billion RMB. The latter is measured by the actual amount of rural energy carbon emissions in each province over the years, and the unit is 1 million tons.

(2) ***Undesirable output SBM directional distance function***. Unlike the traditional radial DEA model that only considers the proportional variation of input and output, the SBM model, namely the non-directional model, can measure inefficiency from both input and output sides simultaneously. Drawing from the study of Fukuyama and Weber [40], this paper constructs the undesirable output SBM directional distance function D_c as follows.

$$Dc(x^{t,k}, y^{t,k}, g^x, g^y, g^z) = \left(\max_{s^x, s^y, s^z}\right) \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{2}\left(\frac{s^y}{g^y} + \frac{s^z}{g^z}\right)}{2} \tag{5}$$

$$s.t.\begin{cases} \sum\limits_{t=1}^{T}\sum\limits_{k=1}^{K}\lambda_k^t x_{kn}^t + s_n^x = x_{k,n}^x, \forall n \\ \sum\limits_{t=1}^{T}\sum\limits_{k=1}^{K}\lambda_k^t y_k^t - s^y = y_k^t \\ \sum\limits_{t=1}^{T}\sum\limits_{k=1}^{K}\lambda_k^t z_k^t + s^z = b_k^t \\ \sum\limits_{k=1}^{K}\lambda_k^t = 1, \lambda_k^t \geq 0, \forall k \\ s_n^x \geq 0, \forall n; s^y \geq 0, s^z \geq 0 \end{cases} \tag{6}$$

where g^x denotes the direction vector of input decrease; g^y denotes the direction vector of desired output increase; g^z denotes the direction vector of undesirable output decrease; s_n^x is the input slack vector, denoting the amount of excessive input; s^y is the desired output slack vector, denoting the amount of insufficient desired output; s^z is the undesirable output slack vector, indicating the amount of excessive undesirable output; and $s.t.$ is the function constraint.

(3) ***Malmquist–Luenberger index model***. Chung defined the Malmquist index model by considering the non-desired output distance function as the Malmquist–Luenberger productivity index [41]. Based on this study, this paper constructs a total factor productivity index of SBM directional distance function from t to $t+1$ based on the multiplicative division structure and adjacent reference [36] and defines it as the rural energy carbon emission efficiency (MI) index, as follows:

$$MI = \left[\frac{D_C^t(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^t(x^t, y^t, z^t; g)} \times \frac{D_C^{t+1}(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^{t+1}(x^t, y^t, z^t; g)}\right]^{\frac{1}{2}} \tag{7}$$

The decomposition is given by the following:

$$MI = \frac{D_C^{t+1}(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^t(x^t, y^t, z^t; g)} \times \left[\frac{D_C^t(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^{t+1}(x^{t+1}, y^{t+1}, z^{t+1}; g)} \times \frac{D_C^t(x^t, y^t, z^t; g)}{D_C^{t+1}(x^t, y^t, z^t; g)}\right]^{\frac{1}{2}} \tag{8}$$

Then we have the following:

$$MI = EC \times TC \tag{9}$$

The further decomposition of TC yields the following:

$$TC = \frac{D_C^t(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^{t+1}(x^t, y^t, z^t; g)} \times \left[\frac{D_C^{t+1}(x^{t+1}, y^{t+1}, z^{t+1}; g)}{D_C^t(x^{t+1}, y^{t+1}, z^{t+1}; g)} \times \frac{D_C^t(x^t, y^t, z^t; g)}{D_C^{t+1}(x^t, y^t, z^t; g)}\right]^{\frac{1}{2}} \tag{10}$$

Then we have the following:

$$TC = MATC \times BTC \tag{11}$$

$$MI = \left[\frac{D_C^t\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^t(x^t, y^t, z^t; g)} \times \frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^{t+1}(x^t, y^t, z^t; g)} \right]^{\frac{1}{2}} \tag{12}$$

The further decomposition of Equation (12) yields the following:

$$MI = \frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^t(x^t, y^t, z^t; g)} \times \left[\frac{D_C^t\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^{t+1}(x^{t+1}, y^{t+1}, z^{t+1}; g)} \times \frac{D_C^t\left(x^t, y^t, z^t; g\right)}{D_C^{t+1}(x^t, y^t, z^t; g)} \right]^{\frac{1}{2}} \tag{13}$$

Then we have the following:

$$MI = EC \times TC \tag{14}$$

The further decomposition of *TC* yields:

$$TC = \frac{D_C^t\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^{t+1}(x^t, y^t, z^t; g)} \times \left[\frac{D_C^{t+1}\left(x^{t+1}, y^{t+1}, z^{t+1}; g\right)}{D_C^t(x^{t+1}, y^{t+1}, z^{t+1}; g)} \times \frac{D_C^t\left(x^t, y^t, z^t; g\right)}{D_C^{t+1}(x^t, y^t, z^t; g)} \right]^{\frac{1}{2}} \tag{15}$$

Then we have the following:

$$TC = MATC \times BTC \tag{16}$$

where *MI* represents the change rate of rural energy carbon emission efficiency from period t to period $t + 1$, and if $MI > 1$, it indicates an increase in rural energy carbon emission efficiency; otherwise, it indicates a decrease in rural energy carbon emission efficiency. Further, *MI* can be decomposed into technical efficiency change (*EC*) and technological change (*TC*). *EC* represents the change rate of technical efficiency from period t to period $t + 1$, and $EC > 1$ means an increase in technical efficiency; otherwise, it indicates a decrease in technical efficiency. *TC* represents the change of technical level from period t to period $t + 1$, and $TC > 1$ indicates an improvement in technology; otherwise, it indicates the degradation in technology. It should be noted that technical efficiency can be further decomposed into magnitude of technological change (*MATC*) and biased technological change (*BTC*) according to Fare R. [42].

2.1.3. Estimation Procedure and Variable Description

After clarifying the carbon productivity of rural energy in China and each province, this paper further explores its influencing factors to ensure the pertinence of countermeasures and suggestions. Specifically, a linear regression equation is constructed with each province's rural energy carbon emission efficiency as the dependent variable and each influencing factor as the explanatory variable. Then this paper estimates the coefficients of the independent variables to judge the impacts of various factors on productivity value. Since the efficiency value is generally greater than 0, it implies that the dependent variable belongs to the left-hand censored truncated variable. The ordinary least square method may lead to a situation in which the parameter estimate value is biased toward 0. Therefore, this paper follows the study of Qian. [35] Furthermore, it uses the Tobit model with restricted dependent variables to estimate the empirical analysis. The basic form of the model is given by the following:

$$\begin{cases} MI_{it} = \beta^T x_{it} + e_{it}, if\ \beta^T + e_{it} = y_0 \\ 0, other \end{cases} \tag{17}$$

$$e_i \sim N\left(0,\ \sigma^2\right),\ i = 1, 2, 3, K, \cdots\cdots n$$

where *MI* is rural energy carbon emission efficiency, i denotes each province, t denotes the time (year), e_i is the restricted dependent variable, x_i is the vector of explanatory variables, and β is the vector of corresponding coefficients.

The dependent variable in this paper is rural energy carbon emission efficiency. The independent variables need to be selected scientifically regarding previous studies. Although there are few studies on rural energy carbon emission efficiency, many scholars have discussed the factors affecting energy or agricultural carbon emission efficiency. Even if independent variables in their studies were different, these studies could also provide some reference for our paper. Previous studies found that the level of agricultural economic development, agricultural industry structure, urbanization rate, the education level, public investment in agriculture, the planting scale, and other factors could influence energy carbon emission efficiency or agricultural carbon emission efficiency [31,43–45]. Based on these studies, this paper intends to identify the potential independent variables from the perspectives of the agricultural industry, rural labor force, and rural residents' living.

First, factors from the agricultural-industry perspective were included in the estimation procedure. In general, the improvement of production efficiency largely depends on energy input [23]. This impacts agricultural energy carbon emissions and, thus, may lead to changes in rural energy carbon emission efficiency. Therefore, concerning existing research [46], this paper takes the level of agricultural development as the independent variable. It specifically refers to the value-added per capita in agriculture, which is equal to the added value of agriculture divided by primary industry employees. In addition, it can be assumed that changes in the expenditures on agriculture would influence the energy demand of agricultural production [47], which, in turn, will affect the amount of carbon emissions and eventually may influence the carbon productivity of rural energy. Therefore, this paper takes the financial support of agriculture as the independent variable, and it is equal to agricultural financial support divided by total financial expenditure. Furthermore, food and cash-crop cultivation usually show certain differences in energy input intensity and economic efficiency level [48], further affecting rural energy carbon emission efficiency. The paper references the research of Liu et al. [49], with the structure of arable land usage being the independent variable. It is equal to the proportion of food sown area in total sown area of crops.

Second, factors from the rural-labor-force perspective were included in the estimation procedure. The difference in human capital level may affect rural residents' production and living behaviors. This is best observed in the usage of advanced equipment, rational allocation, and willingness to adopt low-carbon technologies [50]. As such, it may affect the rural energy carbon emission efficiency. Therefore, the level of rural human capital is concluded in the estimation as the independent variable, which refers to the average years of education in rural areas. The different occupations of the rural labor force influence their household income, agricultural production, and living energy consumption [51,52], which may lead to the differences in rural energy carbon emission efficiency. The continuous reliance on tertiary industries for fertilizers results in over-usage [53]. Therefore, the structure of rural labor force is included in the independent variables and defined as the proportion of primary industry employees in rural employees.

Third, factors from the rural residents' living perspective were included in the estimation procedure. To some extent, the consumption level reflects rural residents' purchasing ability. The higher the consumption level is, the greater the demand for energy in production and living, which may lead to higher carbon emissions and thus affect carbon productivity. The consumption level of rural residents is regarded as the independent variable and is defined as the per capita consumption amount. The concept of urbanization involves resettling rural residents into cities with improved living conditions, further affecting rural energy, consumption intensity, and the optimization of clean energy [54]. This contributes to rural energy carbon emissions and energy carbon emission efficiency. Therefore, the urbanization level is included in the independent variables, and the urbanization rate of each province defines it.

2.2. Data Sources

The data required for measuring the carbon emissions of rural energy were obtained from the annual *China Energy Statistical Yearbook*. The other data were mainly obtained from the annual *China Statistical Yearbook*, *China Energy Statistical Yearbook*, *China Statistical Abstract*, *China Rural Statistical Yearbook*, *China Population and Employment Statistical Yearbook*, *China Financial Yearbook*, and other relevant provincial statistical yearbooks, as well as national reports and statistical bulletins. In particular, in order to ensure the comparability of data in different years, the agricultural value added should be adjusted with reference to the constant price in 2005, while all other data are based on the actual value for each year. The descriptive statistics of each variable are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable	Unit	Sample	Mean	SD	Minimum	Maximum
Rural energy carbon emission efficiency	—	450	1.054	0.114	0.694	2.157
Agricultural development level	10^3 RMB/person	450	1.338	0.680	0.255	5.678
Agricultural financial support	—	450	0.107	0.035	0.014	0.190
Cultivated land use structure	—	450	0.653	0.136	0.328	0.971
Rural human capital level	Year	450	7.612	0.646	5.477	9.741
Structure of rural labor force	—	450	0.644	0.231	0.120	1.002
Consumption of rural residents	10^3 RMB/person	450	0.351	0.154	0.158	1.068
Urbanization level	%	450	0.553	0.136	0.275	0.896

3. Research Results and Discussion

3.1. Spatial–Temporal Comparison of Rural Energy Carbon Emission Efficiency in China

3.1.1. The Overall Characteristics of China's Rural Energy Carbon Emission Efficiency

Table 2 presents the rural energy carbon emission efficiency growth and causes in China from 2006 to 2020. As shown in Table 2, rural energy carbon emission efficiency has been increasing in China since 2005, with an average annual growth rate of 4.82%. More specifically, the carbon productivity in 2020 ranked first and was 1.102, which has increased by 10.22% compared with that in 2019. In contrast, the carbon productivity in 2007 was only 1.005, which indicates that the efficiency of rural energy carbon emissions in China has improved in that year but to a limited extent.

Table 2. The growth and causes of rural energy carbon emission efficiency in China from 2006 to 2020.

Year	MI		EC		TC		MATC		BTC	
	Interannual Value	Accumulation Value	Interannual Value	Accumulation Value	Interannual Value	Accumulation Value	Interannual Value	Accumulation Value	Interannual Value	Accumulation Value
2005	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
2006	1.022	1.022	1.011	1.011	1.011	1.011	1.014	1.014	0.998	0.998
2007	1.005	1.027	1.004	1.015	1.000	1.012	0.994	1.008	1.006	1.004
2008	1.036	1.064	1.019	1.034	1.017	1.028	1.008	1.015	1.009	1.013
2009	1.031	1.097	1.006	1.041	1.025	1.054	1.018	1.034	1.007	1.020
2010	1.025	1.124	0.979	1.019	1.047	1.104	1.041	1.076	1.005	1.025
2011	1.022	1.149	1.057	1.077	0.967	1.067	0.961	1.034	1.007	1.032
2012	1.051	1.207	0.999	1.076	1.052	1.122	1.049	1.085	1.002	1.035
2013	1.056	1.275	0.993	1.068	1.064	1.194	1.063	1.152	1.002	1.036
2014	1.048	1.336	1.030	1.099	1.018	1.216	1.016	1.170	1.002	1.039
2015	1.053	1.407	1.027	1.129	1.025	1.246	1.023	1.197	1.002	1.041
2016	1.074	1.511	0.984	1.111	1.091	1.360	1.089	1.304	1.002	1.043
2017	1.074	1.623	1.011	1.124	1.062	1.444	1.057	1.378	1.005	1.048
2018	1.070	1.737	0.884	0.994	1.210	1.747	1.201	1.654	1.008	1.056
2019	1.059	1.840	1.049	1.042	1.010	1.765	1.005	1.663	1.005	1.062
2020	1.102	2.028	0.982	1.023	1.123	1.982	1.127	1.873	0.997	1.058
Mean Value	1.048	—	1.002	—	1.047	—	1.043	—	1.004	—

Note: 2005 is the base period, so all values are 1.000. MI is the result of Malmquist index, called total factor productivity; EC is the efficiency improvement index; TC is the technical progress index; MATC is the pure technical efficiency index; BTC is the technical change rate of input–output shift.

All in all, the whole investigation period can be divided into two stages, namely the slow growth stage, from 2005 to 2011; and the rapid growth stage, from 2011 to 2020. In the first stage, from 2005 to 2011, the rural energy carbon emission efficiency remained lower than 1.040, and its cumulative value only increased by 14.91%. The average annual growth rate is 2.34%. In the second stage, from 2011 to 2020, the carbon productivity remained higher than 1.050, except that, in 2014, and its cumulative value increased by 76.44%. The average annual growth rate is 6.51%. The growth of rural energy carbon emission efficiency is mainly due to agricultural technological change (TC), as the annual contribution rate is as high as 4.67%. In comparison, the role of agricultural technical efficiency change (EC) in the growth of rural energy carbon emission efficiency is relatively small, as the annual contribution rate is only 0.25%. The decomposition of agricultural technological change reveals that the magnitude of agricultural technological change (MATC) plays a more obvious role than the biased technological change (BTC), since the annual contribution rate of the former is 4.27%, while the annual contribution rate of the latter is only 0.38%.

3.1.2. Interprovincial Differences in Rural Energy Carbon Emission Efficiency in China

Table 3 presents the rural energy carbon emission efficiency on average of 30 provinces in China from 2006 to 2020. As shown in Table 3, during the investigation period, the mean value of rural energy carbon emission efficiency in 30 provinces in China was greater than 1.000, which indicates that the rural energy carbon emission efficiencies of all provinces were all improving. In comparison, Ningxia ranks first, with the mean value of MI 1.135, indicating that its rural energy carbon emission productivity has increased at an annual rate of 13.45% over the past 14 years. Guizhou ranks second with the mean value of MI 1.103. The provinces ranked from 3 to 10 are Hebei, Yunnan, Shanghai, Henan, Jiangsu, Zhejiang, Shandong, and Fujian, and the mean MI values are 1.089, 1.082, 1.073, 1.071, 1.070, 1.065, 1.058, and 1.057, respectively. In contrast, Inner Mongolia has the lowest mean value of rural energy carbon emission efficiency (1.005). Jilin, Xinjiang, Guangxi, and Hainan rank 2 to 5, counting backward, with the mean MI values 1.005, 1.006, 1.020, and 1.024, respectively.

Table 3. Average rural energy carbon emission efficiency of 30 provinces in China from 2006 to 2020.

Province	MI		EC		TC		MATC		BTC	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
Beijing	1.024	25	0.971	26	1.054	11	1.129	12	0.934	21
Tianjin	1.035	20	1.005	11	1.030	25	1.206	4	0.853	27
Hebei	1.089	3	1.012	5	1.077	4	1.054	23	1.021	2
Shanxi	1.028	23	0.994	23	1.035	24	1.033	26	1.002	10
Inner Mongolia	1.005	30	0.956	28	1.051	13	1.087	19	0.967	15
Liaoning	1.035	19	0.974	25	1.063	7	1.099	14	0.967	16
Jilin	1.005	29	0.991	24	1.015	29	1.298	2	0.781	29
Heilongjiang	1.055	13	0.998	20	1.057	9	1.037	25	1.019	3
Shanghai	1.073	5	0.969	27	1.107	2	1.089	18	1.017	4
Jiangsu	1.070	7	1.001	16	1.069	5	1.149	8	0.931	22
Zhejiang	1.065	8	1.004	12	1.061	8	1.134	11	0.936	20
Anhui	1.031	22	1.017	3	1.014	30	1.018	30	0.996	11
Fujian	1.057	10	1.021	2	1.035	23	1.091	17	0.949	18
Jiangxi	1.056	12	1.013	4	1.042	20	1.031	29	1.010	8
Shandong	1.058	9	1.009	8	1.049	16	1.047	24	1.002	9
Henan	1.071	6	1.002	15	1.069	6	1.055	22	1.013	6
Hubei	1.056	11	1.006	10	1.050	15	1.033	27	1.016	5
Hunan	1.044	17	0.999	19	1.046	17	1.033	28	1.012	7
Guangdong	1.026	24	1.009	9	1.017	28	1.251	3	0.813	28
Guangxi	1.020	27	1.000	17	1.020	27	1.152	7	0.885	24
Hainan	1.024	26	1.003	13	1.021	26	1.714	1	0.595	30
Chongqing	1.054	14	1.009	7	1.045	18	1.076	20	0.971	14
Sichuan	1.035	18	0.999	18	1.036	21	1.094	16	0.948	19
Guizhou	1.103	2	1.002	14	1.101	3	1.115	13	0.987	13
Yunnan	1.082	4	1.025	1	1.056	10	1.065	21	0.991	12

Table 3. *Cont.*

Province	MI		EC		TC		MATC		BTC	
	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking	Value	Ranking
Shaanxi	1.046	16	0.996	22	1.051	14	1.142	10	0.920	23
Gansu	1.053	15	1.010	6	1.043	19	1.183	6	0.882	25
Qinghai	1.033	21	0.998	21	1.036	22	1.195	5	0.867	26
Ningxia	1.135	1	0.954	30	1.190	1	1.148	9	1.036	1
Xinjiang	1.006	28	0.955	29	1.053	12	1.098	15	0.959	17

Furthermore, in order to clearly show the interprovincial differences in the rural energy carbon emission efficiency, the 30 provinces are divided into "high growth group", "fast growth group", "medium growth group", and "slow growth group" according to the absolute differences in the respective values of rural energy carbon emission efficiency. In specific, the "high growth group" refers to the provinces of which the rural energy carbon emission efficiency generally grows faster than that of others, and this group consists of Ningxia and Guizhou since the average values of MI are all greater than 1.100. The "fast growth group" refers to all provinces of which the rural energy carbon productivities are between 1.050 and 1.100, and these provinces are Hebei, Heilongjiang, Shanghai, Jiangsu, Zhejiang, Fujian, Jiangxi, Shandong, Henan, Hubei, Chongqing, Yunnan, and Gansu. The "medium growth group" refers to the provinces of which the rural energy carbon productivities are between 1.030 and 1.050, and these provinces are Tianjin, Liaoning, Anhui, Hunan, Sichuan, Shaanxi, and Qinghai. The "slow growth group" refers to the provinces of which the rural energy carbon productivities are between 1.000 and 1.030, and these provinces are Beijing, Shanxi, Inner Mongolia, Jilin, Guangdong, Guangxi, Hainan, and Xinjiang.

Furthermore, the improvement of rural energy carbon emission efficiency in 16 provinces, including Tianjin, Hebei, Jiangsu, Zhejiang, and so on, is mainly due to agricultural technological change and agricultural technical efficiency change, and these provinces are the frontier leaders in low-carbon rural-energy use nationwide. More specifically, frontier technological progress plays a more important role in improving rural energy carbon emission efficiency, as the values of it in 15 provinces are all greater than those of technical efficiency improvement. Meanwhile, the decomposition of agricultural technological change shows that the magnitude of agricultural technological change and the biased technological change all play important roles in the improvement of rural energy carbon emission efficiency in Hebei, Jiangxi, Shandong, Henan, and Hubei. Meanwhile, the magnitude of technological change in the remaining provinces has been improved to varying degrees, but biased technological change is in a deteriorated state.

The improvement in rural energy carbon emission efficiency in 14 provinces, including Beijing, Shanxi, Inner Mongolia, Liaoning, and so on, is entirely dependent on agricultural technological change rather than agricultural technical efficiency change. The decomposition of agricultural technological change shows that both the magnitude of technological change and the biased technological change play important roles in the improvement of rural energy carbon emission efficiency in provinces such as Shanxi, Heilongjiang, Shanghai, Hunan, and Ningxia. The magnitude of agricultural technological change in the remaining provinces has been improved, while the biased technological change has been in a state of deterioration.

All in all, agricultural technological change plays a more important role in promoting the improvement of rural energy carbon emission efficiency in all provinces, except Anhui, while agricultural technical efficiency even deteriorates in these provinces. Therefore, in order to better promote the efficiency of rural energy carbon emission in the future, we should not only pay attention to the research and development of frontier technology but also pay attention to the reasonable application of technologies to achieve its efficiency improvement.

3.2. Analysis of Factors Influencing Rural Energy Carbon Emission Efficiency in China

The Hausman test result ($\chi^2 = 24.54, \ \ P = 0.001$) suggests that the Tobit model with fixed effects for panel data should be used to estimate the regression analysis of rural energy carbon emission efficiency. In this paper, Stata software is used for estimation, and the regression results are shown in Table 4. It can be seen that all variables are statistically significant, except for agricultural financial support.

Table 4. Estimation results of factors influencing rural energy carbon emission efficiency.

Variables		Coefficients	SD	Z
Agricultural industry	Agricultural development level	0.046 ***	0.014	3.27
	Agricultural financial support	0.264	0.249	1.06
	Cultivated land use structure	−0.187 **	0.086	−2.18
Rural labor force	Rural human capital level	−0.034 *	0.018	−1.89
	Structure of rural labor force	0.143 ***	0.051	2.82
Rural residents' living	Rural residents' consumption level	−0.278 **	0.130	−2.14
	Urbanization level	0.574 ***	0.140	4.12

Note: ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

As shown in Table 4, among the factors from the perspective of agricultural industry, agricultural development level has a significantly positive effect on rural energy carbon emission efficiency. That is, when other conditions remain unchanged, the higher the value added per capita in agriculture is, the higher the rural energy carbon emission efficiency would be. The possible explanation is that the increase in agricultural development level promotes agricultural production mode and the adoption of various advanced agricultural production technologies, which could reduce the input of energy and other materials per unit of agricultural added value. Consequently, the rural energy carbon emission efficiency could be improved. Arable land use structure negatively influences rural energy carbon emission efficiency, meaning that the higher the proportion of grain-sown area is, the lower the rural energy carbon emission efficiency would be. In general, the output per unit area of food crops is significantly lower than that of cash crops, but there may be no significant difference in energy demand between the two. Even if the energy input of cash crops is slightly higher, the return may be much higher than that of the input. Therefore, the higher the proportion of grain sown area is, the lower the overall agricultural output level and the energy carbon emission level would be, thus leading to a decrease in rural energy carbon emission efficiency.

Among the factors from the perspective of rural labor force, rural labor force structure has a significantly positive impact on rural energy carbon emission efficiency. That is, when other conditions remain unchanged, the higher the proportion of primary industry employees among rural workers is, the higher the rural energy productivity would be. The high proportion of primary industry employees usually implies that the agricultural production sector has a high status in the local area and that the supply of experienced agricultural producers is sufficient, which could ensure the efficient output of agricultural production. At the same time, households with a high proportion of agricultural personnel are generally more frugal in their daily life and have less demand for energy, such as electricity and gasoline, and this could reduce energy carbon emissions. Correspondingly, rural human capital level shows a significant negative effect on rural energy carbon emission efficiency. The higher the average years of rural residents' education level is, the lower the rural energy carbon emission efficiency would be. A possible explanation is that rural residents with a good education background are more likely to work in non-agricultural industries. Such families attach relatively little importance to agriculture, but the overall income level is more secure. Therefore, their agricultural output is reduced, but domestic energy consumption may increase, thus leading to an increase in rural energy carbon emissions.

Among the factors at the rural residents' living perspective, urbanization level has a significant and positive effect on rural energy carbon emission efficiency. That is, when other conditions remain unchanged, the higher the urbanization rate is, the higher the rural energy carbon emission efficiency would be. In recent years, the improvement of urbanization in various regions mainly relies on rural residents moving to cities. The departure of these people has no great impact on agricultural output, but it could reduce domestic energy consumption and the corresponding carbon emissions. Therefore, the rural energy carbon emission efficiency would increase. In contrast, rural residents' consumption level shows a significant negative effect on rural energy carbon emission efficiency, which means that the higher rural residents' consumption level is, the lower the rural energy carbon emission efficiency would be. The possible explanation is that the improvement of rural residents' consumption level often implies the increase of demand for various types of agricultural machinery, household cars, air conditioners, refrigerators, and other high-energy household appliances, which not only brings convenience to production and life, but also intensifies the demand for energy consumption, thus leading to an increase in corresponding carbon emissions.

4. Discussion

This study reinforces the findings of previous studies in the following three aspects: First, the carbon emissions caused by agricultural production energy consumption and rural residents' daily energy consumption were explored in the study. Second, based on the scientific construction of the input–output index system, this study effectively measured rural energy carbon emission efficiency and described its spatial–temporal characteristics. Third, based on provincial panel data, this study identified the key factors affecting rural energy carbon emission efficiency. The results show that, although the overall growth of rural energy carbon emission efficiency in China is sustained, there are significant interprovincial differences. Technological progress plays a more important role than the technical efficiency improvement in the improvement of rural energy carbon emission efficiency. Factors such as agricultural development level and urbanization level promote rural energy carbon emission efficiency, while factors such as rural human capital level and rural residents' consumption level negatively influence rural energy carbon emission efficiency.

5. Conclusions

5.1. Main Research Findings

This paper firstly measured rural energy carbon emission efficiency and analyzed its spatial–temporal differences in China and then explored the influencing factors with the Tobit model used. The main findings are as follows.

First, rural energy carbon emission efficiency has been improving continuously and is mainly due to frontier technology progress rather than technical efficiency improvement in China. Since 2006, rural energy carbon emission efficiency has been growing at an annual rate of 4.82%. The difference in carbon productivity values by year can be divided into two phases, i.e., the slow growth phase (2006~2011) and the fast growth phase (2012~2020). Technological change is in a state of progress in most years and its role in rural energy carbon emission efficiency is significantly stronger than that of technical efficiency improvement.

Second, rural energy carbon emission efficiency shows significant interprovincial differences. Although the rural energy carbon emission efficiency of all 30 provinces is in a state of improvement, there are still obvious differences among them. The average carbon productivity of Ningxia is as high as 1.1345, while that of Inner Mongolia is only 1.0046. The 30 provinces are further divided into "high growth group", "fast growth group", "medium growth group", and "slow growth group" based on the differences in rural energy carbon emission efficiency values. Agricultural technological change plays a more important role in improvement of rural energy carbon emission efficiency in all provinces, except Anhui, while technical efficiency is not only slightly weak, but also deteriorating in many provinces.

Third, rural energy carbon emission efficiency is influenced by factors from the perspectives of agricultural industry, rural labor force, and rural residents' living. Specific, from the perspective of agricultural industry, the agricultural development level positively influences rural energy carbon emission efficiency, while the cultivated land use structure has a negative impact on the rural energy carbon emission efficiency. Among the factors from the perspective of rural labor force, the structure of the rural labor force has a positive effect, while the rural human capital level exerts a negative effect on rural energy carbon emission efficiency. Among the factors at the rural residents' living perspective, the urbanization level has a positive effect on rural energy carbon emission efficiency, while rural residents' consumption level negatively affects rural energy carbon emission efficiency.

5.2. Policy Implications

In order to better promote the overall rural energy carbon emission efficiency in China, measures can be taken as follows.

Firstly, governments should strengthen the synergy between development and promotion of energy-saving and emission reduction technologies in rural areas. Since technical efficiency plays a small role in promoting rural energy carbon emission efficiency, we need to pay attention to the research and development of various low-carbon technologies, and even to the promotion and application of these technologies either in agricultural production or in rural residents' lives.

Secondly, we need to develop rural industries and promote the revitalization of high-quality rural talents in rural areas. In the process of vigorously promoting rural revitalization, policymakers should actively create favorable policies to attract highly qualified rural talents to return to the countryside and realize the integration of the three rural industries and high-quality development with their intelligence, capital, and technical support.

Thirdly, the structure of arable land utilization should be optimized, and the efficiency of agricultural resources utilization should be improved. The difference in the arable land utilization structure leads to the difference in rural energy carbon emission efficiency. Therefore, it is necessary to further optimize the arable land utilization structure while ensuring the security of food supply, and, at the same time, we should make efforts to improve the efficiency of agricultural resources utilization, so as to effectively reduce arable land carbon emissions.

Fourthly, measures should be taken to enhance rural residents' awareness of energy conservation and to guide their emission reduction behaviors. Since rural residents may waste energy resources both in agricultural production and in their lives, local governments should make full use of various media to actively promote the importance of energy saving and the emission reduction. At the same time, the necessary legislation or institutional guarantee should be adopted to effectively guide rural residents' emission reduction behaviors.

The accuracy of rural energy carbon emission is only partially reliable due to the lack of accurate biomass-fuel-related data. It does not influence the theoretical and practical meaning of this paper. The follow-up research can be further expanded in this regard.

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