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Environmental Impact Assessment of Agricultural Electricity Substitution Technology Based on Carbon Emission Calculation Model in Energy Saving and Emission Reduction Environment

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Abstract Under the environment of energy conservation and emission reduction, electrical energy substitution in agricultural production can effectively reduce carbon emissions and improve environmental quality. This paper proposes a carbon emission calculation model, combines historical data to calculate the total energy carbon emission of the city, and predicts the trend of energy carbon emission changes based on the Mann-Kendall trend analysis test. Improve the single-level gray correlation, propose multi-level gray correlation analysis method to comprehensively assess the environmental impact factors of rural electric energy substitution, and construct an impact assessment model of agricultural electric energy substitution. Utilizing energy and economic data from 2020-2024 in Anhui Province, China, emission monitoring and trend forecasting are conducted, and the environmental impact of its agricultural electric energy substitution technology is assessed. Anhui Province's future carbon emissions will continue to show an overall increase, but carbon emissions from mining (industry) will continue to decrease. In 2026, the rural electricity substitution in Anhui Province is predicted to be 64.72×10^{8}(kW·h), which will increase by 221% compared to 2022, and the rural electricity substitution shows a diversified development trend.

Index Terms carbon emission calculation model, Mann-Kendall trend analysis test, multilevel gray correlation analysis, agricultural electricity substitution

I. Introduction

In traditional agricultural activities, carbon emissions are mainly composed of carbon emissions from the combustion of diesel engines such as rotary tillers, mid-tillers and seeders in the pre-tillage and sowing stage, carbon emissions from the application of pesticides and fertilizers, as well as heating and ventilation in the growth management stage and carbon emissions from the combustion of diesel engines such as harvesters and tractors in the harvesting and transportation stage [1]-[3]. With the development of agricultural modernization, in order to solve the problem of energy shortage and air pollution, it is proposed to implement the rural clean energy construction project and promote electric energy substitution technology [4]. In the production and consumption links with electric energy to fuel oil, coal-fired agricultural machinery and equipment to replace, reduce the use of high energy consumption, high pollution agricultural equipment [5]. Such as the use of electric farm machinery instead of fuel-fired farm machinery, installing water-fertilizer integration equipment to replace the traditional irrigation and fertilization methods, the use of electric temperature-control equipment to replace the coal heating temperature control methods, etc., so as to greatly reduce carbon emissions and improve the efficiency of energy use [6].

Energy is an important factor in the overall efforts to achieve sustainable development, domestic and international experts, policymakers and scholars in energy and environment have begun to implement national energy indicators to monitor the impact of energy policies on the social, economic and environmental aspects of sustainable development [7]. A lot of efforts have been made by foreign scholars on how to rationalize the use of each energy source to improve the overall energy use efficiency of the whole society, for example, Katuwal and Bohara [8] pointed out that Nepal, as one of the least developed countries (LDCs), is characterized by a very low per capita consumption of energy, and due to the lack of alternative commercial sources of energy the country relies heavily on traditional fuels, and in order to solve the problem of energy in agriculture , the country initiated the distribution of several renewable energy technologies. Beuchelt and Nassl [9] pointed out that by replacing fossil fuels through biomass resources, on one hand, it can reduce the availability of fossil fuels and on the other hand, it can reduce the carbon emissions and further improve the quality of the environment but the study did not take food security sufficiently into account.

Electricity substitution technology not only needs to change the energy structure at the energy consumption end, improve the utilization efficiency of energy, and reduce the emission of harmful gases and particles. It is also necessary to change the energy structure of power generation at the power generation end, such as increasing the proportion of renewable energy generation and reducing the proportion of thermal power [10]. For example, Niu, D et al [11] analyzed the electricity substitution efficiency of 30 provinces in China in 2017 through a three-stage DEA model, and found that the electricity substitution efficiency showed a trend of east-high and west-low after considering environmental and stochastic factors. Liu, K et al [12] planned, designed and analyzed the environmental benefits of an electricity substitution project for the tobacco industry in Yunnan Province and used game theory to optimize the strategy. Wang, Y et al [13] combined Salp Swarm Algorithm (SSA) and Least Squares Support Vector Machine (LSSVM) to forecast the electricity substitution potential of industrial activities in the Beijing-Tianjin-Hebei region taking into account the effects of multiple drivers. Dong, J et al [14] conducted a comprehensive comparison of the economic and environmental benefits of electricity substitution for fossil fuels in China through an established energy substitution cost evaluation model and concluded that electricity substitution strategies can improve economic and environmental benefits. Wang, Y et al [15] simulated the impacts of electricity substitution technology on energy demand and CO2 emissions in China from 2015 to 2035 through a system dynamics model, and found that electricity substitution plays an indispensable role in promoting China's energy structure transformation. It can be seen from the above literature that electricity substitution technology is both an important means to accelerate energy structure adjustment and an important measure to promote the climbing share of clean energy consumption [16]. However, there are relatively few studies at home and abroad on the specific potential of electric energy substitution efforts in agricultural activities, and the environmental benefits they bring, and there is no unified research idea and methodology, which requires further in-depth research.

In this paper, we firstly constructed a carbon emission calculation model to calculate the total energy and carbon emissions of the city by combining historical data with the carbon monitoring system covering energy carbon emissions, clean energy power generation and transportation electricity substitution. The Mann-Kendall trend analysis test is proposed to judge and predict the time series, i.e. the trend of the total carbon emissions, based on the historical energy and carbon emissions data. Secondly, the impact assessment model of agricultural electricity substitution is constructed, and the multi-level gray correlation analysis method is proposed to avoid the deficiency of the single-level gray correlation analysis method in view of the limitation of the single-level gray correlation analysis method for the evaluation of the multi-level indicator system. By fully exploring the correlation degree of evaluation indicators at each level, the fusion problem of the weight value of the second-level indicators is effectively solved, and the final objective weight value is calculated. The energy and economic data of Anhui Province, China, from 2020 to 2024 are used as the research object to detect and predict the trend of carbon emissions and assess the environmental impacts of agricultural electric energy substitution technology in Anhui Province.

II. Carbon emission calculation models

With the enhanced global attention to environmental protection and sustainable development, all industries are facing great pressure for energy saving and emission reduction, and the demand for carbon emission calculation and prediction is becoming stronger and stronger. In this chapter, a carbon emission calculation model is constructed under the environment of energy conservation and emission reduction, a carbon emission calculation formula is proposed, and the Mann-Kendall trend test is used to study the trend of energy carbon emission changes.

II. A. Calculation of energy carbon emissions

Clean energy generally refers to renewable energy sources that are developed and utilized on the basis of new technologies, including solar energy, hydroelectric energy, wind energy and so on. Compared with traditional energy sources, the biggest advantage of clean energy is that it is rich in resources and has a very low rate of environmental pollution, so it is the main trend of energy development in the future. The carbon emission reduction of transportation electric energy substitution refers to the carbon emission reduction of new energy vehicles or vehicles mainly driven by electricity instead of traditional vehicles. New energy vehicles themselves do not emit air pollutants, so the promotion of electric vehicles is one of the important measures for energy saving and emission reduction.

The formula for calculating total carbon emissions is as follows:

$$C = C_1 - C_2 - C_3 \tag{1}$$

where: C_1 is the energy carbon emission; C_2 is the clean energy emission reduction; C_3 is the transportation electric energy substitution emission reduction.

II. A. 1) Energy carbon emissions

Since the scope of accounting for GHG emissions from emissions includes both their direct and indirect emissions related to production and operation activities, the calculation of energy carbon emissions can be divided into two parts.

Direct emissions: refers to the GHG emissions generated by the combustion and consumption of fossil fuels such as coal, diesel, fuel oil and natural gas in production systems such as generating units, cogeneration units and heating units, which can be calculated by the following formula:

$$D = \sum_{i=1}^{N} D_i = \frac{44}{12} \sum_{i=1}^{N} E_i L_i C_{i'} O_i \tag{2}$$

where: D is the direct emission; D_i is the emission of the i th fossil fuel; N is the number of fossil fuel types; E_i is the consumption of the fossil fuel; L_i is the Lower Calorific Value (LCV) of the fossil fuel; $C_{i'}$ is the carbon content per unit calorific value of the fossil fuel; and O_i is the oxidation rate of the fossil fuel. Among them, the values of L_i, C_i and O_i for different fossil fuels can be referred to the "Guidelines on Accounting Methods and Reporting of Greenhouse Gas Emissions by Power Generation Enterprises in China (for Trial Implementation)".

Indirect Emission: It refers to the GHG emission caused by the use of purchased electricity and heat, etc. by the emitting entity, which can be calculated by the following formula:

$$D' = \sum \left[(100\% - \beta) E_P P_{EM} \right] \tag{3}$$

where: D' is the indirect emissions; β is the share of clean energy in municipal electricity supply; E_p is the electricity consumption without clean energy on-grid electricity; and the electricity emission factor $P_{EM} = 7.88 \times 10^{-4} t / (kW \cdot h)$.

According to Eq. (2) and Eq. (3), the energy carbon emissions can be calculated by the following formula:

$$C_1 = D + D' \tag{4}$$

II. A. 2) Emission reductions from clean energy generation

In recent years, the development of clean energy in China has progressed rapidly, with the installed capacity of hydropower increasing and the new installations of wind power and photovoltaic power ranking first in the world. The indirect carbon emissions from electricity have been reduced by the indirect carbon emissions from self-generated and self-consumed electricity, as self-generated and self-consumed clean energy electricity (i.e., off-grid clean energy power generation) offsets a portion of the electricity consumption. In this section, the emission reduction from clean energy power generation mainly refers to the emission reduction from the on-grid portion of enterprises' clean energy such as photovoltaic, wind power, and biomass. The calculation formula is as follows:

$$C_2 = E_g P_{EM} \tag{5}$$

where: E_g is clean energy feed-in electricity.

II. A. 3) Emission reductions from electricity substitution in transportation

Transportation electric energy substitution refers to new energy vehicles that utilize electric energy to drive the vehicle through electric power storage technology, which is converted to power plant emissions in accordance with the amount of electricity consumed. New energy vehicles mainly include pure electric vehicles, plug-in hybrid vehicles and fuel cell vehicles. Compared with traditional fuel vehicles, on the one hand, new energy vehicles have a huge energy storage role and can cut peaks and fill valleys; on the other hand, the carbon dioxide emissions of new energy vehicles are significantly reduced. In addition, the same amount of crude oil sent to the power plant for power generation to supply new energy vehicles, its energy utilization rate is higher than after refining into gasoline to supply fuel vehicles. Therefore, new energy vehicles have the advantages of being green and saving energy. With the new energy vehicle technology is becoming more and more mature and perfect, electric vehicles and other new energy vehicles are gradually entering the market and accepted by the public, to promote the transportation of electric energy substitution is conducive to easing the pressure of the environment and energy crisis. The emission reduction of transportation electric energy substitution can be understood as the reduction of carbon emission of new energy vehicles compared with fuel vehicles under the same mileage of new energy vehicles and fuel vehicles. The formula is as follows:

$$C_3 = C_{CO_2} + C_{N_2O} + C_{CH_4} \tag{6}$$

$$C_{CO_2} = \frac{44}{12} E_c M \rho_{oil} L_{HO} C_c \rho_{oil} \frac{O_{HK}}{100} \tag{7}$$

$$C_{N_2O} = E_c M P_{N_2O} G_{N_2O} \tag{8}$$

$$C_{CH_4} = E_c M P_{CH_4} G_{CH_4} \tag{9}$$

where: C_{CO_2} is CO_2 emission; C_{N_2O} is N_2O discounted by CO_2 emission; C_{CH_4} is CH_4 discounted by CO_2 emission; E_c is the charging capacity of new energy vehicles; average kilowatt-hour mileage $M = 5km/(kW \cdot h)$; fuel consumption of fuel automobiles at 100km $O_{HK} = 8.9L$; gasoline density $\rho_{oil} = 0.73kg/L$; gasoline low calorific value $L_{HO} = 4.48 \times 10^{-5} TJ/kg$; carbon content per unit of calorific value $C_c = 8.9t/TJ$; gasoline oxidation rate $O_{oil} = 98\%$; N_2O emission factor $P_{N_2O} = 6mg/km$; CH_4 emission factor $P_{CH_4} = 57mg/km$; G is the greenhouse effect potential, $G_{N_2O} = 310$, $G_{CH_4} = 21$.

II. B.Mann-Kendall trend analysis test

The key core concept involved in the Mann-Kendall trend test method is whether the difference between two measurements is greater than, equal to, or less than 0. It is easy to analyze and compute and practical, so it is applicable to a wide range of non-normally distributed sample data [17]. Since the Mann-Kendall method can be used to analyze time series data with a continuous growth or downward trend (monotonic trend) and is applicable to most distributions, it can be applied to the study of urban carbon peaking state problem.

When analyzed by the Mann-Kendall trend test, the time series samples $(x_1, x_2, \cdots, x_n)$ are n independent, stochastically identically distributed data, and the hypothesis H_0 is that there is no trend in these sample data, and the alternative hypothesis H_1 is a bilateral test, where for all the $i, j \le n$, and at the same time the distributions of $i \ne j$, the distributions of x_i and x_j are different, then the statistical variable S of the test is calculated as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i) \tag{10}$$

$$sgn(x_j - x_i) = \begin{cases} 1, & x_j - x_i > 0 \\ 0, & x_j - x_i = 0 \\ -1, & x_j - x_i < 0 \end{cases} \tag{11}$$

Mann and Kendall proved that when $n \ge 8$, the statistic S roughly obeys a normal distribution with mean 0 and variance:

$$V(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^{g} t_i (i-1)(2i+5)}{18} \tag{12}$$

where: g denotes the number of groups, the same elements of the sequence are divided into a group; t_i denotes the range of the ith node. By transforming the statistic S to Z_{mk}, it allows Z_{mk} to approximately satisfy the standard normal distribution for large sample data:

$$Z_{mk} = \begin{cases} \dfrac{S-1}{(V(S))^{1/2}}, & S > 0 \\ 0, & S = 0 \\ \dfrac{S+1}{(V(S))^{1/2}}, & S < 0 \end{cases} \tag{13}$$

Under the condition of selecting the bilateral trend test, the confidence level α is selected, and if $|Z_{mk}| \geq Z_{1-\alpha/2}$, then the original hypothesis H_0 will be rejected, that is, there is a significant upward or downward trend of the sample data by the time series at the confidence level α. Under the bilateral test, when the absolute value of Z_{mk} is greater than or equal to 1.64, 1.96, and 2.57, it means that it has passed the test of 90%, 95%, and 99% significance at the confidence level, respectively. Meanwhile, the measure of trend size can be expressed as β:

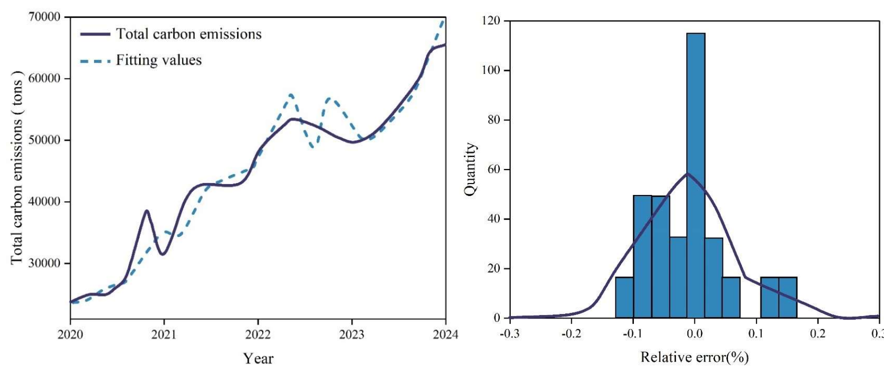
$$\beta = Median\left(\frac{x_i - x_j}{i-j}\right), \quad \forall j < i \tag{14}$$

where: $Median()$ is the median function, $1 < j < i < n$. When $\beta > 0$, it means that the sample data has an upward trend; $\beta < 0$ means a downward trend.

The value of confidence level α is based on the size of the specific sample size, if the sample size is relatively small, such as containing only dozens of cases, then α is taken as 0.05; If the sample size is relatively large, e.g. containing hundreds of cases, α may be taken as 0.01; Assuming that the sample size is very large, such as containing thousands or even more cases, α can take a value of 0.001 or less.

III. Carbon emission monitoring and trend forecasting in Anhui Province

This chapter utilizes the energy and economic data of Anhui Province from 2020 to 2024 to calculate the carbon emission data according to the emission factor method. And then use the carbon emission calculation model in this paper to calculate the fitted value of carbon emission, as shown in Figure 1. Figures (a) and (b) correspond to the comparison between the calculated carbon emission value and the actual value, and the error comparison between the calculated value of the emission factor method and the calculated value of the carbon emission calculation model in this paper, respectively. It can be seen that the total amount of carbon emissions in Anhui Province calculated by the carbon emission calculation model proposed in this paper is basically consistent with the actual total amount of carbon emissions, and the relative error is less than 5%, only 4.87%. This proves the accuracy of the carbon emission calculation model proposed in this paper.

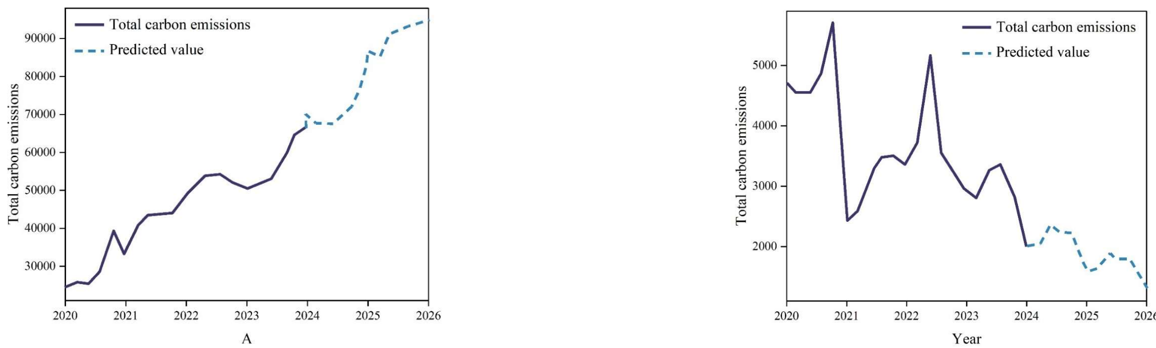


(a)The carbon emissions calculated by model in this paper and the actual value

(b)Absolute value of relative error

Figure 1: Carbon emissions monitoring

In this paper, we use Python language to calculate the carbon emissions of Anhui province based on the carbon emission calculation model proposed in this paper, such as social carbon emissions, carbon emissions from three major industries, carbon emissions from mining (industry), carbon emissions from urban and rural residents' living, carbon emissions from transportation, storage and postal services, carbon emissions from construction, carbon emissions from catering, carbon emissions from agriculture, forestry, animal husbandry and fisheries, and carbon emissions from wholesaling, retailing and lodging, etc., and simulate the calculated values and carbon emission forecasts, which are shown in Figure 2. The simulation calculation values and carbon emission projections are shown in Figure 2. Figures (a) and (b) correspond to the forecast of total carbon emissions and the forecast of carbon emissions from the mining industry (industry), respectively. It can be seen that the total carbon emissions in Anhui Province will continue to rise in the future, while the carbon emissions from the mining industry will continue to decrease.



(a)Prediction of total social carbon emissions (b)Mining carbon emissions (industrial) forecast

Figure 2: Industry, industry carbon emissions and carbon emissions forecast

IV. Agricultural electricity substitution impact assessment model

In the previous section, this paper proposed a carbon emission calculation model to realize the monitoring and trend prediction of carbon emissions, and provide a research data base for the assessment of the impact of agricultural electricity substitution technology on the environment. In this chapter, a multi-level gray correlation analysis will be proposed to provide a comprehensive assessment of the impact factors of agricultural electricity substitution.

IV. A. Improving single-level gray correlation analysis

The basic idea of single-level gray correlation analysis (SGRA) is to quantitatively describe the development trend of a system by determining the degree of geometric correlation between a reference data series and several comparative data series. The greater the degree of correlation, the more important the influence of the corresponding indicator on the evaluation object.

Assuming that the reference data column is $X_0 = \{x_0(1), x_0(2), \cdots, x_0(n)\}$, the comparative data sequence is notated as $X_1 = \{x_1(1), x_1(2), \cdots, x_1(n)\}$, $X_1 = \{x_1(1), x_1(2), \cdots, x_1(n)\}, k$ is the number of indicators.

Step1, Calculate the gray correlation coefficient [18]:

$$\delta_i(j) = \frac{\min_i \min_j |x_0(j) - x_i(j)| + \rho \max_i \max_j |x_0(j) - x_i(j)|}{|x_0(j) - x_i(j)| + \rho \max_i \max_j |x_0(j) - x_i(j)|} \tag{15}$$

ρ as the gray discrimination coefficient reflects subjectively the degree of importance attached by the evaluator to the maximum sequence difference, and objectively the degree of indirect influence of each factor on the gray correlation. Checking the literature, it is known that when $\rho \le 0.5463$ has the best discriminatory power for weight values. In addition, the degree of fluctuation of the series will directly affect the final results. For this reason, the value of ρ is determined by the degree of fluctuation of the sequence within the system.

Step2, Calculate the fluctuation factor:

$$F_v = \frac{1}{n \times k} \sum_{j=1}^{n} \sum_{k=1}^{k} (x_i(j) - \frac{1}{n} \sum_{k=1}^{n} x_i(j))^2 \tag{16}$$

If $F_v \le 0.5463$, $\rho = F_v$; if $F_v \ge 0.5463$, $\rho = 0.5466$.

Step3,Calculate the gray correlation:

$$r_i = \frac{1}{n} \sum_{j=1}^{n} \delta_i(j) \tag{17}$$

Determining the value of ρ according to this method can fully reflect the wholeness of the gray system, which not only eliminates the interference of subjective factors on the weight value, but also ensures the optimal discriminatory ability of the weight value, and guarantees the relative accuracy of the evaluation results.

IV. B. Multi-level gray correlation analysis

Among different grey correlation analysis methods, single-level grey correlation analysis is suitable for the evaluation of small sample indicators, but has certain limitations for the evaluation of multi-level indicator system, while multi-level grey correlation analysis (MGRA) can effectively avoid the shortcomings of single-level grey correlation analysis, and not only effectively solves the problem of integration of the weight values of each secondary indicator while fully exploring the correlation of each level of evaluation indexes, it not only effectively solves the integration problem of each secondary index, but also covers a richer amount of information than the single-level gray correlation analysis, making the evaluation results more accurate [19].

It is assumed that the comprehensive evaluation index system of electric energy substitution contains m first-level indicators, and each first-level indicator contains q_m second-level indicators.

Step1, take the secondary indicators $x=\{x_{11},x_{12},\cdots,x_{1q_1},\cdots,x_{mq_m}\}$ as a comparative data series, and get the degree of association between the secondary indicator series and the reference series according to the improved single-level gray correlation analysis method, which is noted as $\lambda=\{\lambda_{11},\lambda_{12},\cdots,\lambda_{1q_1},\cdots,\lambda_{mq_m}\}$.

Step2, take the first-level indicator $y=\{y_1,y_2,\cdots,y_m\}$ as a comparative data series, and get the degree of association between the first-level indicator and the reference series according to the improved gray correlation analysis method, which is recorded as $\varphi=\{\varphi_1,\varphi_2,\cdots,\varphi_m\}$.

Step3, calculate the final objective weight value:

$$\eta_l=\frac{1}{q_j}\sum_{j=1}^{q_j}\lambda_{ij}\varphi_i \tag{18}$$

Table 1: Effect evaluation index system

Target layer	Criterion layer	Sub-criterion layer	Indicator layer
A Evaluation of the effect of agricultural electricity substitution	$B1$ Technical indicators	$C1$ Technical applicability	$D1$ The difficulty of implementation and debugging
			$D2$ Environmental adaptability
			$D3$ Matching with related technologies
			$D4$ Energy efficiency ratio
		$C2$ Technical feasibility	$D5$ Safety index
			$D6$ Equipment life
		$C3$ Technology maturity	$D7$ Degree of automation
			$D8$ Extensiveness of application
	$B2$ Economic indicators	$C4$ Technical cost	$D9$ Investment
			$D10$ Energy consumption
			$D11$ Daily operating costs
			$D12$ Equipment maintenance costs
		$C5$ Technology gains	$D13$ Internal revenue of the enterprise
			$D14$ Net annual value
			$D15$ Annual alternative electricity
	$B3$ Environmental indicators	$C6$ Environmental benefits	$D16$ Ability to reduce emissions of harmful gases
			$D17$ Emission reduction energy for dust and other particulate matter
	$B4$ Social indicators	$C7$ Resource utilization	$D18$ Promoting Sustainable Energy Development
		$C8$ Social value	$D19$ Social influence degree
			$D20$ Driving force for other industries

V. Environmental impact assessment of agricultural electricity substitution technology in Anhui Province

In the previous chapter, this paper utilized the carbon emission calculation model proposed in this paper to calculate the carbon emission data and projected carbon emissions in Anhui Province, China. In this chapter, we analyze the environmental impacts of agricultural electricity substitution technologies in Anhui Province based on the carbon emission data for 2022-2026 detected and predicted above, and the impact assessment model for agricultural electricity substitution constructed in this paper.

V. A. Determination of indicator weights

The process of impact assessment of electricity substitution in agriculture involves a number of influencing factors. In this paper, an experienced expert group was engaged to consult on the impact assessment indicators for agricultural electricity substitution. According to the experts' opinions, the weights of agricultural electric energy substitution evaluation indicators are analyzed. Firstly, the technical impact indicator system of agricultural electric energy substitution is established, as shown in Table 1.

The weights of the indicator layer relative to the target layer are shown in Table 2. The indicator with the highest total weight in the indicator layer is $D5$ safety coefficient, with a total weight of 0.0869, followed by $D19$ social impact degree and $D15$ annual replacement power, with a total weight of 0.044 and 0.0425, respectively. $D10$ energy consumption has the lowest total weight among all the indicators, with a total weight of only 0.0032.

Table 2: Weights of factors in the index layer to the target layer

Indicators	Weight								Total weight
	$C1$	$C2$	$C3$	$C4$	$C5$	$C6$	$C7$	$C8$	
	0.0637	0.1158	0.0351	0.0263	0.0788	0.602	0.0197	0.0587	
$D1$	0.4182	0	0	0	0	0	0	0	0.0266
$D2$	0.277	0	0	0	0	0	0	0	0.0172
$D3$	0.125	0	0	0	0	0	0	0	0.0077
$D4$	0.196	0	0	0	0	0	0	0	0.0121
$D5$	0	0.75	0	0	0	0	0	0	0.0869
$D6$	0	0.25	0	0	0	0	0	0	0.029
$D7$	0	0	0.3333	0	0	0	0	0	0.0117
$D10$	0	0	0	0.1223	0	0	0	0	0.0032
$D11$	0	0	0	0.227	0	0	0	0	0.006
$D12$	0	0	0	0.227	0	0	0	0	0.006
$D13$	0	0	0	0	0.1634	0	0	0	0.0129
$D14$	0	0	0	0	0.297	0	0	0	0.0234
$D15$	0	0	0	0	0.5396	0	0	0	0.0425
$D16$	0	0	0	0	0	0.5	0	0	0.301
$D17$	0	0	0	0	0	0.5	0	0	0.301
$D18$	0	0	0	0	0	0	1	0	0.0197
$D19$	0	0	0	0	0	0	0	0.75	0.044
$D20$	0	0	0	0	0	0	0	0.25	0.0147

Combined with the above indicators, the electric boiler technology and heat pump technology used in rural electric energy substitution are evaluated and analyzed, as shown in Table 3. According to the data in the table, the total score of electric boiler and heat pump technology is 0.472 and 0.494 respectively, respectively calculate the value of the indicators of electric boiler and heat pump to form the evaluation of the broadening matrix, the evaluation of the broadening matrix specification processing, calculate the correlation coefficient, constitute the correlation coefficient matrix. The weighted correlation coefficients of electric boiler and heat pump are γ_1=0.8196 and γ_2=0.5139 respectively.

The analysis of the results shows that the electric boiler has low initial investment, lower equipment maintenance costs, large annual replacement power, outstanding market potential, and higher annual operating costs compared to the heat pump technology. The latter's energy consumption is low, and the technical benefits are slightly higher than the former; both have significant environmental benefits, both do not produce harmful gases and dust and other particulate matter. Secondly, the electric boiler technology is more mature, more stable and has wider applicability. Air-source heat pump technology, high energy efficiency, energy saving, high safety index, long equipment life, but the technology is not yet mature, there is a potential consumption, which should be considered. For the time being, the performance of the electric boiler is slightly better than that of the heat pump technology, which should be given full play to on the basis of its high technological maturity, and increase the advantages of high efficiency and energy saving, so as to make it widely used in rural electricity substitution.

Table 3: Value of two kinds of evaluation indices

Indicators	Weight	Electric boiler	Heat pump
$D1$	0.0266	0.3333	0.6667
$D2$	0.0172	0.6667	0.3333
$D3$	0.0077	0.6667	0.3333
$D4$	0.0121	0.2	0.8
$D5$	0.0869	0.3333	0.6667
$D6$	0.029	0.3333	0.6667
$D7$	0.0117	0.6667	0.3333
$D8$	0.0234	0.6667	0.3333
$D9$	0.0111	0.75	0.25
$D10$	0.0032	0.2	0.8
$D11$	0.006	0.2	0.8
$D12$	0.006	0.8	0.2
$D13$	0.0129	0.3333	0.6667
$D14$	0.0234	0.5	0.5
$D15$	0.0425	0.25	0.75
$D16$	0.301	0.5	0.5
$D17$	0.301	0.5	0.5
$D18$	0.0197	0.25	0.75
$D19$	0.044	0.6667	0.3333
$D20$	0.0147	0.3333	0.6667

V. B. Characterization of electricity substitution and distribution in agriculture

According to the analysis of statistical data, it can be seen that during the period of 2022-2026, the substitution of electricity caused by the promotion and implementation of rural electricity substitution in Anhui Province reaches a total of 230.41×10^8 (kW·h). During the period of new annual rural alternative power specific as shown in Figure 3. In general, it can be seen that the substitution of electricity shows a rising trend year by year, based on the wide application of electric boiler technology, the rural substitution of electricity in 2026 is predicted to be 64.72×10^8(kW·h), compared with 2022, will have increased by 221%. In the annual substitution of electricity, the industrial (agricultural) production and manufacturing field occupies an absolute position, followed by the transportation field, both of which account for more than 95% of the total substitution of electricity, and are the key areas of priority implementation of rural electricity substitution technology transformation in Anhui Province.

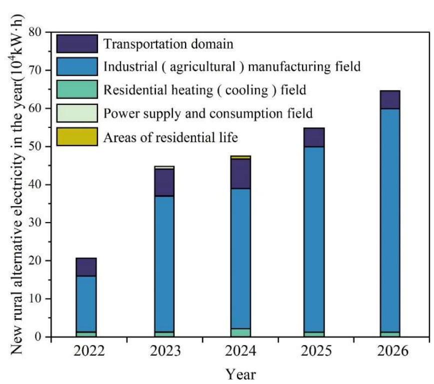


Figure 3: New rural alternative electricity added every year

The industrial (agricultural) production and manufacturing areas can be further subdivided into seven different types of electricity substitution technology, as shown in Table 4. Among them, metallurgy electric furnace, building materials electric kiln, the replacement of electricity in the field of industrial (agricultural) production and manufacturing accounted for the highest proportion, respectively, 37.77%, 33.63%, followed by mining, auxiliary electric power and industrial electric boilers, the replacement of electricity accounted for the field of the total replacement of electricity, respectively, 10.49%, 9.54%, 7.27%. Agricultural auxiliary production and processing of agricultural products in the field of alternative power and the sum of less than 1.5%, alternative power is lower. In summary, it can be seen that Anhui Province in the future to promote rural electricity substitution technology transformation projects for the main object of industrial production and manufacturing in the field of metallurgical furnaces and building materials electric kilns.

Table 4: Different types of electric energy substitution technology

Types of electric energy substitution technology	Proportion in the field of industrial (agricultural) production and manufacturing(%)
Metallurgical electric furnace	37.77
Building materials electric furnace	33.63
Mine mining	10.49
Auxiliary electric power	9.54
Industrial electric boiler	7.27
Agricultural auxiliary production	0.6
Processing of agricultural products	0.7

The new rural replacement electricity in different prefecture-level cities in Anhui Province is specifically shown in Figure 4. The horizontal coordinates 1~16 in the figure represent Wuhu City, Hefei City, Maanshan City, Tongling City, Anqing City, Chuzhou City, Yicheng City, Bengbu City, Huainan City, Suzhou City, Huaibei City, Huizhou City, Chizhou City and Huangshan City in turn. As can be seen from the figure, the cumulative substitution power of four prefectures, Wuhu, Hefei, Maanshan and Tongling, is higher, with 29.37×10^8, 28.02×10^8, 24.42×10^8, and 21.56×10^8 (kW·h), respectively. The three prefectural-level cities with lower substitution amounts are Huangshan City, Chizhou City and Bozhou City, with substitution amounts of 3.46×10^8, 7.35×10^8 and 7.62×10^8 (kW·h), respectively. Due to the rural electricity substitution project is mainly concentrated in the field of industrial production and manufacturing, so its substitution of electricity and the distribution of industrial characteristics of the region is highly correlated, Wuhu City, Hefei City, Ma'anshan City and Tongling City is a more developed industrial areas in Anhui Province, but also the focus of the rural electricity substitution of technological transformation of the region. Huangshan City, Chizhou City and Bozhou City, mostly tourism and agricultural products manufacturing and processing industry, the implementation of rural electricity substitution technology transformation potential is not large.

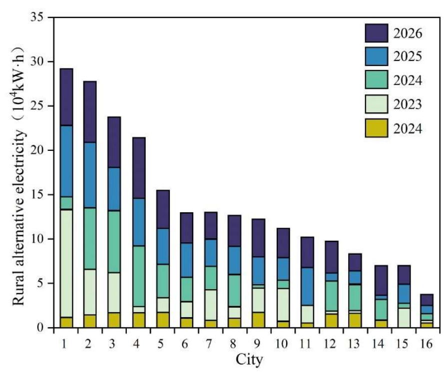


Figure 4: New rural alternative electricity in different prefecture-level cities

The specific rural electricity substitution of each technology type in Anhui Province from 2022 to 2026 is shown in Figure 5. The horizontal coordinates of 1~15 represent decentralized electric heating, heat pumps, industrial electric boilers, metallurgical furnaces, mining, processing of agricultural products, rail transportation, airport bridge equipment, oil drilling rigs oil to electricity, household electrification. 2022 rural electric energy substitution transformation of 13 types of technology, of which metallurgical furnaces and building materials electric kiln substitution of electricity accounted for the total substitution of electricity in that year, 74.4%, to 2026, predicted rural electricity substitution of 19 types of technology, and metallurgical furnaces and building materials electric kiln substitution of electricity accounts for 74.4%, to 2026, predicted rural electric energy substitution of 19 types of technology, and metallurgical furnaces and building materials electric kiln substitution of electricity. In 2026, it is predicted that there will be 19 types of rural electric energy substitution technologies, and the proportion of substitution power of metallurgical electric furnace and building materials electric kiln is predicted to drop to 49.6% in 2026, and the substitution technologies such as auxiliary electric power, mining, industrial electric boiler, and rail transportation will contribute to more than 40% of the substitution power. It can be seen that the rural electricity substitution in Anhui Province from individual industry to multi-industry diffusion process, showing a diversified development trend.

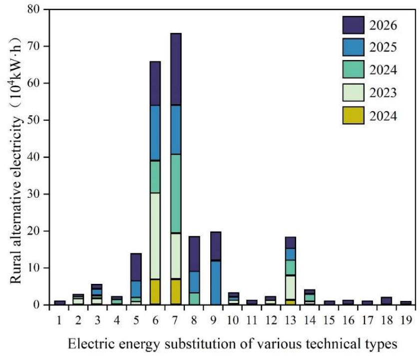


Figure 5: Rural alternative electricity of various technical types in Anhui Province

VI. Conclusion

This paper constructs a carbon emission calculation model to realize the monitoring and trend prediction of carbon emission, and proposes an impact assessment model for agricultural electricity substitution to realize the comprehensive assessment of the impact of agricultural electricity substitution. Using the energy and economic data of Anhui Province from 2020 to 2024, the carbon emission calculation model in this paper is used to detect and predict the carbon emission in Anhui Province. The carbon emissions calculated by the carbon emission model in this paper are basically consistent with the actual value, with a relative error of only 4.87, which is lower than the level of 5%. The total carbon emissions are predicted to continue to rise in the future, but mining (industrial) carbon emissions will continue to decrease.

Using the impact assessment model of agricultural electricity substitution constructed in this paper, the environmental impacts of agricultural electricity substitution technologies in Anhui Province are analyzed. The technical impact indicator system of agricultural electric energy substitution was established, and the weights of each indicator were determined to evaluate and analyze the electric boiler technology and heat pump technology used in rural electric energy substitution, and the total technical scores of the electric boiler and heat pump were obtained to be 0.472 and 0.494, respectively, with weighted correlations corresponding to $\gamma_1 = 0.8196$ and $\gamma_2 = 0.5139$. The comprehensive performance of electric boilers is slightly better than that of heat pump technology and should be widely used in rural electricity replacement. Based on the wide application of electric boiler technology, the rural electricity substitution in Anhui Province in 2026 is forecast to be 64.72×10^8(kW·h), an increase of 221% compared to 2022. In the field of industrial (agricultural) production and manufacturing, the highest proportion of replacement power for metallurgical electric furnaces, building materials, electric kilns, followed by mining, auxiliary electric power and industrial electric boilers, respectively, accounting for 10.49% of the total replacement power in the field, 9.54%, 7.27%, while agricultural auxiliary production and processing of agricultural products is less than 1.5%. Among the different prefecture-level cities in Anhui Province, the cumulative substitution of electricity in four prefecture-level cities, Wuhu City, Hefei City, Maanshan City and Tongling City, is higher, with 29.37×10^8, 28.02×10^8, 24.42×10^8, and 21.56×10^8 (kW·h), while that in Huangshan City, Chizhou City and Bozhou City is lower, with 3.46×10^8, 7.35×10^8, 7.35×10^8, and 7.27×10^8, respectively. Obviously, the potential for rural electricity substitution technology transformation in Huangshan City, Chizhou City and Bozhou City, which are dominated by tourism and agricultural product manufacturing and processing industries, is relatively low. In 2026, the number of rural electricity substitution technology types in Anhui Province will grow from 13 in 2022 to 19, with metallurgical electric furnaces and building materials electric kilns predicted to decline to 49.6% of the electricity substitution, and auxiliary electric power, mining and extraction, industrial electric boilers, and rail transportation will occupy the substitution technologies of auxiliary electric power, mining and extraction, industrial electric boilers, and rail transportation. In general, Anhui Province's rural electricity alternative presents a diversified development trend, its rural electricity subject is gradually from individual industries continue to multi-industry proliferation.

References

[1] Balsalobre-Lorente, D., Driha, O. M., Bekun, F. V., & Osundina, O. A. (2019). Do agricultural activities induce carbon emissions? The BRICS experience. Environmental Science and Pollution Research, 26, 25218-25234.

[2] Huang, X., Xu, X., Wang, Q., Zhang, L., Gao, X., & Chen, L. (2019). Assessment of agricultural carbon emissions and their spatiotemporal changes in China, 1997–2016. International Journal of Environmental Research and Public Health, 16(17), 3105.

[3] Zhu, Y., & Huo, C. (2022). The impact of agricultural production efficiency on agricultural carbon emissions in China. Energies, 15(12), 4464.

[4] Zhang, X., Fu, X., Xue, Y., Chang, X., & Bai, X. (2024). A review on basic theory and technology of agricultural energy internet. IET Renewable Power Generation, 18(7), 1318-1331.

[5] Rokicki, T., Perkowska, A., Klepacki, B., Bórawski, P., Bełdycka-Bórawska, A., & Michalski, K. (2021). Changes in energy consumption in agriculture in the EU countries. Energies, 14(6), 1570.

[6] Khalilian, S. (2025). Multiple Effects of Energy Substitution, Technology Development and Growth Rate in Agricultural Sector. The Economic Research, 25(1), 1-30.

[7] Yu, S., Zheng, S., & Li, X. (2018). The achievement of the carbon emissions peak in China: The role of energy consumption structure optimization. Energy Economics, 74, 693-707.

[8] Katuwal, H., & Bohara, A. K. (2009). Biogas: A promising renewable technology and its impact on rural households in Nepal. Renewable and sustainable energy reviews, 13(9), 2668-2674.

[9] Beuchelt, T. D., & Nassl, M. (2019). Applying a sustainable development lens to global biomass potentials. Sustainability, 11(18), 5078.

[10] Li, L., Xiong, W., Duan, W., & Xiong, Y. (2023). Evaluation on substitution of energy transition—An empirical analysis based on factor elasticity. Frontiers in Energy Research, 10, 1068936.

[11] Niu, D., Gao, T., Ji, Z., Liu, Y., & Wu, G. (2021). Analysis of the efficiency of provincial electricity substitution in China based on a three-stage DEA model. Energies, 14(20), 6650.

[12] Liu, K., Wang, Q., Luo, Z., Zhao, X., Su, S., & Zhang, X. (2020). Planning mechanism design and benefit analysis of electric energy substitution: A case study of tobacco industry in Yunnan province, China. IEEE Access, 8, 12867-12883.

[13] Wang, Y., Wang, S., Song, F., Yang, J., Zhu, J., & Zhang, F. (2020). Study on the forecast model of electricity substitution potential in Beijing-Tianjin-Hebei region considering the impact of electricity substitution policies. Energy Policy, 144, 111686.

[14] Dong, J., Li, R., & Huo, H. (2017). Economical-environment impact of electricity substitution of fossil energies in China. Journal of Renewable and Sustainable Energy, 9(6).

[15] Wang, Y., Zhang, Y., Yang, J., Zhang, F., Wang, S., & Ma, Y. (2019). The effect of electric-power substitution policy on the energy transformation in China: A system-dynamics approach. Journal of Renewable and Sustainable Energy, 11(6).

[16] Kabeyi, M. J. B., & Olanrewaju, O. A. (2022). Sustainable energy transition for renewable and low carbon grid electricity generation and supply. Frontiers in Energy research, 9, 743114.

[17] Yavuz Selim Güçlü,Ramazan Acar & Kemal Saplıoğlu. (2025). Seasonally adjusted periodic time series for Mann-Kendall trend test. Physics and Chemistry of the Earth,138,103848-103848.

[18] Guo Anfu,Kong Dekun,Zhou Xiaoyan,Qu Peng,Wang Shaoqing,Li Jianfeng... & Hu Yingbin. (2022). Evaluation of material reuse degree in additive manufacturing by the improved resolution coefficient grey correlation method. Process Safety and Environmental Protection,166,451-460.

[19] Deniz Koçak. (2020). Green growth dynamics in OECD countries: an application of grey relational analysis. Grey Systems Theory and Application,ahead-of-print(ahead-of-print),545-563.