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Assessing the Contribution of the Dual Constraints of Government Regulation and Agricultural Insurance to the Low-Carbon Transition in Agriculture Based on Big Data Analysis

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Abstract Currently, the impact of agricultural carbon emissions on the environment is becoming more and more significant, and low-carbon agricultural transformation has become a key topic in the construction of ecological civilization. This study applies entropy weight method and gray comprehensive evaluation method to construct an assessment model, and analyzes the impact of the dual constraints of government regulation and agricultural insurance on low-carbon agricultural transformation based on the panel data of 20 counties in a city from 2015 to 2024. The results show that the gray correlation between economic level, arable land size, government regulation and agricultural carbon emission is 0.943, 0.906, 0.873 respectively, with high correlation. The two-way fixed effect model empirically shows that the impact coefficients of agricultural insurance and government regulation on agricultural carbon efficiency are 15.3% and 18.8%, respectively, and are significant at the 0.001 confidence level; under the double constraint, the impact coefficients are elevated to 29.1%.During the period of 2015-2024, the city's agricultural carbon emission intensity decreases from 79.36 tons/million yuan to 36.32 tons/million yuan, which is a significant decrease. The study shows that the dual constraint mechanism of government regulation and agricultural insurance can effectively promote the low-carbon transformation of agriculture, in which agricultural insurance reduces carbon emissions through the expansion of the scale of operation of agricultural land, the restructuring of agricultural industry, and the improvement of agricultural business income; and government regulation prompts agribusinesses to strengthen their environmental responsibility through regulatory constraints and policy guidance.

Index Terms Agricultural low-carbon transition, Government regulation, Agricultural insurance, Double constraint, Agricultural carbon efficiency, Big data analysis

I. Introduction

In recent years, carbon dioxide (CO2) and other greenhouse gas emissions have been increasing, extreme weather events occur frequently, and the problem of climate change is becoming more and more prominent, seriously threatening the ecological balance and the survival and development of human beings [1], [2]. According to the survey report of the United Nations Environment Programme, the total global carbon emissions in 2023 have exceeded 60 billion tons of CO2 equivalent, hitting a record high while continuing the trend toward the end of the 21st century warming of more than 3 ℃ [3]. Therefore, the implementation of carbon emission reduction to cope with the impact of climate change has become a global consensus, countries around the world have put forward their own contribution to the goal, is committed to the early realization of the global “net-zero emissions”, as well as carbon emissions down to “2 ℃ temperature control” level [4]-[7].

As an active participant and supporter of global climate governance, in September 2020 China proposed a nationally owned contribution target of “striving to achieve carbon peaking by 2030 and carbon neutrality by 2060” at the general debate of the United Nations General Assembly at its seventy-fifth session [8]. According to a report released by the Food and Agriculture Organization of the United Nations (FAO) at the COP 26 Climate Summit, over the past 30 years, global greenhouse gas (GHG) emissions from agriculture and food production have increased by 17%, and more than 30% of global anthropogenic emissions in 2024 will come from the agrifood system, which shows that the agricultural sector has become an important source of GHG emissions [9]-[13].

The goal of low-carbon transition in agriculture is high-quality development of agriculture, which centers on improving the total factor efficiency of agriculture and reducing resource consumption, while increasing the carbon sink function of the agricultural system [14]. Its main means is the change of agricultural production methods relying on technological innovation, such as the use of green agricultural technology, the promotion of circular agricultural models, the resource utilization of agricultural waste, and the application of advanced equipment [15]-[17]. The impact of low-carbon transformation of agriculture on food security is mainly reflected in multiple levels of food production, food quality and production efficiency, specifically in the safety of food, feed, planting and processing food [18]. In addition, policy regulation and agricultural insurance are also important factors in promoting the low-carbon transition in agriculture [19]. Agricultural low-carbon transition is based on the requirements of green, ecological and low-carbon development of agriculture, and is also an important path to help realize a strong agricultural country, and an important initiative to realize Chinese-style agricultural and rural modernization [20]-[23].

Climate change has become a global challenge, and the reduction of greenhouse gas (GHG) emissions has become a common responsibility and mission of all countries. As an important economic industry, agriculture is not only the basis of food security, but also one of the main sources of greenhouse gas emissions. The use of chemical fertilizers and pesticides in the agricultural production process, as well as the intestinal fermentation of ruminants in the animal husbandry industry, will generate a large amount of carbon emissions, which will have a significant impact on the ecological environment. Promoting the low-carbon transformation of agriculture has become the core task of building a green modern agricultural system. However, the process of shifting the traditional agricultural production model to low-carbonization faces multiple challenges such as technological risks, increased costs and uncertain returns. How to effectively incentivize and constrain agricultural business entities to adopt low-carbon production behaviors has become an important issue in the field of practice and theory. In this context, government regulation and agricultural insurance, as two kinds of external constraint mechanisms, are worth exploring in depth for the promotion of low-carbon transformation in agriculture. Government regulation regulates and restricts agricultural production activities through laws, regulations and policy guidance, prompting agricultural operators to follow environmental standards; while agricultural insurance provides protection for agricultural producers through risk-sharing mechanisms, enhancing their confidence and ability to adopt new low-carbon technologies. There may be complementary and synergistic effects of these two mechanisms in promoting low-carbon transition in agriculture, but few studies have systematically examined the comprehensive impact of the dual constraints on agricultural carbon efficiency, and there is a lack of empirical evidence based on big data analysis. In addition, the measurement and assessment methods of agricultural carbon emissions have not yet formed a unified standard, and there are certain difficulties in assessing the effects of different interventions. Therefore, an in-depth study of the promotion of the dual constraints of government regulation and agricultural insurance on the low-carbon transformation of agriculture has important theoretical value and practical significance.

This study takes 20 counties in a city as the research object, collects county-level panel data from 2015 to 2024, uses entropy weighting method to determine the weights of each index, adopts the gray comprehensive evaluation method to analyze the correlation characteristics between each variable and agricultural carbon emission, and constructs a two-way fixed-effects model to empirically test the effects of government regulation and agricultural insurance on agricultural carbon efficiency. The study firstly analyzes the three major mechanisms of agricultural insurance to promote agricultural carbon emission reduction: reducing carbon emissions by expanding the scale of agricultural land operation, adjusting the structure of agricultural industry and improving the income of agricultural operation; secondly, it explores the role of government regulation in promoting the low-carbon development of agriculture; and finally, it evaluates the synergistic effect of the dual constraints through the empirical analysis and puts forward the corresponding policy recommendations.

II. Mechanisms for agricultural insurance to promote carbon mitigation in agriculture

(1) Scale of agricultural land operation

The larger the scale of agricultural operations, the more uncertainties caused by natural and price risks, so the risk management tools have the ability to guarantee the risk, to a certain extent, can incentivize agricultural operators through the transfer of land and other ways to promote the expansion of their production scale. The moderate scale operation can make up for the shortcomings of decentralized operation, promote the development of agricultural modernization, but also promote the transformation of agricultural operators for the use of agricultural land. Agricultural producers based on the actual operation of the area of agricultural land, the application of fertilizers, pesticides and other factors of production to optimize the allocation of the choice of soil testing and formulation and other low-carbon production behavior, through the substitution of the structure of the agricultural factor inputs and the improvement of the efficiency of the agricultural factor inputs, which brings about a corresponding change in the agricultural carbon emissions, so as to achieve the economic effect of the size of the land operation, improve the efficiency of chemical fertilizer application, reduce the use of fertilizer intensity.

Agricultural insurance helps to expand the scale of operation of agricultural land, thereby realizing economies of scale in agrochemicals, reducing the input of agrochemicals per unit area, improving the operational efficiency of agricultural machinery, and further reducing carbon emissions from agricultural activities.

(2) Structure of the agricultural industry

At present, policy-based agricultural insurance accounts for as much as 95% of the agricultural insurance market, and the types of crops covered by such insurance are mostly related to food security. At the same time, with the continuous promotion of agricultural insurance and the increasing awareness of risk management among farmers, agricultural insurance helps to guide agricultural operators to engage in the operation of food crops to a certain extent, thus enhancing the professional level of agricultural production.

Specifically, the carbon emission structure of the plantation industry has the highest proportion of straw utilization methods and the lowest proportion of crop cultivation. That is to say, the structural adjustment of crop cultivation can play a role in mitigating the growth of fertilizer application intensity to a certain extent by changing the consumption of fertilizer in the agricultural system, which in turn has an impact on agricultural carbon emissions. By increasing the share of food cultivation in the agro-industrial structure, agricultural insurance contributes to the reduction of agricultural carbon emissions in the region.

(3) Agricultural business income

Agricultural producers for the choice of production methods, by the risk of uncertainty, and most of the traditional agricultural production technology, generally has a poor risk-resistant ability, that is to say, the adoption of new agricultural technology often need a certain risk protection. On the one hand, a higher level of protection through the insurance payout can not only protect the business income of agricultural producers, but also effectively prevent the emergence of disaster caused by (return to) poverty. On the other hand, farmers are able to use the insurance payout to increase the input of agricultural production and living materials for the next period, realizing an increase in business income. Increasing the income of farmers helps to increase the choice of agricultural production and management methods: farmers with higher incomes have a relatively strong risk-resistant ability, and can better bear the losses brought about by risks, such as the use of highly concentrated chemical fertilizers, improving agricultural production equipment and other aspects of technology, that is, the agricultural insurance provided by the agricultural base of the guarantee can help agricultural operators to cope with the uncertainty of the choice of risky technology, thus increasing the agricultural household income.

In summary, the hypothesis is proposed: agricultural insurance has a significant role in promoting low-carbon development in agriculture.

III. Study on government regulation for low-carbon development in agriculture

As a pillar industry of the national economy and a key carbon emitting industry, agriculture's carbon reduction behavior should be subject to laws, regulations and government regulators. As regulators and investors increasingly demand greater climate-related corporate accountability, the importance of the environment is more pronounced than ever. Government regulations and oversight play an important role in promoting positive carbon reduction behaviors among agricultural contractors.

After agricultural contractors perceive the pressure of environmental protection regulations or policies, the attitude of conducting green and low-carbon behaviors usually improves and strengthens, and gradually begins to reduce emissions. Moreover, measures such as improving regulations and strengthening government supervision can not only improve the environmental efficiency of enterprises, but also promote the development and application of green technologies to drive the development of the agricultural economy. At the same time, government regulation is usually accompanied by government supervision and support, and this supervision and support behavior has a great impact on the willingness of employees to promote eco-initiatives that will improve environmental performance and reduce the impact of the natural environment. It can be inferred that government regulation, as an important predictor of CSR, can to some extent have a direct impact on strengthening the ethical obligations of agricultural contracting firms.

Therefore, the hypothesis is formulated that government regulation has a significant contributory impact on low-carbon development in agriculture.

IV. Variables, data and modeling

(1) Selection of variables

a) Explained variables

This paper chooses agricultural carbon efficiency as an explanatory variable, which refers to the economic or biomass output produced by unit carbon emissions in agricultural production, reflecting how to achieve high output with less carbon emissions, in line with this paper's research on the low-carbon transformation of agriculture. The sources of agricultural carbon emissions include two major areas, plantation carbon emissions and animal husbandry, plantation carbon emissions specifically include fertilizers, pesticides, agricultural films, diesel fuel, tilling, irrigation, and carbon emissions caused by agricultural products cultivation, and animal husbandry carbon emissions specifically include methane and nitrous oxide and other greenhouse gases emitted by ruminants, such as pigs, cows, sheep, horses, donkeys, mules, etc., from their intestinal fermentation and manure management activities.

b) Core explanatory variables

The core explanatory variable of this paper is the level of agricultural insurance development. Drawing on the research ideas and methods of existing literature, this paper adopts agricultural insurance density as a key indicator to measure the level of agricultural insurance development. Specifically, this paper calculates the agricultural insurance density by dividing the agricultural insurance premium income of each province and city by the number of people working in the primary industry, and then logarithmically processing the result. This calculation method not only reflects the development level of agricultural insurance in different regions, but also indirectly indicates the importance attached to agricultural insurance in the region.

c) Control variables

Referring to the existing studies and combining with the research object of this paper, the economic level, the size of arable land, the total agricultural output value, the industrial structure, the level of financial expenditure, the urban-rural income gap, the agricultural financial expenditure and the degree of agricultural mechanization are selected as the control variables. Existing literature suggests that the above variables have an impact on agricultural carbon emissions and there is also a correlation between them and agricultural insurance. In view of this, a control analysis of these variables is necessary in order to more accurately analyze the impact of agricultural insurance development on agricultural carbon emissions.

(2) Data sources

In the empirical analysis part, this paper takes 20 counties in a city as the research object and selects county-level panel data from 2015 to 2024 for the study, which mainly contains data related to agricultural insurance and data on the sources of agricultural carbon emissions. In this study, the data related to agricultural insurance mainly come from the Insurance Yearbook of a City, while the carbon source data of agricultural carbon emissions are collected from the Rural Statistics Yearbook of a City. In addition, the sources of other required data include the Statistical Yearbook of a City, the Statistical Yearbook of Water Conservancy of a City, and the statistical yearbooks released by provinces. Meanwhile, this study implements logarithmic transformation for all absolute value data involved, so as to avoid affecting the results of empirical analysis due to the non-stationarity of macro data. This study implemented logarithmic transformation for all absolute value data involved.

(3) Modeling

According to the part of mechanism analysis and research hypothesis, a two-way fixed effect model is constructed to empirically test the relationship between government regulation and agricultural insurance development on agricultural carbon efficiency. The basic model is set as follows:

$$carbom = \beta + \beta_1 pinsdem + \beta_2 regulation + \beta_3 pr + \beta_4 X_{it} + u_i + \theta_t + \varepsilon_{it} \tag{1}$$

The subscripts i denotes the region, $(i = 1, 2, \cdots, 30)$, t denotes the time, $(t = 2015, \cdots, 2024)$, and $carbom$ are the explanatory variables. $pinsdem$ is the density of agricultural insurance, $regulation$ is government regulation, pr is “insurance + regulation”, which are the core explanatory variables, and X_{it} represents a series of control variables affecting agricultural carbon efficiency. u_i represents region fixed effects in the model. θ_i represents the time fixed effect in the model. ε_i is the error term in the model.

V. Model for assessing the effectiveness of carbon emission reduction in agriculture based on big data analysis

In this section, the entropy weight method [24] will be used to determine the weight value of each indicator, and the optimal value of each indicator will be selected to form the optimal sequence. The gray comprehensive evaluation method [25] is used to calculate the gray correlation of the effectiveness of agricultural carbon emission reduction in a city from 2015 to 2024, and the effectiveness of agricultural carbon emission reduction is evaluated by ranking the resulting correlation.

Among the current methods for determining the weights of indicators, the subjective assignment method is easily influenced by personal experience and the subjectivity of industry experts, which leads to a high degree of subjective arbitrariness in the decision-making results. In contrast, the objective assignment method is based on real data and sound theories, and determines the weights of indicators according to the relationship between the values of each indicator, which is more objective and referable. Therefore, the study adopts the objective assignment method - entropy weight method to determine the weight of the indicators, and assigns the variables by measuring the level of variable entropy. The specific calculation steps of the method are as follows:

Suppose there is m evaluation sample, n evaluation indicators, and the original evaluation matrix is $X=(x_{ij})_{m\times n}, i=1,2,\ldots,m; j=1,2,\ldots,n$, where x_{ij} is the original evaluation value of the j th indicator of the i th sample:

$$X=\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \dots & \dots & \dots & \dots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix}_{m\times n} \tag{2}$$

(2) The original evaluation matrix $X=(x_{ij})_{m\times n}$ is standardized using the extreme value method to obtain the standardized matrix $C=(c_{ij})_{m\times n}$:

$$c_{ij}=\begin{cases} \dfrac{x_{ij}-\min\limits_{1\le j\le n} x_{ij}}{\max\limits_{1\le j\le n} x_{ij}-\min\limits_{1\le j\le n} x_{ij}}, & j\in J_B \\ \dfrac{\max\limits_{1\le j\le n} x_{ij}-x_{ij}}{\max\limits_{1\le j\le n} x_{ij}-\min\limits_{1\le j\le n} x_{ij}}, & j\in J_C \end{cases} \tag{3}$$

In the above equation: J_B is a positive indicator. J_C belongs to negative indicator $P=(p_{ij})_{m\times n}$

(3) Normalize the collected data to get the normalization matrix:

$$p_{ij}=\frac{c_{ij}}{\sum\limits_{i=1}^{m} c_{ij}} \tag{4}$$

(4) Calculate the entropy value of the j st indicator:

$$e_j=\begin{cases} -\dfrac{1}{\ln m}\sum\limits_{i=1}^{m} p_{ij}\ln p_{ij} & p_{ij}\ne 0 \\ 0 & p_{ij}=0 \end{cases} \tag{5}$$

The higher the variability of indicator j in the evaluation system, the lower the e_j. The smaller the variability, the larger e_j. If $e=1$, it means that the j th indicator has no influence on the evaluation system.

(5) Calculate the coefficient of variation of the entropy of the j th indicator:

$$g_j=1-e_j, j=1,2,...,n \tag{6}$$

(6) Determine entropy-based indicator weights $\delta=(\delta_1,\delta_2,...,\delta_n)$:

$$\delta_j=\frac{g_j}{\sum\limits_{j=1}^{n} g_j}, j=1,2,...,n \tag{7}$$

VI. Linkage characteristics of agricultural carbon emissions

This section examines the intensity of agricultural carbon emissions from 2015 to 2024 in a city that began to promote the dual constraints of government regulation and agricultural insurance to reduce agricultural carbon emissions in 2019. Total carbon emissions usually include planting and animal husbandry, and the scope of the study is the total carbon emissions from both planting and animal husbandry. The measurement of total carbon emissions is calculated through the following equation:

$$C_{it} = \sum C_{kit} = \sum \delta_{it} w_{it} \tag{8}$$

where C_{it} represents the total agricultural carbon emissions of each province in each year. k and t are the categories and years of carbon emissions, respectively. C_{kit} represents the emissions of each carbon emission category in each province. δ_{it} and w_{it} are the emission coefficients and factor usage of different carbon emission categories in each province, respectively.

In addition, the agricultural carbon intensity (CI) is the ratio of the total agricultural carbon emissions to the total output value of agriculture, forestry, animal husbandry and fishery:

$$CI_{it} = C_{it} / PGDP_{it} \tag{9}$$

where $PGDP_{it}$ is the ratio of the gross value of agricultural, forestry, livestock and fishery production.

Figure 1 shows the trend of agricultural carbon emission intensity in a city from 2015 to 2024. Overall, the total agricultural carbon emission intensity in a city shows a clear downward trend, i.e., from 79.36 tons/million yuan in 2015 to 36.32 tons/million yuan in 2024. Specifically, the agricultural carbon emission intensity of a city shows a relatively gentle decline between 2015 and 2020, but the decline in carbon emission intensity between 2020 and 2024 rises faster, and in terms of the current trend of changes in agricultural carbon emission intensity, it may also be in a continuous decline in the coming years. This shows that the dual constraints of government regulation and agricultural insurance have a certain propulsive effect in the low-carbon development of agriculture and promote the sustainable effect of agriculture. In addition, the development trend of agricultural carbon emission intensity is basically similar in all perspectives, whether from the planting industry and animal husbandry, for a clear downward trend.

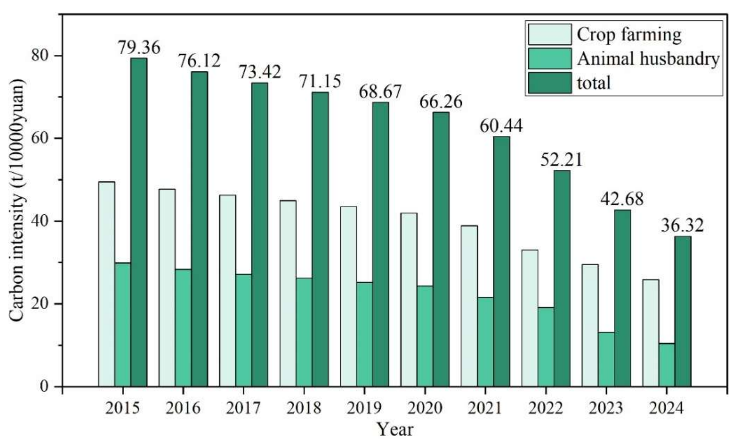

Figure 1: The change of agricultural carbon intensity in a certain city in 2015~2024

This section further explores the variables constructed above, including the explanatory variables: agricultural insurance intensity, government regulation, and the control variables: economic level, size of arable land, total agricultural output value, industrial structure, level of fiscal expenditure, urban-rural income gap, agricultural fiscal expenditure, and the degree of agricultural mechanization, and the characteristics of the association with carbon emissions.

The results of the correlation between the research indicators and agricultural carbon emissions are shown in Table 1. As can be seen from the table, there are different degrees of gray correlation between each variable and carbon emissions, that is, there is a certain degree of correlation. In general, the order of correlation between each variable and carbon emission is as follows: economic level>cultivated land scale>government regulation>agricultural insurance density>industrial structure>financial expenditure in agriculture>degree of mechanization in agriculture>level of financial expenditure>gross agricultural output value>rural-urban income gap. Specifically, the gray correlation between economic level and carbon emission is relatively leading, with a degree of correlation of 0.943, which may be due to the fact that the economic level can effectively improve the efficiency of energy use and energy saving, and has a strong emission reduction effect on high-carbon emission and high-pollution areas, so that the gray correlation with carbon emission is more prominent. The correlation between government regulation and agricultural insurance density and carbon emissions is 0.873 and 0.841 respectively, ranking 3rd and 4th after the economic level and arable land size, which indicates that the correlation between government regulation, agricultural insurance density and carbon emissions is higher. However, the gray correlation analysis can only verify the degree of correlation between the research variables and carbon emissions, and it is difficult to judge the direction of their influence, so this study will be further explored in depth in the next section.

Table 1: Results of agricultural carbon correlation

Index	Correlation coefficient	Sort
Agricultural insurance density	0.841	4
Government regulation	0.873	3
Economic level	0.943	1
Scale of cultivated land	0.906	2
Gross agricultural output	0.733	9
Industrial structure	0.832	5
Financial expenditure level	0.766	8
Urban and rural income gap	0.603	10
Agricultural expenditure	0.814	6
Agricultural mechanization	0.798	7

VII. Empirical analysis of agricultural insurance and carbon efficiency gains in agriculture

In order to test the role of the dual constraints of government regulation and agricultural insurance in promoting the low-carbon transition in agriculture, this section examines the role of agricultural carbon efficiency enhancement by constructing a regression model.

Explained variable: agricultural carbon efficiency.

Explanatory variables: government regulation and agricultural insurance development level and “regulation + insurance”.

Control variables: economic level, size of arable land, gross agricultural output value, industrial structure, level of financial expenditure, urban-rural income gap, agricultural financial expenditure and degree of agricultural mechanization.

Table 2 shows the descriptive statistics of all variables, including 20 county areas in a city, with a time span of 5 periods from 2020 to 2024, and a total sample size of 100. From the table, it can be seen that the maximum value of agricultural insurance density is 449.287, the minimum value is 200.432, and the standard deviation is 176.272. The standard deviation of agricultural insurance density is large, which indicates that agricultural insurance inputs have a greater impact on agricultural carbon efficiency. In addition, the level of government regulation has a mean value of 0.535 and a standard deviation of 0.337, which also shows a large impact on agricultural carbon efficiency.

Table 2: Descriptive statistics of all variables

Variable	Mean	SD	Min	Max
Agricultural insurance density	341.646	176.272	200.432	449.287
Government regulation	0.535	0.337	0.226	0.813
Economic level	8.625	1.309	5.442	11.076
Scale of cultivated land	7.481	1.136	5.179	10.243
Gross agricultural output	10.875	2.419	7.365	13.771
Industrial structure	0.443	0.084	0.219	0.664
Financial expenditure level	0.094	0.053	0.043	0.132
Urban and rural income gap	0.186	0.061	0.121	0.243
Agricultural expenditure	0.117	0.037	0.053	1.925
Agricultural mechanization	0.372	0.097	0.196	0.554

For government regulation and agricultural insurance on agricultural carbon efficiency empirical results are analyzed as shown in Table 3. From the regression results of model 1 in the table, it can be seen that the impact coefficient of the explanatory variable agricultural insurance development level on the explanatory variable agricultural carbon efficiency is positive and significant at the 0.001 confidence interval, with an impact coefficient of 15.3%, which indicates that the total effect of the development level of agricultural insurance on the agricultural carbon efficiency is significant and that with the increase in the level of agricultural insurance, the level of agricultural carbon efficiency will be increased in relative terms. Model 2 in the table is a test of government regulation, which tests the effect of the level of government regulation on agricultural carbon efficiency. It can be seen that the level of government regulation on agricultural carbon efficiency has a positive coefficient of influence, the coefficient of influence is 18.8% and passed the test of significance at the level of 0.001. Model 3 in the table is a test of the double constraints of government regulation and agricultural insurance, from which it can be seen that the impact coefficient of agricultural carbon efficiency under the double constraints rises substantially to 29.1% and passes the test of significance at the 0.001 level, which indicates that the effect of agricultural carbon efficiency enhancement under the double constraints is much better, i.e., it can promote the low-carbon transformation of agriculture.

In addition to this, the three models also show that the control variables regional economic level, cultivation scale, and agricultural mechanization have an impact on the improvement of carbon efficiency. Among them, the planting scale has the greatest influence, with an influence coefficient of between 0.287 and 0.306. And the control variables such as industrial structure have no effect on the improvement of agricultural carbon efficiency. In summary, the empirical results confirm the previous hypothesis that the dual constraints of government regulation and agricultural insurance can promote the low-carbon transformation of agriculture.

Table 3: Empirical results on agricultural carbon efficiency

Variable	Agricultural carbon efficiency		
	Model 1	Model 2	Model 3
Agricultural insurance density	0.153***		
Government regulation		0.188***	
Insurance & regulation			0.291***
Economic level	0.258***	0.246***	0.231***
Scale of cultivated land	0.287***	0.306***	0.295***
Gross agricultural output	0.051	0.017	0.033
Industrial structure	0.037	0.043	0.045
Financial expenditure level	0.059	0.051	0.078
Urban and rural income gap	0.027	0.015	0.013
Agricultural expenditure	0.051	0.037	0.043
Agricultural mechanization	0.147*	0.191**	0.209***
R^2	0.374	0.445	0.519
F	18.279***	26.731***	27.624***

Note: In the table, *, **, and *** are passed 0.05, 0.01, and 0.001 level significance tests, respectively.

VIII. Conclusion

The results of the big data analysis show that the double constraints of government regulation and agricultural insurance have a significant promoting effect on the low-carbon transformation of agriculture. From 2015 to 2024, the intensity of agricultural carbon emissions in the study area declined from 79.36 tons/million yuan to 36.32 tons/million yuan, a decrease of 54.2%. Gray correlation analysis shows that the correlation between economic level, arable land size, government regulation and agricultural insurance intensity and agricultural carbon emissions are 0.943, 0.906, 0.873 and 0.841, respectively, which rank in the top four, indicating that these factors are closely related to agricultural carbon emissions. The empirical results further confirm that the impact coefficients of the level of agricultural insurance development and government regulation on agricultural carbon efficiency are 15.3% and 18.8%, respectively, which are both significant at the 0.001 level; under the synergistic effect of the two, the impact coefficient is elevated to 29.1%, reflecting the multiplier effect of the double constraint. In addition, the regional economic level, planting scale and degree of agricultural mechanization also have a positive impact on agricultural carbon efficiency, with impact coefficients of 0.231, 0.295 and 0.209, respectively.In the future, we should strengthen the synergy of policies, improve the agricultural insurance system, and strengthen the supervision of the government, so as to give full play to the synergistic effect of the double constraints. At the same time, differentiated low-carbon agricultural development strategies should be formulated for the characteristics of different regions, to promote the moderate-scale operation of agricultural land, optimize the structure of agricultural industry, and promote the transformation of agricultural production mode to green and low-carbon, so as to achieve a win-win situation of economic and ecological benefits.

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