

# The Impact of Digital Economy Development on Agricultural Carbon Emissions: An Empirical Study from Major Grain-producing Areas

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Manuscript received July 7, 2023; revised August 11, 2023; accepted September 17, 2023; published March 14, 2024.

**Abstract**—Based on the panel data from 2011 to 2019 of 13 provinces (autonomous regions) of major grain-producing area of China, this paper uses emission factor method and entropy weight method to construct the index measurement system of agricultural carbon emissions and digital economy development respectively and analyzes the impact of digital economy development on agricultural carbon emissions. At the same time, the variable, energy structure, is introduced to verify how digital economy affects agricultural carbon emissions. The results show that the promotion of digital economy can significantly reduce agricultural carbon emissions, which is still confirmed after several robustness tests; the optimization of energy structure plays an intermediary role in the inhibition of agricultural carbon emissions by digital economy; the impact of digital economy on carbon emission is heterogeneous in different regions and regions with different carbon emission levels.

**Keywords**—agricultural carbon emissions, major grain-producing areas

## I. INTRODUCTION

As a responsible major country, China is committed to addressing climate change, advocates international cooperation at the global level, and has played an important role in promoting global climate and environmental governance. Faced with increasingly complex environmental problems, China solemnly pledged at the 75th session of the United Nations General Assembly that it would strive to achieve a peak of carbon dioxide emissions by 2030, and then achieve carbon neutrality by 2060. With the continuous promotion of agricultural modernization in China, the resulting carbon dioxide emissions can not be underestimated. According to the IPCC assessment results, agriculture has become the world's second largest source of greenhouse gases, of which 13.5% of greenhouse gas emissions from agricultural activities and the total agricultural carbon emissions are still growing (Tian, 2015). In view of this, it is of great theoretical and practical significance to analyze the influencing factors and emission reduction paths of agricultural carbon emissions for formulating feasible carbon emission reduction policies in China.

With the rapid development, digital economy has now become a powerful tool to deal with global climate change and environmental problems. Existing studies believe that the realization of carbon peaking and carbon neutrality goals needs to break through the restrictions of traditional economic development mode, and the current digital transformation of China's economy provides an important

historical opportunity, and its characteristics of changing economic structure and production mode will provide an important opportunity for the realization of emission reduction target (Yu, 2023). Xie (2022) made use of provincial panel data and found that the development of digital economy significantly reduced regional carbon emission intensity. Based on the dynamic panel model, Tian (2022) found that the development of digital economy significantly reduces the level of carbon emissions in grain production. Miao (2022) discovered that the development of digital economy has an inverted U-shaped nonlinear relationship with carbon emissions. In the study of the impact mechanism of digital economy on carbon emissions, researchers usually explore its carbon reduction effect from the perspective of promoting technological innovation and industrial structure upgrading. Studies have found that digital economy can directly promote the improvement of technological innovation level through digital industrialization and industrial digitalization (Zuo, 2020) and effectively promote the optimization and upgrading of industrial structure by improving the speed of industrial transformation (Li, 2021). In the process of technological innovation and industrial structure adjustment, the digital economy continuously improves the efficiency of energy utilization (Li, 2015) and gradually eliminates enterprises with high carbon emission during the continuous transformation and upgrading of industrial structure, so as to achieve carbon emission reduction.

The academic circle has also carried out in-depth research on agricultural carbon emissions. Some scholars believe that agricultural carbon sources are mainly composed of rice fields, consumption of agricultural production materials, agricultural waste, and agricultural energy (Wei, 2014; He, 2016). Agricultural carbon emissions can be suppressed through agricultural low-carbon technology (Jiang, 2018), conservation farming (Li, 2019), mechanization process (Chen, 2018), industrial accumulation (Hu, 2016), land transfer (Long, 2016), and other ways. In 2003, in order to ensure the security of national grain supply, China designated 13 provinces (autonomous regions) as the main grain producing areas (He, 2023). Their total grain production accounted for about 80% of the country's total grain production (Luo, 2021). However, the 13 provinces in major grain-producing areas still adopt the traditional development mode of high input and high emission, resulting in a large amount of greenhouse gas emissions (Tian, 2012). Therefore, it is worth thinking about how to

achieve carbon peaking and carbon neutrality goals on the premise of ensuring food security.

However, there is little literature on the impact of digital economy on agricultural carbon emissions in major grain-producing areas. In view of this, the possible marginal contributions of this paper are as follows: First, this paper uses panel data of 13 provinces in major grain-producing areas from 2011 to 2019 for empirical analysis, providing empirical evidence at the provincial level for evaluating the impact of digital economy on agricultural carbon emissions in major grain-producing areas. Second, compared with previous studies on digital economy to curb carbon emissions, this paper innovatively studies the impact of digital economy on agricultural carbon emissions in major grain-producing areas, which helps to make up for the shortage of relevant literature. Third, this study reveals the possible mechanism of digital economy affecting agricultural carbon emissions in major grain-producing areas, contributing to a deeper understanding of the complex relationship between digital economy and agricultural carbon emissions.

## II. THEORETICAL ANALYSIS AND RESEARCH HYPOTHESIS

With the gradual penetration of digital economy into various fields of social economy, it not only drives various industries towards green development and high-quality development but also has a profound impact on agricultural carbon emissions. The application of digital technology and other new science and technology in the whole process of agricultural production has made agricultural production step towards data, automation and intelligence, and gradually formed digital agricultural productivity. Meanwhile, digital transformation and intelligent upgrading of traditional planting industry will be carried out to realize precision agriculture, green production and sustainable development. Therefore, this paper argues that the development of digital economy has direct and indirect effects on the level of agricultural carbon emissions.

Firstly, data and digital technology, as key elements of the digital economy, are gradually penetrating into the agricultural field and directly reducing carbon emissions. The rise of the digital economy has promoted the precision development of modern agriculture. By using digital technology to carry out accurate analysis of soil and crops, farmers can more comprehensively understand the quality of soil and the growth stage of crops, and thereby obtain the best recommendations for fertilizer application time and quantity. The utilization of digital information in agricultural production enables precision fertilization, effectively reducing fertilizer waste, avoiding problems such as land degradation, environmental pollution, and resource waste caused by excessive fertilization, and at the same time, reducing carbon emissions. In summary, this paper proposes hypothesis H1: the digital economy can inhibit agricultural carbon emissions.

Secondly, the impact of digital economy on agricultural carbon emissions will be realized indirectly through the channel of optimizing the energy structure. Wang Xueting (Wang, 2022) believe that due to the unreasonable structure of agricultural energy consumption, especially the low proportion of clean energy, agricultural carbon emission in

our country is always high. The digital technology can utilize intelligent technology and big data analysis to optimize the energy consumption in agriculture production. Specifically, by monitoring and analyzing the energy usage during agriculture production process, we can identify the potential space for energy saving and continuously optimize the equipment operation status. Additionally, new clean energy technologies, such as solar and biomass energy, can be promoted to reduce dependence on traditional fossil fuels. By enhancing the energy utilization efficiency, we not only could reduce the energy consumption and carbon emissions during the agriculture production process but also could provide sustainable clean energy to the agriculture production. In summary, this paper proposes hypothesis H2: optimizing the energy structure is an indirect pathway for the digital economy to reduce agricultural carbon emissions.

## III. RESEARCH DESIGN

### A. Model Setting

The regression equation constructed is set as follows.

$$Y_{it} = \beta_0 + \beta_1 \text{Indige}_{it} + \sum_j \beta_j \text{control}_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (1)$$

In this equation, represents the agricultural carbon emission level of province  $i$  in year  $t$ ; is the intercept term; is the coefficient of focus in this paper, and if is significantly negative, it indicates that the development of digital economy can effectively reduce agricultural carbon emissions. represents the fixed effects of the region; represents the fixed effects of time; represents the random error term; represents the digital economy index of various provinces in the main grain producing area; represents a series of control variables at the provincial level in the main grain producing areas.

### B. Variable Selection

#### 1) Explained variable: Agricultural carbon emission (Incarb)

For the calculation of agricultural carbon emissions, this article draws on the research of Fan Dongshou (Fan, 2022), and measures the carbon emissions of grain-producing areas from three aspects: Firstly, the carbon emissions generated by the input of agricultural materials. Specifically, the carbon emissions generated by chemical fertilizers, pesticides, agricultural film and agricultural diesel in the process of use need to be examined, and the amount of agricultural materials input is subject to the actual use of the year. The second is the methane emission caused by rice planting. Since the planting time and growth cycle of rice in different parts of China are different, the median rice production cycle of 130 days (Wu, 2014) is chosen, and the actual planting area of rice in the current year shall prevail. The third is the carbon dioxide emissions caused by crop ploughing and irrigation. The estimated area is based on the actual sown area and the effective irrigated area of the crop in the current year.

As some of the carbon sources in the above three aspects do not directly produce carbon dioxide, but methane, nitrous oxide and other gases that cause greenhouse effect, in order to facilitate the sum, this paper uniformly converts these greenhouse gases into standard carbon dioxide equivalent in

actual calculation. In terms of the selection of measurement methods, emission factor method is the most widely used and widely used method for measuring carbon emissions at present because it has a series of core advantages such as convenient operation, easy access to data, and controllable cost. Besides, this method is simple and universal, and has been widely used in macro and micro carbon emission accounting. The basic calculation formula of carbon emissions provided by IPCC is as follows:

$$E = AD \times EF \quad (2)$$

E is CO<sub>2</sub> emission, AD is activity data, and EF is emission factor. The relevant carbon emission coefficient is as follows:

Table 1. Agricultural carbon emissions sources, coefficients and reference sources

| Input Elements          | Carbon Emission Coefficient  | Reference Sources  |
|-------------------------|------------------------------|--|
| Rice                    | 3.136g/(m <sup>2</sup> ·day) | (Wu, 2014)   |
| Fertilizer              | 0.8956kg/kg                  | Oak Ridge National Laboratory  |
| Pesticide               | 4.9341kg/kg                  | (Zhi, 2009)  |
| Agricultural film       | 5.1800kg/kg                  | Institute of Resources and Ecological Environment, Nanjing Agricultural University |
| Agricultural diesel oil | 0.5927kg/kg                  | Intergovernmental Panel on Climate Change  |
| ploughing               | 312.60kg/km <sup>2</sup>     | College of Biology and Technology, China Agricultural University                   |
| Irrigation              | 20.476kg/hm <sup>2</sup>     | (Li, 2011)   |

2)Core explanatory variable: Digital economy index (Indige)

In recent years, the rapid development of digital economy has prompted people to adopt quantitative indicators to measure its development status. However, limited by the availability of quantitative data, the current research is mostly carried out at the provincial level, and there are few research on prefectures and cities. In view of this situation, this paper learns from the practice of scholars such as Hui (2022), Zhao (2020) and Tian (2022) and combines the actual development of provincial digital economy and the convenience of relevant provincial data acquisition to measure rural digital economy from two aspects of rural digital infrastructure and rural digital development ability. The specific construction indicators are as follows: (1) The level of digital infrastructure is an important support for the development of rural digital economy, which mainly benefits from the popularization of the Internet, smart phones and computers as well as the improvement of rural transportation system. Therefore, this paper selects rural mobile phone penetration rate, rural computer penetration rate, rural Internet penetration rate, rural radio and television network coverage and rural delivery lines as measurement indicators. (2) Rural digital development ability is an important index to evaluate the development ability of rural areas using digital economy. Zhang Zhijian (2018) believed that the informatization construction of agriculture and rural areas cannot be separated from the use of informatization equipment, and its use degree and operation status can be directly displayed on the electricity consumption. Tian

(2022) took agrometeorological observation business as a measurement indicator of agricultural digital economy, which they believed could be an important indicator of the deep integration of digital technology and agricultural production and management. In addition, the consumption level of agricultural and rural digital bases and digital products and services can represent the current situation of rural digital industrialization. Therefore, Mu (2021) evaluated the regional agricultural and rural digital bases by using the number of Taobao villages and took the rural Engel coefficient as a negative indicator to measure the consumption of digital products and information services. To sum up, this study selected rural electricity consumption, the number of agricultural meteorological observation stations, the number of Taobao villages and rural Engel coefficient as measuring indicators.

Table 2. Evaluation index system of rural digital economy development

| Index Category                                | Index Name                                  | Evaluating Indicator   |
|---|---|--|
| Digital infrastructure                        | Rural mobile phone penetration              | Mobile phone ownership per 100 rural households at the end of the year (+) |
|   | Computer penetration rate in rural areas    | Computer ownership per 100 rural households at the end of the year (+)     |
|   | Internet penetration in rural areas         | Rural broadband access users (+)   |
|   | Rural radio and television network coverage | Rural cable broadcast TV users (+)   |
|   | Rural delivery line                         | Rural delivery line (+)  |
| Rural digital economy development environment | Rural electricity consumption               | Rural electricity consumption (+)  |
|   | Agrometeorological observation station      | Number of agrometeorological observation stations                          |

3) Control variable

Due to the numerous factors affecting agricultural carbon emissions, this paper draws on the research of Wu (2017), Hu (2018) and Miao (2022) and selects the following relevant variables to control the accuracy of digital economy development on agricultural carbon emissions.1) Rural living standard (lninco), which is measured by logarithm of rural gross agricultural output per capita. 2) Agricultural mechanization degree (lnmech), which is measured by logarithm of total power of agricultural machinery. 3) Population size (lnpopu), which is measured by logarithm of total population. 4) Urbanization rate (lncity), whose measurement index is logarithm of the ratio of urban population to total population.

4) Mechanism variable

Energy structure (lnnyjg). Referring to Shao Shuai (2016), the ratio of coal consumption to total energy consumption in each region is selected to reflect the energy structure.

C. Data Sources and Descriptive Statistics

In this paper, 13 major grain-producing provinces in China from 2011 to 2019 were selected as the research objects. The basic data of each index used were derived from China Statistical Yearbook, China Rural Statistical Yearbook, China Agricultural Statistical Data and other yearbooks over the past years, and were properly processed. The descriptive statistics of main variables in this paper are shown in Table 3.

Table 3. Descriptive statistics of each variable

| Variable | N   | Mean    | SD    | Min    | Max    |
|----------|-----|---------|-------|--------|--------|
| lncarb   | 117 | 8.261   | 1.031 | 6.298  | 9.533  |
| lndige   | 117 | -1.938  | 0.466 | -2.643 | -0.501 |
| lninco   | 117 | -0.0490 | 0.365 | -0.962 | 0.945  |
| lnmech   | 117 | 8.516   | 0.508 | 7.608  | 9.499  |
| lnpopu   | 117 | 8.637   | 0.432 | 7.817  | 9.217  |
| lncity   | 117 | -0.585  | 0.135 | -0.905 | -0.322 |
| lnnyjg   | 117 | -0.810  | 0.208 | -1.279 | -0.393 |

#### IV. EMPIRICAL ANALYSIS AND TEST

##### A. Baseline Regression Analysis

This paper uses the two-way fixed effect model to empirically analyze the direct impact of digital economy development on agricultural carbon emissions and test whether energy structure optimization is the channel of their relationship. The regression results are shown in Table 4. Column (1) of Table 4 only shows the regression results of core explanatory variables. The column (2) of Table 4 shows the regression results after adding a series of control variables. The regression results show that if only the effects of time fixed effect and individual fixed effect are considered, the influence coefficient of digital economy level on agricultural carbon emissions is  $-0.2526$ , passing the 1% significance test. After adding control variables, the digital economy regression coefficient is still negative at the significance level of 1%, and its coefficient value is  $-0.4724$ . Therefore, the development of digital economy can effectively reduce agricultural carbon emissions, hypothesis one proof.

Table 4. Baseline regression result

|                 | (1)                     | (2)                      |
|-----------------|-------------------------|--------------------------|
|                 | lncarb                  | lncarb                   |
| lndige          | -0.2526***<br>(-4.5428) | -0.4724***<br>(-5.2866)  |
| lninco          |                         | -0.0491<br>(-0.6484)     |
| lnmech          |                         | 0.1452***<br>(3.3491)    |
| lnpopu          |                         | 4.0414***<br>(3.8645)    |
| lncity          |                         | -0.1573<br>(-0.4081)     |
| _cons           | 7.6849***<br>(62.2422)  | -29.0050***<br>(-3.1270) |
| Province ffixed | YES                     | YES                      |
| Year ffixed     | YES                     | YES                      |
| N               | 117                     | 117                      |
| R2 -adjust      | 0.0227                  | 0.2026                   |

According to the regression results in column (2), the total power (lnmech) coefficient of agricultural machinery is positive and passes the significance test of 1%. The increasing improvement of the agricultural mechanization level in our country has continuously increased the total quantity of agricultural machinery, which leads to the increase of agricultural carbon emission. The regression coefficient of total population (lnpopu) was also positive and significant at the 1% significance level. This indicates that with the continuous expansion of population size, the demand for agricultural production increases to some extent. In order to meet the demand for production and

consumption, the scale of agricultural production will also expand, resulting in the increase of agricultural carbon emissions in major grain-producing areas. Both the coefficient of rural living standard (lninco) and the coefficient of urbanization (lncity) were negative, but they did not pass the significance test, indicating that their impact on agricultural carbon emissions in major grain-producing areas was not significant.

##### B. Robustness Test

###### 1) Replace the explained variable

In the baseline regression, this paper uses total agricultural carbon emissions as the explained variable for regression estimation. In order to increase the robustness of the conclusion, agricultural carbon emission intensity, that is, the ratio of total agricultural carbon emission to total regional output value, was also calculated in this paper, and the robustness test was conducted based on this. Column (1) in Table 5 reports the regression results with carbon emission intensity as the explained variable. The results show that the regression coefficient of digital economy development is still negative at the significant level of 1%, which is consistent with the conclusion above. This indicates that the development of digital economy can still significantly reduce the level of agricultural carbon emissions when replacing the explained variables.

###### 2) Control variable

This paper further extends the time window of the influence of digital economy on the level of agricultural carbon emissions to ensure the reliability of the results, so the explained variables were treated with a delay of 1 period. As can be seen from column (2) of Table 5, the regression coefficient of digital economy on total agricultural carbon emissions is negative at the significance level of 1%, indicating that the development of digital economy significantly reduces the level of agricultural carbon emissions. The conclusion of this paper is still robust after extending the time window, which fully proves the robustness of the core conclusion of this paper.

###### 3) Control variable

There may be a reverse causal relationship between the development of the digital economy and agricultural carbon emissions. Digital economy can restrain agricultural carbon emissions. Similarly, regions with high agricultural carbon emissions may accelerate the digital upgrading of local agriculture under the pressure of carbon reduction. In order to reduce the impact of endogenous problems on the role of digital economy in restraining agricultural carbon emissions, this paper uses the lag of digital economy development level as an instrumental variables estimation for 2SLS regression (She, 2022). The results of the two-stage regression are respectively shown in column (3) and (4) of Table 5. The results of the first stage show that instrumental variables have a significant positive impact on the level of digital economy, and the F statistic is greater than the critical value 10, indicating that there is no weak instrumental variable problem. The results of the second stage show that the level of digital economy is significant, and the estimated coefficient is negative. In addition, compared with the baseline regression, the absolute value of the coefficient obtained after the use of instrumental variables is larger,

which indicates that the instrumental variables have an amplification effect, and that the estimated results of the baseline regression may be underestimated. In conclusion, after further alleviating the potential endogenous problem, the digital economy still has a significant inhibition effect on agricultural carbon emissions.

Table 5. Robustness test and mechanism analysis results

|                  | (1)                     | (2)                     | (3)                   | (4)                     | (5)                   |
|------------------|-------------------------|-------------------------|-----------------------|-------------------------|-----------------------|
|                  | lncarbqd                | L.lncarb                | lndige                | lncarb                  | lnnyjg                |
| lndige           | -0.3678***<br>(-3.6911) | -0.3557***<br>(-4.0954) |                       | -0.6967***<br>(-6.3398) | -0.2214*<br>(-1.6865) |
| L.lndige         |                         |                         | 0.9471***<br>(0.1045) |                         |                       |
| F                |                         |                         | 435.45                |                         |                       |
| Control variable | YES                     | YES                     | YES                   | YES                     | YES                   |
| Province         | YES                     | YES                     | YES                   | YES                     | YES                   |
| fixed            | YES                     | YES                     | YES                   | YES                     | YES                   |
| Year             | YES                     | YES                     | YES                   | YES                     | YES                   |
| N                | 117                     | 104                     | 104                   | 104                     | 117                   |
| R2               | 0.9180                  | 0.1565                  | 0.9974                | 0.9974                  | 0.6366                |
| -adjust          |                         |                         |                       |                         |                       |

### C. Mechanism Analysis

According to the theoretical analysis, digital economy can reduce agricultural carbon emissions by optimizing energy structure. Based on the mechanism analysis method proposed by Jiang (2022), this paper tests the significance of the relationship between the development level of digital economy and energy structure on the basis of baseline regression, and the results are shown in column (5) of Table 5. The coefficient of digital economy on energy structure is negative and passes the significance test of 10%. This shows that the digital economy can optimize the energy structure and thus reduce agricultural carbon emissions. Hypothesis two is verified.

### D. Regional Heterogeneity Analysis

The results of baseline regression show that with the development of the digital economy, the level of agricultural carbon emissions in major grain-producing areas has decreased overall. In order to study whether the carbon emission reduction effect of digital economy is widespread in different regions, this paper divides the major grain producing areas into three regions: Yangtze River Basin, Yellow River Basin, and Songhua River Basin, and conducts regional regression analysis. The regression results are shown in Table 6: Digital economy has an inhibitory effect on carbon emissions in the Yangtze River Basin, Yellow River Basin, and Songhua River basin, which is significant at the 5% level in the Yangtze River Basin and significant at the 1% level in the Yellow River Basin and Songhua River Basin, with the estimated coefficients being -0.2143, -0.5046 and -0.5263, respectively. The coefficient of Songhua River Basin has the largest absolute value, and an increase of 1% in digital economy level will reduce agricultural carbon emissions by 0.5263%. The Songhua River basin, which includes Liaoning, Jilin and Heilongjiang provinces, is a traditional grain province with high grain production, which also lead to higher agricultural carbon

emissions (Shao, 2022). With the development of digital economy, agricultural production mode will continue to develop and improve agricultural production efficiency (Fu, 2023). Such progress leads to a more obvious inhibitory effect in areas with high agricultural carbon emissions.

In order to further analyze the differences between different regions in the impact of digital economy development on agricultural carbon emissions, quantile regression is adopted in this paper. This method has the advantage of not being affected by extreme values and can explore the effects of different quantiles. In this paper, five representative sub-sites (25%, 40%, 50%, 60% and 75%) were selected to correspond to regions with different carbon emission levels, and the impact of digital economy on the heterogeneity of carbon emission levels in these regions was investigated. The regression results were shown in Table 7. The results show that the digital economy has a significant inhibition effect on agricultural carbon emissions at each sub-site, all of which pass the significance test at the 1% level, and the absolute value of the quantile is increasing gradually, which further proves that the digital economy has a stronger carbon inhibition ability in regions with high agricultural carbon emissions.

Table 6. Regional heterogeneity regression results

|                  | Yangtze River basin<br>lncarb | Yellow River basin<br>lncarb | Songhua River basin<br>lncarb |
|------------------|-------------------------------|------------------------------|-------------------------------|
| lndige           | -0.2143**<br>(-2.3806)        | -0.5046***<br>(-5.7258)      | -0.5263***<br>(-2.7499)       |
| Control variable | YES                           | YES                          | YES                           |
| Province fixed   | YES                           | YES                          | YES                           |
| Year fixed       | YES                           | YES                          | YES                           |
| N                | 54                            | 36                           | 27                            |

Table 7. Quantile regression results

|                  | 25%<br>lncarb           | 40%<br>lncarb           | 50%<br>lncarb           | 60%<br>lncarb           | 75%<br>lncarb           |
|------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| lndige           | -0.2082***<br>(-3.5008) | -0.3669***<br>(-3.9510) | -0.5686***<br>(-4.6265) | -0.5715***<br>(-4.6148) | -0.5781***<br>(-6.3605) |
| Control variable | YES                     | YES                     | YES                     | YES                     | YES                     |
| Province fixed   | YES                     | YES                     | YES                     | YES                     | YES                     |
| Year fixed       | YES                     | YES                     | YES                     | YES                     | YES                     |
| N                | 117                     | 117                     | 117                     | 117                     | 117                     |

## V. CONCLUSIONS AND POLICY RECOMMENDATIONS

### A. Conclusion

As a new form of economic and social development, digital economy has gradually become a “new engine” to promote the high-quality growth of our national economy. Under the strategic background of carbon peaking and carbon neutrality goals, it is also worth exploring whether digital economy has emission reduction effect on agricultural carbon emission. Based on the panel data of 13 provinces (autonomous regions) in major grain-producing areas of China during 2011–2019, this paper studies the influencing factors of China’s digital economy development on agricultural carbon emissions and draws the following conclusions: The rapid development of digital economy has played a significant role in reducing agricultural carbon

emissions and promoting the green transformation of China's agriculture. The analysis results of the two-way fixed effect benchmark model show that with the rapid development of China's digital economy, the level of China's agricultural carbon emission has shown an obvious downward trend. As a new factor of production, digital technology is deeply integrated with agricultural industry to effectively improve resource utilization and agricultural production efficiency and allows digital economy to inhibit agricultural carbon emissions. After the robustness test, such as replacing the explained variables and extending the time window, the conclusion is still valid. Through the mechanism of action, it is found that the optimization of energy structure is the basic path of digital economy to restrain agricultural carbon emissions. The heterogeneity test shows that the development of digital economy in the Songhua River basin has a more significant inhibitory effect on it.

### B. Policy Suggestion

First, we need to provide a sound environment for the development of digital economy in rural areas. We will attach importance to the construction of digital economy infrastructure in rural areas, accelerate the application and popularization of advanced digital technologies such as the Internet of Things, cloud computing, and big data analysis in all links of agricultural production, and lay the foundation for the digital economy to promote modern agriculture.

Second, we should actively promote clean energy and low-carbon technologies in rural areas. We will increase financial support for low-carbon technologies, introduce advanced clean energy equipment and technologies, and encourage farmers to use clean energy instead of coal, gasoline, diesel, and other traditional high-emission energy sources.

Third, differentiated carbon reduction strategies should be implemented according to local conditions. For rural and remote areas and poor mountainous areas, it is necessary to increase the policy preference and financial support, clarify the target of digital infrastructure construction, strengthen the construction of communication network, improve the penetration rate of Internet and mobile communication equipment, and comprehensively improve the informatization level of rural areas.

### CONFLICT OF INTEREST

The authors declare no conflict of interest.

### AUTHOR CONTRIBUTIONS

Ying Liu conducted the research; Shaoxiong Xu analyzed the data; Shaoxiong Xu wrote the paper; all authors had approved the final version.

### ACKNOWLEDGEMENT

The authors thanks for the complete support from the Miss Liu.

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