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EDITED BY
Arti Choudhary,
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REVIEWED BY
Shuokai Wang,
Beijing Forestry University, China
Dungang Zang,
Sichuan Agricultural University, China

*CORRESPONDENCE
Ming Xu,
b2023140200181@stu.swupl.edu.cn
Yang Shen,
yangs996@foxmail.com

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# Achieving sustainable green agriculture: analyze the enabling role of data elements in agricultural carbon reduction

Lidong Shi[1], Jiahui Zhao[1], Xinyi Du[1], Yuntao Tan[2], Ting Lei[1], Ming Xu[1,3]* and Yang Shen[4]*

[1]School of National Security, Southwest University of Political Science and Law, Chongqing, China, [2]College of Business Administration, Chongqing Technology and Business University Chongqing, Chongqing, China, [3]School of Economics, Southwest University of Political Science and Law, Chongqing, China, [4]Institute of Quantitative Economics and Statistics, Huaqiao University, Xiamen, China

**Introduction:** Controlling agricultural carbon emissions is an important part of promoting the green development of agriculture. This paper explores the relationship between data elements (DE) and agricultural carbon emissions (ACE), which is an important manifestation of achieving green emission reduction and sustainable agricultural development in agriculture.

**Methods:** Based on the empirical data of 30 provinces in China from 2012 to 2022, this paper evaluated the influence between the two by using the fixed effects model and the mediating effects model, and explored the heterogeneous effects in geographical location and grain production areas.

**Results:** First, data elements have a significant inhibitory effect on agricultural carbon emissions. Second, data elements have obvious heterogeneity in agricultural carbon emissions. Thirdly, fintech and land use play a significant mediating role in the impact of data elements on agricultural carbon emissions.

**Discussion:** This paper not only enriches the theoretical research on the impact of data elements on agricultural carbon emissions, but also provides corresponding empirical evidence. It offers significant reference for deepening the green development reform of industry, optimizing the allocation of human resources, promoting high-quality agricultural development, and achieving rural revitalization in China.

KEYWORDS

**data elements, agricultural carbon emissions, financial technology, land utilization, green emission reduction**

## 1 Introduction

Global climate change poses serious challenges to the world economy and the human living environment (Liu et al., 2024; Shen and Zhang, 2024a). In the past course of agricultural development, to ensure food security and adequate supply of various agricultural products, the pursuit of output has become the priority, while the extensive development mode relying on resource consumption has led to a huge cost to the ecological environment, resulting in the constant increase of agricultural carbon emissions (ACE). The

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Food and Agriculture Organization (FAO) and the Intergovernmental Panel on Climate Change (IPCC) have consistently pointed out that China is the world's largest greenhouse gas emitter, its agricultural sector is the second source of greenhouse gas emissions, and carbon dioxide emissions from the agricultural and food system exceed 30% of the global total anthropogenic emissions (Behera and Sharma, 2019; Lu et al., 2025a). With the rapid development of modern agriculture, the application of agricultural production factors such as fertilizers, pesticides, and films in the production process has led to the tightening constraints of resources and environment on the high-quality development of agriculture (Huo et al., 2024). Although China's ecological environment has improved to some extent in recent years, it is still facing a severe situation of carbon reduction and reduction. Green low-carbon is an inherent requirement of high-quality agricultural development, promoting ACE reduction and sequestration is not only an important content of promoting the construction of agricultural ecological civilization but also an inherent requirement of implementing the strategy of rural revitalization (Usman and Makhdum, 2021). Therefore, accelerating the pace of ACE reduction, further implementing the concept of green development, and exploring a green and low-carbon transformation path of ACE reduction and carbon sequestration are of great significance for the realization of green, modern, and high-quality development of agriculture.

The digital economy is a new engine for rapid economic growth (Shen and Zhang, 2023). Data elements (DE), as the core production factors in the era of the digital economy, play a key role in driving economic growth and promoting the green development of agriculture (Shen and Zhang, 2024b). As a kind of integration factor, the DE not only breaks the shackles of the traditional agricultural factor market, and optimizes the industrial division of labor, but also further promotes technology spillover and reduces agricultural resource mismatch and market distortion (Hu et al., 2022; Shen and Zhang, 2024b). Different from traditional production factors, DE can not only be put into agricultural production activities to generate value and exert the additive effect of production factors like traditional production factors, but also be integrated with other production factors to stimulate the potential of traditional production factors and exert the multiplier effect (Xu et al., 2025b). More importantly, DE has the characteristics of infinite replication, non-scarcity, green, and other high quality, and plays a role in agricultural production different from the traditional elements. The role of DE is more based on the actual application scenario of agriculture and indirectly promotes the green development of agriculture by optimizing the allocation of agricultural resources, influencing management decisions, and doubling the value of factors, to better reduce pollution emissions in agricultural development (Khan et al., 2009). In this context, DE, as an important driving factor in dealing with agricultural environmental pollution, plays an important role in promoting China's rural revitalization and agricultural green emission reduction (Xie, 2023).

At present, the studies on DE mainly focus on three aspects. First, from the perspective of economic development, studies have analyzed how DE can optimize resource allocation (Shen et al., 2022; Wang et al., 2023), improve the competitiveness of enterprises (Bakator et al., 2019), realizing industrial upgrading and transformation (Zhang et al., 2024; Zhao et al., 2024) and other ways to promote economic development. Second, from the perspective of technical application, the present studies have explored the application of DE in large data processing (Maroufkhani et al., 2022; Bose et al., 2023; Korherr and Kanbach, 2023), artificial intelligence algorithm (Aldoseri et al., 2023; Jan et al., 2023; Salvagno et al., 2023; Sohail, 2023), cloud computing Platform (Islam et al., 2023; Katal et al., 2023; Kunduru, 2023) and how these techniques can improve the efficiency and quality of data processing. Third, from the perspective of law and ethics, the role of DE in the protection of personal privacy (Tang, 2024), data security (Li and Liu, 2021; Quach et al., 2022; Zwilling et al., 2022), and data property rights and how to guarantee the rational use and healthy development of DE by improving relevant laws, regulations and ethical norms.

In addition, studies on ACE are also mainly focused on three aspects: (1) From the perspective of policy implementation, the present studies analyze environmental policy (Carlsson et al., 2021), political will (Colgan et al., 2021; Adebayo, 2022), land policy (Lu et al., 2025c), and other policy tools to reduce ACE and ensure sustainable agriculture. (2) From an environmental impact perspective, by analyzing the impact of extreme weather on soil organic carbon (Christensen et al., 2021; Kane et al., 2021), the feedback effect caused by forest area reduction (Te Wierik et al., 2021; Usman and Makhdum, 2021; Li et al., 2022), climate risks to smallholder farmers (Mbuli et al., 2021; Mizik, 2021), and other international typical ACE risk issues, the studies respond to the issue of carbon mitigation at the risk level. (3) From the perspective of agricultural development, the studies focus on improving the level of agricultural technology (Shen et al., 2022; Zhang et al., 2022), optimizing the production and supply system (Akintuyi, 2024), improving the level of economic development (Ergashev and Ravshanov, 2021; Khudoynazarovich, 2021; Solarin et al., 2021), and other methods to reduce carbon emissions to achieve high-quality agricultural development. These strategies not only help reduce greenhouse gas emissions but also enhance the climate resilience of agricultural systems.

Therefore, to address the identified gaps regarding mechanisms and heterogeneity, this study specifically asks: (1) Does DE exert a significant inhibitory effect on ACE in China? (2) Through what mechanisms, (particularly via financial technology (FT) and land utilization ratio (LUR) does DE influence ACE? (3) Does the effect of DE on ACE vary across regions with different economic development levels and agricultural functional orientations? What mechanism does DE employ to have an impact on the ACE? This paper aims to establish the mechanism assessment of DE's impact on ACE through scientific exploration methods, provide decision-making guidance for the government to promote agricultural ecological construction, and provide reference significance for other developing countries to manage agricultural pollution and promote agricultural digitalization construction. The purpose of this study is to make use of the advantages of DE to better promote the improvement of the agricultural ecological governance system and realize the dual benefits of agricultural digital transformation and agricultural green development under the background of a digital economy.

To sum up, this study makes the following distinct contributions to the existing literature, addressing key gaps identified. (1) Building upon the theoretical potential of DE for environmental improvement, yet acknowledging the limited empirical evidence on its specific pathways to reduce ACE, this research pioneers a systematic empirical investigation into the mediating mechanisms. By rigorously introducing and validating FT and LUR as critical transmission channels, we provide robust evidence on how DE acts to curb ACE. This significantly advances beyond studies focusing solely on direct effects or descriptive potential, offering a deeper understanding of the causal pathways linking digitalization to agricultural decarbonization. (2) Recognizing the notable neglect of regional heterogeneity in prior assessments of DE's environmental impact, particularly within China's diverse economic and agricultural landscape, this paper conducts a granular heterogeneity analysis. We reveal that the inhibitory effect of DE on ACE is significantly more pronounced in western regions, major grain-producing areas, and major grain-selling areas. This critical finding challenges the assumption of uniform effects and underscores the imperative of tailoring data-driven agricultural carbon reduction policies to local contexts, providing a crucial supplement to homogeneous perspectives in existing research. (3) Confronting the scarcity of comprehensive, empirically grounded analysis linking DE theory to ACE outcomes within the Chinese context, this study delivers robust empirical validation. Utilizing a meticulously constructed multi-dimensional DE index and applying rigorous econometric techniques (including fixed-effects modeling, mediation analysis, endogeneity controls via IV-2SLS, and extensive robustness checks) to a rich provincial panel dataset, we furnish concrete, China-specific evidence supporting the proposition that DE empowers agricultural green transformation. This substantially enriches the empirical foundation in the intersecting fields of data economics and agricultural environmental management.

# 2 Theoretical mechanism

## 2.1 Theoretical mechanism of DE on ACE

Data has typical characteristics such as high flow, easy replication, and increasing marginal effect. Data is the basis of the digital economy, without which there is no digital technology. The development of DE promotes the improvement of digital technology and the reduction of ACE intensity. To be specific, firstly, in the application of digital technology, Chinese agricultural enterprises often face the problem of agricultural pollution in the production and operation process (Zou and Mishra, 2024; Shen and Zhang, 2024c). To better respond to the call for green emission reduction, enterprises will constantly promote the upgrading of agricultural technology and increase the application of digital technology. The rational use of satellite remote sensing, land detection, smart agriculture, and other digital technologies to optimize the use of chemical pollutants such as agricultural fertilizers and pesticides, further reduce the generation of ACE and then promote the green development of agriculture. Secondly, in terms of capital investment, through the advantages of the Internet, DE can help farmers better access financial support, promote the popularization and use of digital inclusive finance, improve the liquidity and utilization efficiency of farmers' funds, reduce the threshold for farmers to use financial services, contribute to the digital transformation of the agricultural industry, promote the green development of agricultural enterprises, and better reduce agricultural pollution (He and Jiang, 2024; Shen et al., 2023). Finally, in terms of agricultural green development, through analyzing, and controlling agricultural production data, DE can scientifically and accurately locate the source of agricultural pollution through the collection, promote the transformation of traditional agricultural development to the development of digital agriculture, and realize agricultural green emission reduction (Chen et al., 2023). Based on this, this paper proposes the following hypothesis:

**Hypothesis 1:** DE helps to inhibit ACE production.

## 2.2 DE influences carbon emissions through fintech

Leveraging advanced technologies such as big data, cloud computing, and blockchain, FT significantly enhances the efficiency of data collection, processing, and application. Crucially, in the agricultural context, FT acts as a key mediator through which DE reduces ACE via three primary pathways. Firstly, AI-driven agricultural technology tools such as satellite imaging, Internet of Things sensors, and farm management applications have enabled real-time monitoring of soil conditions, crop health, and weather patterns (Sarker et al., 2021). By integrating these DE, FT platforms provide farmers with dynamic credit scoring and customized insurance premiums (Liu et al., 2023). This helps to obtain loans for precision agricultural equipment in projects such as variable fertilizer applicators and intelligent irrigation systems, directly reducing the excessive application of synthetic fertilizers, pesticides, and irrigation water, which are the main sources of ACE caused by energy-intensive pumping. Secondly, the big data analysis within the fintech platform has identified significant agricultural decarbonization opportunities such as biogas digesters and solar cold storage facilities. By developing green financial products specifically for agriculture, such as low-interest loans for farms using renewable energy or "carbon sink" mortgage loans for agroforestry, and empowering fintech with data, capital can be directed towards sustainable practices. Take platforms like Ant Forest as examples. They combine carbon footprint tracking with small loans for environmental protection investment, significantly reducing the agricultural carbon emission intensity in the pilot areas (Bose et al., 2023). Finally,blockchain-based fintech solutions can trace the agricultural product supply chain and reduce food loss by optimizing logistics and warehousing financing (Bu et al., 2024). Meanwhile, artificial intelligence models process data related to drought and flood prediction climate risks to provide parametric insurance payouts. This mechanism has stabilized farmers' income and curbed preventive logging or excessive hoarding, which are the main drivers of agricultural carbon emissions in developing economies (Wang et al., 2020).

**Hypothesis 2:** FT plays a mediating role in the effect of DE on ACE.

### 2.3 DE influences carbon emissions through land utilization ratio (LUR)

Relying on advanced information technology means, the collection, processing, analysis, and application of land use data can be more accurate and efficient, thus promoting the improvement of LUR and reducing carbon emissions. Firstly, through the intelligent planning technology driven by DE, big data analysis can be used to optimize the allocation and use of land resources, reduce waste and ineffective use of land resources, and avoid the increase of carbon emissions caused by over-development and inefficient use (Lu et al., 2020). For example, using GIS (Geographic Information System) and remote sensing technology, key indicators such as land cover type, land use intensity, and ecological environment quality can be accurately measured and monitored to provide a scientific basis for land use planning, reduce land resource waste, and thus reduce carbon emissions. Secondly, by elevating LUR, DE can promote the development of green agriculture and ecological industries, and further promote the development of the low-carbon economy (Ge et al., 2022). For example, through precision agriculture technology, farmers can make optimal planting plans according to soil, climate, and crop growth data, reduce the use of fertilizers and pesticides, and reduce carbon emissions in agricultural production. Finally, data-driven land resource management and policy formulation can help the government accurately formulate the "dual carbon" target path and promote the implementation of related policies. For example, through the establishment of a land use carbon emissions database and monitoring platform, the government can also identify the carbon emissions risk in the process of land use in advance, take timely measures to intervene and adjust, promote the improvement of land use efficiency, and reduce carbon emissions (Udara Willhelm Abeydeera et al., 2019). Therefore, this study puts forward the following research hypotheses.

**Hypothesis 3:** LUR plays a mediating role in the influence of DE on ACE.

### 2.4 Heterogeneity in the effect of DE on ACE

Due to the significant differences in economy, resources, and digitalization degree in various regions of China, the inhibition effect and effect of DE on ACE in different regions are different according to the actual situation in China. On the one hand, the degree of DE inhibition is more significant in regions with general economic conditions. In areas with average economic conditions, more attention is paid to the green development of agriculture, and the energy released by DE may be greater. Relatively speaking, government departments may pay more attention to agricultural green emission reduction and more attention to the agricultural environment, and DE may have a more obvious inhibitory effect on ACE. On the other hand, there will be different effects in various grain-producing areas, especially in the main grain production and sales areas. In these two regions, as the core areas of agricultural production, the higher the level of mastery and application of agricultural digital technology, the more popular the analysis and use of data. At the same time, these production areas themselves have a higher level of agricultural capital, and the investment of capital in production areas may be more used in the field of data. In addition, while vigorously developing agriculture in these producing areas, they also attach great importance to the degree of agricultural ecological pollution and devote themselves to the development of efficient and green agriculture to a certain extent, which is conducive to the green transformation of agriculture and better achieve agricultural emission reduction. Based on this, this paper proposes the following hypothesis:

**Hypothesis 4:** There is regional heterogeneity in the effect of DE on ACE.

## 3 Data and methods

### 3.1 Measurement model and estimation method

From the above theoretical analysis, it can be seen that DE can effectively inhibit agricultural carbon emissions. To alleviate heteroscedasticity and reduce the order of magnitude, this paper performs logarithmic processing on some variables and uses a fixed effect model to evaluate the relationship between them. The specific formula is shown in Equation 1:

$$ACE_{it} = \alpha_0 + a_1 DE_{it} + a_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{1}$$

In Equation 1, $ACE$ is agricultural carbon emission; $DE$ represents data elements, $X$ represents a series of control variables; $\mu_i$ represents an individual fixed effect that does not change over time; $\delta_t$ represents time fixed effect; $\varepsilon_{it}$ is a random disturbance term. According to the theoretical part mentioned above, $DE$ may inhibit $ACE$ through the path mechanism of promoting the development of fintech and improving land utilization rate, so it is necessary to test whether fintech and land use efficiency are intermediary variables between them. Specific testing steps are as follows: On the basis of testing the coefficient significance of linear regression model (1) of $DE$ on agricultural carbon emissions, two intermediary variables of financial technology and land use efficiency are selected for regression again, and the intermediary variables are represented by $Z$. The significance of regression coefficients such as $\beta_1$ and $\gamma_1$ was used to determine whether the intermediary effect existed. The specific calculation formulas of the above regression models are as follows: Equations 2, 3:

$$Z_{it} = \beta_0 + \beta_1 DE_{it} + \beta_2 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

$$ACE_{it} = \gamma_0 + \gamma_1 DE_{it} + \gamma_2 Z_{it} + \gamma_3 X_{it} + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

### 3.2 Definition and description of variables

#### 3.2.1 Explained variables

Agricultural carbon emissions (ACE). Some scholars believe that the carbon emissions of the planting industry are limited to

TABLE 1 Main carbon emission sources and carbon emission coefficient of the planting industry.

| Carbon sources | Carbon emission factor | Reference sources |
|---|---|---|
| Diesel oil | 0.59 kg/kg | IPCC |
| Fertilizer | 0.89 kg/kg | Oak Ridge National Laboratory, United States |
| Pesticides | 4.93 kg/kg | Oak Ridge National Laboratory, United States |
| Agricultural Film | 5.18 kg/kg | Institute of Agricultural Resources and Ecological Environment |
| Irrigation | 266.48 kg/hm$^2$ | IPCC |
| Plowing | 312.60 kg/km$^2$ | College of Biotechnology, China Agricultural University |

the greenhouse gas emission effect directly or indirectly caused by human activities in the production process (Bhatti et al., 2024; Rabbi and Kovács, 2024). This paper, referring to the methods by published literature (Li and Liu, 2021; Shen et al., 2023; Wu et al., 2024), surveys 6 aspects including the chemical fertilizers, pesticides, agricultural film, diesel oil, irrigation, and plowing, to calculate the carbon emissions of the planting industry using the relevant carbon emission coefficients of each carbon source. The specific formula is as follows:

$$E = \sum E_i \sum T_i \times \varepsilon_i \tag{4}$$

In Equation 4, $E$ represents the total carbon emissions of the planting industry, $T_i$ represents the input amount of the carbon source, $\varepsilon_i$ and represents the carbon emission coefficient. The main carbon emission sources and carbon emission coefficient of the planting industry are shown in Table 1.

### 3.2.2 Explanatory variables

Data element (DE). As an intangible production factor, DE is different from traditional production factors such as capital and labor which are difficult to be characterized by a single indicator. As the core driving force of agricultural modernization, the configuration of DE affects carbon emissions by penetrating the entire agricultural industrial chain. Meanwhile, this paper constructs DE from four dimensions: data unit management (CP1), data development and innovation (CP2), data dissemination and sharing (CP3), and data application scale (CP4). The role of data on agricultural digital infrastructure, agricultural innovation environment, and agricultural market is explored by measuring DE, and the entropy method is adopted to measure DE scientifically and reasonably, capturing the data ecosystem more macroscopically rather than being limited to specific agricultural variables. And there are already references (Yu et al., 2024). The specific construction indicators and weights are shown in Table 2 below.

### 3.2.3 Intermediary variables

Financial technology (FT), is represented by a digital financial inclusion index. The digital financial inclusion index covers multiple dimensions of access, use, and quality of financial services, and quantifies how fintech complements and improves traditional banking services, especially in remote areas and among low-income groups. The digital financial inclusion index not only measures the coverage of financial services but also includes users' satisfaction with financial services and the innovation capability of financial services (Liu J. et al., 2024); LUR, measured by the ratio of the total agricultural output value to the total sown area of crops (100 million yuan/thousand hectares), which reflects the maximum economic output that can be obtained by rational allocation of agricultural resources on a given land area, is the priority emission reduction measure in the food system (Cui et al., 2024).

### 3.2.4 Control variables

Based on the practice of existing literature, this study selected five indicators as control variables: rural financial industry (RFI), agricultural processing industry (API), traditional infrastructure construction (TIC), agricultural mechanization intensity (AMI), and dependence on agricultural product exports (DAPE). From a practical point of view, the popularity of rural finance has a direct impact on farmers' ability to access financial services. The more rural financial institutions have outlets, the easier it is for farmers to obtain financial support such as loans and insurance, thereby reducing production risks, increasing productive investment, and improving agricultural production efficiency. The level of development of the agricultural processing industry reflects the added value and processing capacity of agricultural products. The more enterprises in the agricultural processing industry, the stronger the processing capacity, which can reduce carbon emissions during the transportation and storage of primary agricultural products. The quality and density of traditional infrastructure construction directly affect the transportation efficiency of agricultural production. The higher the ratio of rural road mileage to rural resident population, the higher the fuel efficiency of vehicles, and the fewer times and distances of transportation, thus reducing carbon emissions. The intensity of agricultural mechanization reflects the level of mechanization of agricultural production. The higher the ratio of the total power of agricultural machinery to the total sown area of crops, the higher the agricultural production efficiency and the lower the carbon emission intensity per unit area. The degree of dependence on agricultural exports reflects the degree of internationalization of agricultural production. The higher the ratio of the export volume of agricultural products to the added value of the primary industry, the stronger the international competitiveness of agricultural production, more advanced technologies, and management experience can be

TABLE 2 Index system of data elements.

| Target layer | Primary indicators | Secondary indicators | Weights | Quality |
|---|---|---|---|---|
| DE | Data unit management | Degree of enterprise informatization | 0.034 | + |
| | | Number of R&D institutions in high-tech industries | 0.101 | + |
| | | Number of high-tech industry projects | 0.074 | + |
| | | R&D funds for high-tech industries | 0.096 | + |
| | | High-tech industry R&D personnel full-time equivalent | 0.080 | + |
| | Data transmission and sharing | Number of Internet domains | 0.062 | + |
| | | Number of Internet access users | 0.028 | + |
| | | Total postal services | 0.088 | + |
| | | Number of Internet pages | 0.101 | + |
| | | Mobile phone penetration | 0.011 | + |
| | Innovation in data development | Technology market turnover | 0.087 | + |
| | | Number of patent applications in high-tech industries | 0.099 | + |
| | | The proportion of enterprises carrying out product and process innovation | 0.007 | + |
| | | Index of innovation and entrepreneurship in core digital industries | 0.014 | + |
| | | Intensity of R&D investment | 0.020 | + |
| | Data application scale | Optical cable line length | 0.029 | + |
| | | Postal outlet service area | 0.040 | + |
| | | Proportion of enterprises with e-commerce transaction activities | 0.016 | + |
| | | Overall population coverage of TV programs | 0.002 | + |
| | | Digital Economy Index | 0.011 | + |

introduced to optimize the export structure, reduce the export of agricultural products with high carbon emissions, and increase the proportion of low-carbon agricultural products. In a word, the above variables are closely related to DE and ACE, so it is scientific and reasonable to add the above variables to empirically test the relationship between DE and ACE. Their specific measurement methods and references are shown in Table 3 below.

## 3.3 Data sources and descriptive statistics

The panel data of 30 provinces and cities from 2012 to 2022 are collected in this paper. Due to serious deficiencies in the data of Hong Kong, Macao, Taiwan, and Xizang, it is not included in the statistical category. The basic data involved in the calculation of ACE and DE are mainly from official websites such as *China Statistical Yearbook*, *China Rural Statistical Yearbook*, and the National Bureau of Statistics. In the actual analysis, for the data gaps and omissions of some indicators in individual years, the linear interpolation method and the mean interpolation method are used to complete them. For individual outliers, necessary corrections are made. The description of variables and descriptive statistics are shown in Table 4.

# 4 Results and discussion

## 4.1 Panel model regression results

Based on research Hypothesis 1 and Equation 1, this study calculated and obtained the results in Table 5.

Before the baseline regression is carried out, it is first verified whether there is collinearity among variables. After testing, the VIF value is 1.53 and less than 10, so it is considered that there is no collinearity problem between variables. At the same time, after the Hausman test (Hausman value is 13.76, the p-value is 0.08), the fixed effect model is chosen in this paper. Model (1) in Table 5 is a direct regression equation for the effect of DE on ACE. The observation results show that DE significantly inhibits

TABLE 3 Control variables.

| Indicator Information | Variable name | Symbol | Variable description | Literature |
|---|---|---|---|---|
| Control variables | Rural finance industry | RFI | Number of outlets of rural financial institutions by province | Liu et al. (2024b) |
| | Agricultural processing industry | API | Quantity and stock of Agricultural product processing enterprises by province (number) | Aguilera et al. (2019) |
| | Traditional infrastructure construction | TIC | Rural road mileage and rural population by province (sq. m/person) | Waheed et al. (2018) |
| | Agricultural mechanization intensity | AMI | Total power of agricultural machinery/Total sown area of crops (kW*10/ha) | Xu et al. (2025a) |
| | Dependence on agricultural product exports | DAPE | Trade volume of Outlet of agricultural products/Value added of primary industry (%) | Udara Willhelm Abeydeera et al. (2019) |

TABLE 4 Descriptive statistics of variables.

| Variables | Sample | Mean | Standard error | Min | Max |
|---|---|---|---|---|---|
| ACE | 330 | 335.686 | 227.656 | 13.913 | 995.728 |
| DE | 330 | 0.110 | 0.110 | 0.015 | 0.785 |
| FT | 330 | 260.910 | 90.543 | 61.47 | 475.23 |
| LUR | 330 | 0.445 | 0.246 | 0.147 | 1.799 |
| RFI | 330 | 2653.894 | 1625.816 | 360 | 6166 |
| API | 330 | 14158.43 | 14954.2 | 613 | 107859 |
| INF | 330 | 24064.59 | 31135.19 | 6.897 | 114187 |
| AGR | 330 | 0.654 | 0.232 | 0.281 | 1.387 |
| AED | 330 | 0.130 | 0246 | 0.004 | 1.839 |

ACE at a 1% level regardless of whether control variables are added, preliminarily verifying the Hypothesis 1 mentioned above. The results of adding control variables indicate that the influence coefficient of DE is −0.241, significant at the 1% level. This suggests that increasing DE by 1 percentage point can effectively reduce ACE intensity by 0.241 percentage points. It indicates that DE can enhance the quality and efficiency of agricultural production by improving resource utilization efficiency, optimizing production mode, enhancing regulatory transparency promoting scientific and technological progress, and making joint efforts to achieve the target of ACE reduction. From the perspective of other control variables, the three control variables rural finance, agricultural processing industry, and agricultural mechanization significantly promoted ACE growth, however, traditional infrastructure construction significantly inhibited ACE. Besides, the influence of agricultural outlet dependence on ACE was not significant. Specifically, the expansion of rural finance made it easier for farmers, large grain growers, and agricultural enterprises to obtain loans and investments, which also affected ACE from many aspects, such as the expansion of production scale, The increased use of fertilizers and pesticides, and the change of land development and utilization (Sun et al., .2024). The reason why the agricultural processing industry promotes the growth of ACE may lie in the lack of proper management and control in energy consumption, waste disposal, transportation, and logistics of agricultural processing enterprises (Karwacka et al., 2020). The main reasons for the increase of ACE by agricultural mechanization are the increase of fuel, the increase of fertilizer and pesticide use, and the destruction of the soil carbon pool (Guan et al., 2023). In terms of inhibiting ACE control variables, the higher the level of traditional infrastructure construction, the higher the transportation efficiency of agricultural products, in this way, it can reduce the carbon emissions in the transportation process, and inhibit ACE.

## 4.2 Mediating effect

Above, from the perspective of FT and LUR, the conduction mechanism of DE's influence on ACE was theoretically analyzed. As shown in model (3) in Table 5, DE still significantly inhibited the generation of ACE even after the addition of FT and LUR. In addition, the results showed that FT and LUR showed significant inhibition at the level of 1% and 5% respectively. These results indicate that both FT and LUR are important mediating variables of DE inhibition of ACE, which supports the hypotheses Hypothesis 2 and Hypothesis 3 mentioned above.

By providing wider coverage of financial services and deeper use of financial services, FT can significantly reduce agricultural production risks, increase productive investment, and promote cropland scale management. These factors help optimize resource allocation and improve agricultural output level (AOL), thereby effectively reducing carbon emissions per unit of output. Specifically,

TABLE 5 Results of baseline regression and mediation effects.

| Variable | Model (1) | | Model (2) | | Model (3) | |
|---|---|---|---|---|---|---|
| | AEC | ACE | FT | LUR | ACE | ACE |
| DE | −0.151*** (0.014) | −0.241*** (0.029) | 0.858*** (0.047) | 0.393*** (0.035) | −0.164*** (0.043) | −0.107*** (0.032) |
| FT | | | | | −0.089** (0.036) | |
| LUR | | | | | | −0.340*** (0.044) |
| RFI | | 0.854*** (0.090) | 0.760*** (0.143) | 0.313*** (0.109) | 0.922*** (0.093) | 0.748*** (0.083) |
| API | | 0.071*** (0.027) | 0.068 (0.043) | 0.155*** (0.033) | 0.078** (0.027) | 0.124*** (0.026) |
| INF | | −0.008*** (0.002) | 0.009** (0.003) | 0.001 (0.002) | −0.008*** (0.002) | −0.008*** (0.002) |
| AGR | | 0.063* (0.035) | 0.039 (0.055) | 0.183*** (0.042) | 0.067* (0.034) | 0.125*** (0.033) |
| AED | | 0.010 (0.019) | −0.012 (0.030) | −0.166*** (0.023) | 0.009 (0.019) | −0.047** (0.019) |
| Con | 5.063*** (0.035) | −2.213*** (0.728) | 1.158 (1.158) | 0.615 (0.878) | −2.109*** (0.723) | −2.004*** (0.666) |
| $R^2$ | 0.284 | 0.497 | 0.921 | 0.828 | 0.507 | 0.581 |
| N | 330 | 330 | 330 | 330 | 330 | 330 |

Note: *means $p < 0.1$; **means $p < 0.05$; ***means $p < 0.01$, standard deviation in parentheses (same below).

the wider coverage of financial services has made it easier for farmers to obtain financial support such as loans and insurance, thus reducing the shortage of funds and risks that farmers face in the production process. For example, by increasing the number of outlets of rural financial institutions, farmers can more quickly apply for low-interest loans to buy advanced agricultural equipment and technology and improve production efficiency (Yi et al., 2021). Simultaneously, the widespread adoption of insurance services can assist farmers in managing uncertainties, including natural disasters and market price fluctuations, and reduce resource waste and carbon emissions caused by production disruptions. The deeper use of financial services helps farmers better manage production and market risks and optimize resource allocation by providing diversified financial products and services, such as futures and options. For example, participation in the futures market for agricultural products allows farmers to lock in prices in advance and reduce production decision-making errors caused by market price fluctuations, thereby improving resource utilization efficiency and reducing unnecessary carbon emissions (Zhou, 2022). In addition, FT can also enhance the scale management of cultivated land and decrease the carbon emission intensity per unit area through large-scale production. Scale management can introduce more advanced management expertise and production techniques, enhancing the overall efficiency of agricultural production and reducing carbon emissions per unit of output.

At the same time, the promotion of LUR means more rational allocation of land resources and more efficient land use, which is directly related to the reduction of carbon emissions in the agricultural production process. Optimized land use can achieve this in several ways, including reducing the overuse of fertilizers and pesticides, increasing crop yields, and reducing the carbon intensity of agricultural production. First, by optimizing land use, the overuse of fertilizers and pesticides can be reduced. Rational planning of land use to avoid continuous cropping of single crops can reduce the frequency of pests and diseases, thus reducing the need for pesticides (Xu and Lu, 2025). At the same time, precision fertilization technology is adopted to accurately apply chemical fertilizers according to the specific conditions of the soil and the actual needs of the crops to avoid environmental pollution caused by excessive use. Second, optimizing land use can improve crop yields. Reasonable cultivation methods such as crop rotation and intercropping can make full use of land resources and improve crop growth quality and yield. Crop rotation can improve soil structure, increase soil organic matter content, and improve soil fertility, thus promoting crop growth. Intercropping enhances land use efficiency and boosts yield per unit area by leveraging the complementary effects of different crops. In addition, soil fertility can be maintained and carbon emissions caused by over-cultivation can be reduced through proper crop rotation and fallow. Crop rotation and fallow not only help restore the natural fertility of the soil but also reduce soil erosion and degradation and extend the useful life of the land (Shah et al., 2021).

## 4.3 Robustness testing

(1) Endogeneity test. Although this paper has mitigated the endogeneity problem caused by missing variables as much as possible by introducing multiple control variables, there may still be endogeneity bias caused by reverse causality in the model setting. For example, regions with high carbon emissions may require the agricultural sector to actively

TABLE 6 Results of endogeneity test regression.

| Variables | (1) | | (2) | (3) | (4) |
|---|---|---|---|---|---|
| | One-phase-lag regression | IV- tool change measurement | Sample of excluded municipalities | Replace the explained variable | Increase control variables |
| DE | | −0.572*** (0.074) | −0.054** (0.025) | −0.463*** (0.151) | −0.080** (0.033) |
| L1.DE | −0.143*** (0.033) | | | | |
| Control Variable | Control | Control | Control | Control | Control |
| Con | −2.357*** (0.732) | −6.594*** (0.452) | 1.239** (0.552) | −8.268** (3.481) | −0.465 (0.803) |
| $R^2$ | 0.622 | 0.802 | 0.594 | 0.174 | 0.597 |
| N | 300 | 300 | 286 | 330 | 330 |
| Unrecognizable Test | | 295.391*** | | | |
| Weak Instrumental Variable Test | | 9356.351 | | | |
| Sargan P | | 0.234 | | | |

develop and adjust DE to achieve higher productivity or meet environmental requirements, in which case the causality may run in both directions. To effectively identify the causal effect of DE on ACE, this paper uses the research ideas of Wang et al. (2018) and adopts the method of regression of core solution variables with a one-stage lag and the method of instrumental variables (2SLS) to deal with the potential endogenous problems. In terms of instrumental variables, referring to the research of Lu et al. (2025b), the interaction terms of DE with a one-period lag in the number of telephones per 100 people in each province in 1984 and the national IT service income in the previous year are selected as instrumental variables. The results in Table 6 show that the DE coefficients of the two endogenous tests are significantly negative, and the P of the instrumental variable method over recognition test is 0.234. It does not reject the null hypothesis that all instrumental variables are exogenous, thus the setting of instrumental variables can be considered valid. In addition, the results of the under-recognition test and weak instrumental variable test also prove the validity of the instrumental variables, which proves the rationality and validity of the regression results.

(2) The sample of municipalities is excluded and then regression is performed. Municipalities are usually important economic centers of the country, and their economic structure is significantly different from that of ordinary provinces, usually dominated by the tertiary industry, and agriculture accounts for a very small proportion of their total economy. Therefore, their performance in ACE may not be representative, and by excluding the sample of municipalities, the robustness of the study results can be improved to ensure the applicability of the conclusions to most regions and the effectiveness of policy recommendations. The results show that the results are still significant when municipalities are excluded, which once again proves that DE can effectively inhibit ACE.

(3) Replace the explained variables and then regression. The ACE measurement method was changed, and the principle of "electric (thermal) carbon allocation" was adopted. The ACE intensity of each province from 2012 to 2022 was recalculated based on the $CO_2$ emissions from thermal power generation (heating), taking into account the proportion of electricity and heat consumption in the agricultural sector within the final energy consumption. The regression was carried out by replacing the explained variables, and the result was still robust. It is proved that DE does have a significant inhibitory effect on ACE.

(4) Add control variables. Increasing the control variables financial support and forest coverage rate, and financial support for agriculture will affect the research development and promotion of agricultural technology, such as the use of low-carbon agricultural machinery, improving the efficiency of fertilizer and pesticide use, improving irrigation system and other aspects of ACE. However, forest cover may reduce ACE through carbon storage and absorption, ecosystem improvement, microclimate regulation, and other aspects. The results showed that the control variables of financial support intensity and forest cover were added, and the results were still robust, indicating the validity of baseline regression.

## 4.4 Further test analysis

According to the classification criteria of geographical location and economic development level of the National Bureau of Statistics, the samples in the observation period were divided into three groups: eastern, central, and western regions. The regression results

TABLE 7 Regression results of regional heterogeneity test.

| Variables | Geolocation zoning | | | Agricultural function zoning | | |
|---|---|---|---|---|---|---|
| | Eastern | Central | Western | Grain producing areas | Grain-consuming areas | Grain balance areas |
| DE | −0.324 (0.052) | −0.136*** (0.029) | −0.077 (0.050) | −0.148*** (0.026) | −0.388*** (0.079) | 0.070 (0.060) |
| Control Variable | Control | Control | Control | Control | Control | Control |
| Con | −4.815*** (1.608) | −1.213 (1.009) | 1.962** (0.921) | 1.383 (0.894) | −10.531*** (2.882) | 3.625*** (0.953) |
| $R^2$ | 0.676 | 0.774 | 0.390 | 0.660 | 0.704 | 0.440 |
| N | 121 | 88 | 121 | 143 | 77 | 110 |

are shown in Table 7. The results showed that DE inhibited ACE in the eastern, central, and western regions, and its influence coefficient and influence significance gradually decreased. After the provinces were divided into main grain-producing areas, main grain-selling areas, and balanced grain-selling areas, the regression results showed that DE in the main grain-producing areas and main grain-selling areas have obvious inhibition on ACE, while the balanced grain-selling areas have no significant effect on ACE.

The influence efficiency of DE on ACE shows a gradual decreasing gradient in the east, middle, and west, which may be mainly due to the following four aspects: First, there are differences in the levels of economic development. The East has a higher level of economic development and a more advanced industrial structure. In the allocation and utilization of DE, the eastern region may be more inclined to adopt efficient and low-carbon technologies and management methods, to have the most obvious inhibition effect on carbon emissions. The degree of economic development in the central region is between the eastern and western regions, and although new technologies are being actively introduced, the overall technology and management level may be slightly worse than that of the eastern region, so the inhibition effect is relatively weak. In the western region, the economic development is relatively backward, traditional agriculture accounts for a large proportion, and the application of modern technology and DE is relatively limited, leading to the weakest inhibitory effect. Second, there are differences in technological level and innovation ability. The eastern region, with its higher level of technology and stronger innovation capacity, can translate DE into actual productivity improvements more quickly, thus effectively reducing carbon emissions. In the central and western regions, where technology and innovation capabilities are insufficient, the impact of DE on carbon emissions takes longer to emerge. Third, there are certain differences in policy and institutional environment. The eastern region has strong policy support, and the government may have formulated more policies to encourage low-carbon agriculture, and the implementation is strong, to ensure that DE can better serve the agricultural carbon reduction. The relatively weak policy support in the central and western regions may lead to less effective DE allocation than expected. Fourth, there are differences in the level of infrastructure and talent education. The eastern region has better information technology and infrastructure, more professionals, and higher education levels, and can effectively interpret and apply DE to optimize agricultural production. The infrastructure in the central and western regions is relatively backward, and the level of talent and education is low, so the collection, transmission, application, and effective use of DE are all limited to a certain extent (Wang et al., 2024).

The primary grain-producing regions, the main grain-selling regions, and the production-marketing balance regions indicated that the main grain-selling regions have the most significant inhibitory effect on ACE, followed by the primary grain-producing regions, while the production-marketing balance region exhibited no inhibitory effect. The reasons may be the following three aspects: First, the level of economic development and technical application gap. The main grain-selling regions are usually economically developed areas, which are more receptive to new technologies and management models. The efficient modern agricultural technologies and management practices, such as precision agriculture, smart irrigation, data-driven crop management, and other new production models, can significantly improve AOL and reduce carbon emissions. The primary grain-producing regions may not be as widely used as major marketing areas due to economic conditions or limitations in technology promotion, however, due to the large production scale, the application of any effective technology can still bring some emission reduction effects. The economic level and technical application of the production-marketing balance regions are usually behind other regions, due to the limitations of resource allocation, and the goals of production and marketing, on which the effectiveness of emission reduction measures is not significant enough (Zaller et al., 2022). Second, the market demand and driving force are inconsistent. The proximity of the main grain-selling regions to consumer markets leads to a higher demand for green and sustainable products, and this market driving force encourages agricultural producers to adopt low-carbon and environmentally friendly production methods. The primary grain-producing regions, where the main goal is to produce high-yield grain for national supply or Outlet, may not have as strong an incentive to reduce emissions as major selling areas. The market pressure of the production-marketing balance regions is relatively small, and the external demand for low-carbon production may not be as urgent as that of the main marketing areas. Third, the disparity in resource allocation and efficiency is evident. The main grain-selling regions possess superior resource distribution and exhibit greater efficiency in the utilization of labor, land, and capital, which contributes to lower carbon emissions per unit of output (Xu et al., 2025c). Due to the large scale of production, the efficiency of resource allocation in primary grain-producing regions may be limited, but they still have certain emission reduction potential. The production-marketing balance regions may face more balancing problems in resource allocation, leading to less obvious emission reduction effects (Lu et al. (2025b)).

# 5 Discussion and policy recommendations

## 5.1 Conclusion and discussion

This study selected data from 30 provinces in China (excluding Hong Kong, Macao, Taiwan, and Xizang) from 2012 to 2022 as samples to investigate the impact of DE on ACE. The results show that:

(1) The panel model regression results show that DE can significantly inhibit (Yu et al., 2023) ACE intensity, and this result remains stable after the addition of control variables, proving that ACE level will significantly decrease with the continuous increase of DE level. To a certain extent, it explains the achievements of developed countries in promoting intelligent agriculture. By improving the level of data configuration, ACE can be reduced and low-carbon and sustainable development of agriculture can be promoted (Song et al., 2021; Yu et al., 2023). Although China, as a big agricultural country, has consistently paid attention to promoting low-carbon and green development of agriculture, there are still some problems in agricultural development, such as low DE levels, large regional differences, and poor transformation and application. The root cause is that the government has not yet built a perfect DE system and failed to promote the integration of DE and the agricultural industry (Pei et al., 2019). This suggests that in the context of the digital age, while promoting the low-carbon and green development of agriculture, we should pay attention to the important role of improving the level of DE and driving the transformation and upgrading of agriculture.

(2) The heterogeneity test shows that DE has the most obvious inhibitory effect on ACE in the economically developed east and regions, the inhibitory effect is weak in the middle region of the middle level of development, and the weakest effect in the economically underdeveloped western region. Therefore, it can be observed that in economically more developed areas, governments can enhance the level of data allocation, which can effectively inhibit the ACE quantity. The main reason is that the DE level is closely related to economic development. In economically developed areas, the level of data management, sharing, development and application, and environment is higher, and the change of DE can quickly affect the development of agricultural production, thus more effectively inhibiting ACE, while in economically backward areas, the data infrastructure hardware is not perfect, and the reflection efficiency of DE changes is low. For example, in the big data analysis of crop irrigation, areas with sufficient data samples can more accurately grasp the agricultural irrigation scheme to save water resources, and reduce energy consumption, thereby promoting the greener and more sustainable development of agriculture at a faster pace (Yu et al., 2023; Zou and Mishra, 2024). This suggests that the government should directly promote the green development of agriculture by enhancing the level of data allocation in areas with sufficient funds and high management levels. In areas with insufficient funds and low management levels, the government should first promote the coverage of data infrastructure, promote the data-oriented and intelligent transformation of agriculture, and increase policy support.

(3) The mediation effect test shows that AOL has an intermediary effect in the process of DE's influence on ACE, which indicates that the improvement of AOL level is an important factor of DE's inhibition of ACE, and plays a bridge role between DE and ACE. By improving AOL, the configuration of DE makes agricultural production more environmentally friendly and efficient, thus reducing carbon emissions (Zou and Mishra, 2024). The specific configuration of DE is affected by many factors. Under the requirements of promoting green and low-carbon agricultural development, the government should take the improvement of AOL as its guiding principle, formulate specific DE mechanisms, promote intelligent agricultural technology, utilize big data and AI technology to optimize the agricultural production process and enhance resource utilization efficiency (Zhou et al., 2021).

## 5.2 Policy recommendations

Based on the empirical findings and theoretical insights, this study proposes the following targeted policy recommendations:

(1) The data empowerment strategy for specific regions. Establish county-level agricultural data hubs integrating satellite, soil, and climate data with open APIs, enabling smallholders to access precision farming tools. Prioritize FT-enabled microloans for solar irrigation and biogas projects, leveraging DE's highest marginal emission reduction effect. Implement field-level carbon accounts linking IoT-collected machinery or fertilizer data to subsidies. Develop blockchain-based supply chain finance to accelerate payments for high land-utilization ratio farms, reducing storage emissions. Scale carbon data mortgages allowing farms to collateralize verified emission reduction data, lowering green tech financing costs.

(2) Integrate financial data to control the emission mechanism. Second, finance-data Integrated Emission Control Mechanisms. Create agricultural carbon reduction bonds funding solar-smart greenhouses, with returns tied to blockchain-tracked ACE reductions. Mandate carbon-inclusive procurement for state-owned enterprises, prioritizing high-LUR suppliers and deducting carbon credits via FT platforms.

(3) Establish a market-oriented data governance framework. Establish agricultural data asset exchanges. Formulate agricultural carbon data valuation standards covering

indicators. Offer to refinance for FT loans funding DE applications. Allocate quotas based on regional ACE decline. Certify third-party carbon audit firms to validate farm emission data, enabling participation in national carbon markets.

### 5.3 Research deficiencies and prospects

Future research can be in-depth from the following two levels. Firstly, deepen the sample data. The data samples used in this study are at the provincial level, which can provide us with a macro-level analysis, but the impact of DE on ACE in deeper and more detailed geographical areas can be discussed from a deeper perspective. Future studies can refine the granularity of DE and ACE data from the perspective of prefecture-level cities or even county-level cities, which will help to more accurately show the role of DE in different geographical, and economic backgrounds and resource endowments, and further evaluate the role of DE on ACE. Secondly, deepen the evaluation of the implementation and effects of DE. Although this paper uses the fixed effect model to evaluate the relationship between DE and ACE, the consideration of the application and implementation of DE is still missing. Future studies can choose to use a richer and more detailed DE system as an evaluation index and use a more comprehensive evaluation model to explore the long-term effect and potential impact of DE on ACE.

## Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: Data derived from public domain resources. The data presented in this study are available in China Statistical Yearbook [https://data.stats.gov.cn/easyquery.htm?cñE0103].

## Author contributions

LS: Writing – original draft, Methodology, Data curation, Conceptualization. JZ: Writing – original draft, Validation, Investigation, Methodology. XD: Formal Analysis, Data curation, Writing – original draft, Investigation. YT: Software, Writing – original draft, Methodology. TL: Methodology, Validation, Funding acquisition, Writing – original draft, Visualization. MX: Writing – original draft, Conceptualization, Validation, Funding acquisition, Formal Analysis, Supervision. YS: Writing – review and editing, Software, Formal Analysis, Resources, Validation, Project administration, Supervision.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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