HAS DATA CAPITAL REDUCED AGRICULTURAL CARBON EMISSIONS? EVIDENCE FROM CHINA

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Abstract. Data capital has emerged as a key driver of green and low-carbon development in China's agricultural sector. Utilizing panel data from 31 Chinese provinces spanning 2012 to 2023, this study employs a two-way fixed effects model to examine the direct impact and underlying mechanisms of data capital on agricultural carbon emissions. The empirical results reveal that: (1) Data capital significantly reduces agricultural carbon emissions, with notable regional heterogeneity. The mitigation effect is more pronounced in major grain-producing regions compared to non-grain-producing areas; (2) Fiscal support for agriculture positively moderates the impact of data capital on carbon emissions reduction; (3) Land management scale serves as a threshold variable, with a single threshold identified. Based on these findings, this study recommends that the government further promote investment in agricultural data capital, encourage land consolidation to achieve economies of scale, and enhance fiscal policies supporting digital agriculture. These strategies collectively advance agricultural digitalization and facilitate the transition toward low-carbon agriculture.
Keywords: *digital transformation, low-carbon agriculture, data capital, agricultural carbon emissions, threshold effects*

Introduction

Reducing agricultural carbon emissions is essential to achieve high-quality, sustainable agricultural development. However, China's agricultural sector remains heavily reliant on traditional input-intensive practices and extensive management, resulting in low resource-use efficiency and persistently high carbon intensity (Zhang and Shen, 2025). This not only compromises the sustainability of agricultural production but also poses significant challenges to achieving the global 1.5°C climate target. With the rapid development of the digital economy, data has become increasingly integrated into agricultural production processes (FAO, 2021), offering promising pathways for emissions reduction. Against this backdrop, investigating the impact of data capital on agricultural carbon emissions is of both theoretical and practical significance. It enriches the understanding of how digital and green development strategies can be synergized, and informs policy measures for promoting low-carbon agricultural transitions.

The concept of data capital has evolved along with advances in internet technology, cloud computing, and artificial intelligence (Ye and Li, 2017). Officially introduced at the 2015 Institute of Electrical and Electronics Engineers (IEEE) Cloud Computing Conference, data capital is defined as a unique form of capital based on data elements, which creates value through digital technologies and intelligent platforms (Teece, 2018). Traditional approaches to managing agricultural carbon emissions are hindered by inefficient factor allocation, outdated monitoring tools, and in-sufficient policy integration

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(Cai et al., 2025). In contrast, the application of data capital offers a new technological paradigm. For instance, Internet of Things (IoT) devices can collect real-time data on soil moisture, equipment usage, and fertilizer application. With the aid of algorithmic models to track carbon footprints, farmers can adopt precision farming techniques such as variable-rate fertilization and automated machinery scheduling (Bocca et al., 2016). These practices not only improve productivity but also substantially reduce carbon emissions.

However, the efficacy of data capital in reducing agricultural carbon emissions is influenced by contextual factors, particularly production conditions and policy support. Inadequate fiscal support can undermine stakeholders' willingness to invest in digital infrastructure and adopt low-carbon practices (Yang, 2023). Meanwhile, land management scale plays a critical role in determining the effectiveness of digital and low-carbon agricultural technologies (Lowder et al., 2016). Larger-scale landholdings facilitate broader adoption of these technologies by lowering fixed costs and improving carbon efficiency. Understanding the moderating roles of fiscal policy and land scale is essential for maximizing the emission-reduction potential of data capital.

Prior research in this field falls into three broad categories: (1) Determinants of agricultural carbon emissions: Studies employing models such as LMDI (Tian et al., 2014), Tapio decoupling (Xiong et al., 2020), and extended STIRPAT (Wei et al., 2023) have found that factors including rural labor migration (Xiong et al., 2016), economic development, mechanization (Guan et al., 2023), human capital (He et al., 2018), land transfer (Tang and Chen, 2022), agricultural service provision (Chen et al., 2022), and public investment (Song et al., 2023) can reduce emissions. (2) Digitalization and emissions reduction: Scholars have confirmed that green Information and Communications Technology (ICT) (Xiu and Min, 2025) and the broader development of the digital economy (Wang et al., 2024; Jin et al., 2024) significantly curb emissions, although regional disparities persist. (3) Economic effects of data capital allocation: Existing literature highlights data capital's role in enhancing farmer incomes (Xu et al., 2022) and promoting economic growth (Tang, 2021).

Despite these contributions, two major research gaps remain. First, while existing studies explore agricultural digitalization, they tend to emphasize internet usage or specific technologies, with limited focus on data capital as an economic production factor. Second, research on data capital primarily investigates its economic benefits, overlooking its ecological value, particularly in reducing agricultural carbon emissions. To address these research gaps, this study constructs a two-way fixed effects model using China's provincial panel data from 2012 to 2023. Furthermore, it utilizes both moderating and threshold models to examine the roles of fiscal support and land management scale. The study aims to: (1) quantify the impact of data capital on agricultural carbon emissions using interprovincial panel data, (2) investigate how fiscal support moderates the relationship between data capital and agricultural carbon emissions, and (3) identify threshold effects of land management scale. The findings will provide theoretical insights into digital-green synergies and offer practical policy levers for low-carbon agricultural transformation.

Theoretical analysis

Impact of data capital on agricultural carbon emissions

Data capital reduces carbon emissions by enabling precision in the allocation of production factors. According to the Resource-Based View (RBV) (Peteraf and Barney, 2003), the integration of heterogeneous internal and external resources can generate

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sustainable competitive advantages. Traditional agricultural production is often limited by the low mobility of land, labor, and capital (Han et al., 2018), resulting in inefficient resource allocation and high carbon emission intensity. In contrast, data capital—characterized by non-rivalry and near-zero marginal cost (Yang et al., 2024)—transcends the constraints of traditional resource endowments, redefining the logic of factor configuration within agricultural ecosystems. By leveraging technologies such as the IoT, blockchain, and artificial intelligence, data capital optimizes resource allocation mechanisms (Ahmed et al., 2022), promoting a transformation model centered on precision and efficiency.

In the dimension of resource allocation, data-driven intelligent decision-making systems contribute to both emission reduction and efficiency improvement. For instance, IoT-enabled water-fertilizer integrated management systems collect real-time multidimensional environmental data (e.g., soil moisture, air temperature, humidity, pH levels) to dynamically adjust fertilization and irrigation strategies (Zhang et al., 2021), thereby reducing redundant inputs and lowering emissions. Regarding resource utilization, data capital breaks through the physical limitations of traditional production factors, enabling collaborative allocation across multiple agents. By aggregating heterogeneous data from machinery operations, irrigation systems, and storage facilities (Arif et al., 2024), agricultural big data centers utilize algorithms to identify emission sources with precision and enhance the utilization efficiency of idle resources. Simultaneously, data-driven operational guidance reduces reliance on experience-based decision-making, lowering the carbon footprint per unit of output (Luo et al., 2024).

Data capital also promotes carbon emission reduction by driving industrial up-grading and transformation. Obstacles to low-carbon agricultural development—such as being locked into low-end industrial structures and lacking decarbonization technologies—persist throughout the supply chain (Sovacool and Geels, 2016). With its high fluidity, data capital dissolves industrial boundaries, supports the digital reconstruction of supply chains (Pickren, 2018), and accelerates industrial transformation. In terms of industrial structure, data capital propels agriculture from traditional extensive modes toward low-carbon operations across production, supply, and sales. For example, supply chain big data plat-forms can optimize logistics routes, reducing transportation energy consumption (Li, 2019), while blockchain technologies improve the transparency of green certification, enhance consumer trust, and expand demand for low-carbon products. In terms of sup-ply chain coordination, data capital integrates upstream and downstream information flows, opening new paths for emission reduction. It empowers specialty agriculture (e.g., organic farming) through market analysis and brand building, thereby enhancing product value and reducing carbon intensity per unit (Agbelusi et al., 2024). Moreover, the integration of agriculture with e-commerce, tourism, and other sectors—enabled by data capital—creates comprehensive low-carbon industrial chains encompassing "production–processing–services" (Zhang and Zhang, 2024). Through the digital empowerment of the entire supply chain, data capital effectively curbs agricultural carbon emissions.

Based on the above, the following hypothesis is proposed:

Hypothesis 1 (H1): Data capital significantly inhibits agricultural carbon emissions.

The moderating role of fiscal support policy for agriculture

The development and deployment of data capital in agriculture rely heavily on new infrastructure such as broadband networks, IoT platforms, and digital communication systems—investments that entail high initial costs and generate considerable positive externalities (Chao, 2020). Fiscal support thus plays a vital role in addressing market failures

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and infrastructure gaps. Government investment in new infrastructure reduces operational costs for agricultural stakeholders (Pinstrup-Andersen and Shimokawa, 2006). For instance, intelligent pesticide spraying systems can reduce pesticide drift and usage by 65%–75% (Zhao, 2021), but their widespread adoption depends on fiscal expenditures in base station construction and network integration. Simultaneously, subsidies for agricultural machinery and conservation programs ease capital constraints faced by operators, thereby accelerating the diffusion of low-carbon technologies. Smart agricultural machinery equipped with precision irrigation, fertilization, and pesticide application functions significantly reduces energy consumption and methane emissions compared to traditional practices, with the extent of its adoption directly affecting carbon intensity (Chachei, 2024).

In addition, fiscal policies can internalize the externalities of carbon emissions through mechanisms such as ecological compensation and carbon tax rebates, reshaping stakeholders' emission-reduction decisions. Effective agricultural carbon governance requires a coordinated advancement of digital infrastructure and technological innovation, wherein fiscal support acts as a key moderating variable.

Based on the above, the following hypothesis is proposed:

Hypothesis 2 (H2): Fiscal support for agriculture positively moderates the inhibitory effect of data capital on agricultural carbon emission intensity.

The threshold role of land management scale

The effectiveness of data capital is closely tied to the configuration of agricultural resources, particularly the spatial characteristics of land use. The degree of land consolidation significantly influences the coupling between data capital and traditional production factors (Ge et al., 2017). In regions with highly fragmented landholdings, dispersed plots impede the efficient collection, transmission, and analysis of data, weakening the ability of data capital to regulate machinery deployment, fertilization, and pesticide use with precision (Adhikari and Manandhar, 2024). Smaller-scale operations are also less likely to invest in digital infrastructure, which limits the potential of data capital to coordinate land and labor inputs and constrains the large-scale application of low-carbon technologies.

Conversely, expanding the scale of land management amplifies the effectiveness of data capital by generating scale effects. Through the establishment of farmland in-formation sensing networks, large-scale operations can monitor soil conditions and crop growth in real time, enabling precise machinery scheduling and efficient irrigation and fertilization strategies (SS et al., 2024), thereby significantly reducing emissions per unit area. Moreover, large-scale operators can accumulate and mine data assets, enabling iterative upgrades in low-carbon production technologies and establishing a virtuous cycle of "data-driven precision management → emission reduction → efficiency improvement."

Based on the above, the following hypothesis is proposed:

Hypothesis 3 (H3): The impact of data capital on agricultural carbon emissions is contingent on land management scale as a threshold condition.

Materials and methods

Model design

Building on Chen et al.'s (2022) approach and supported by Hausman test results (significant at 1%), we employ a two-way fixed effects model to examine data capital's impact on agricultural carbon emissions, having rejected random effects:

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$$AC_{it} = \alpha_0 + \alpha_1 DC_{it} + \mu Controls_{it} + Province_t + Year_i + \varepsilon_{it} \quad \text{(Eq.1)}$$

In *Equation 1*, i denotes province, t denotes year; AC_{it} represents the agricultural carbon emissions; DC_{it} denotes data capital; $Controls_{it}$ are control variables; $Province_{it}$ and $Year_{it}$ represent province and year fixed effects, respectively; and ε_{it} is the random error term.

To further assess the moderating effect of fiscal support for agricultural policy, we specify the following interaction model (Tang et al., 2025):

$$\begin{aligned} AC_{it} = \alpha_0 + \alpha_1 DC_{it} + \alpha_2 EC_{it} + \alpha_3 AC_{it} \times EC_{it} + \mu Controls_{it} \\ + Province_t + Year_i + \varepsilon_{it} \end{aligned} \quad \text{(Eq.2)}$$

In *Equation 2*, EC_{it} is the moderating variable fiscal support for agriculture, and $DC_{it} \times EC_{it}$ is the interaction term between data capital and fiscal support for agriculture.

To test the potential nonlinear impact of land management scale, we employ a threshold regression model (Zhang et al., 2024):

$$\begin{aligned} \mathrm{AC_{it}} = \alpha_0 + \alpha_1 \mathrm{DC_{it}} \times \mathrm{I_{it}}(\mathrm{SC_{it}} \leq \mathrm{q}) + \alpha_2 \mathrm{DC_{it}} \times \mathrm{I_{it}}(\mathrm{SC_{it}} > \mathrm{q}) \\ + \mu \mathrm{Controls_{it}} + \mathrm{Province_t} + \mathrm{Year_i} + \varepsilon_{it} \end{aligned} \quad \text{(Eq.3)}$$

In *Equation 3*, I (·) is the indication function of the model, SC_{it} is the threshold variable (land management scale), and q is the threshold value.

Variable definitions

The dependent variable is agricultural carbon emissions. Due to substantial data limitations in livestock statistics, this study focuses on crop farming. Following the methodology of Wei et al. (2023) and Wu et al. (2024) agricultural carbon emissions are decomposed into three categories: production input emissions (fertilizers, pesticides, agricultural films, diesel, and irrigation), soil emissions (N_2O), and paddy field emissions (CH_4). The calculation formula is as follows:

$$\mathrm{AC}_{it} = \Sigma(P_i \times T_{it}) \quad \text{(Eq.4)}$$

In *Equation 4*, AC_{it} denotes agricultural carbon emissions; P_i represents the carbon emission coefficient of the i-type carbon source; T_{it} is the amount consumed. The specific coefficients are (Wei et al., 2023; Li et al.,2022): fertilizer (0.8956 kg/kg), pesticide (4.9341 kg/kg), agricultural film (5.18 kg/kg), diesel (0.5927 kg/kg), irrigation electricity (266.48 kg/hm²). The soil N_2O emission coefficients for major crops were determined as follows (Shang et al., 2015): rice (0.24 kg/hm²), spring wheat (0.40 kg/hm²), winter wheat (2.05 kg/hm²), soybean (0.77 kg/hm²), maize (2.53 kg/hm²), vegetables (4.21 kg/hm²), and other upland crops (0.95 kg/hm²). Following the methodology of Li et al. (2020), the CH_4 emission coefficients for paddy field were determined according to regional growing seasons (see *Table 1*). The total carbon emissions are obtained by summing emissions from all sources. For regression analysis, the values are logarithmically transformed.

The core explanatory variable is data capital. Based on the logical sequence of "infrastructure → factor flow → value transformation," the data capital index is

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constructed across three dimensions: Data infrastructure, measured by indicators such as internet penetration rate (%), length of long-distance optical cables (10^4 km), and mobile switchboard capacity (10^4 households), which reflect the physical foundation enabling data value realization. Data dissemination capacity, captured through the number of webpages (10^4), domain names (10^4), mobile penetration rate (%), and per capita telecom revenue (CNY 100 million), quantifying the intensity and efficiency of data flow in agricultural supply chains. Data application level, evaluated by the number of Information Technology (IT) service providers (units), the proportion of IT personnel (%), and the digital financial inclusion index (%), indicating the practical integration of data into low-carbon agricultural productivity. Weights are assigned using the entropy method.

Table 1. *CH_4 emission coefficients from paddy fields (g/m^2)*

Province	Early rice	Medium-season rice	Late rice
Beijing	0	13.23	0
Tianjin	0	11.34	0
Hebei	0	15.33	0
Shanxi	0	6.62	0
Inner Mongolia	0	8.93	0
Liaoning	0	9.24	0
Jilin	0	5.57	0
Heilongjiang	0	8.31	0
Shanghai	12.41	53.87	27.5
Jiangsu	16.07	53.55	27.6
Zhejiang	14.37	57.96	34.5
Anhui	16.75	51.24	27.6
Fujian	7.74	43.47	52.6
Jiangxi	15.47	65.42	45.8
Shandong	0	21.00	0
Henan	0	17.85	0
Hubei	17.51	58.17	39.0
Hunan	14.71	56.28	34.1
Guangdong	15.05	57.02	51.6
Guangxi	12.41	47.78	49.1
Hainan	13.43	52.29	49.4
Chongqing	6.55	25.73	18.5
Sichuan	6.55	25.73	18.5
Guizhou	5.10	22.05	21.0
Yunnan	2.38	7.25	7.6
Tibet	0	6.83	0
Shaanxi	0	12.51	0
Gansu	0	6.83	0
Qinghai	0	0	0
Ningxia	0	7.35	0
Xinjiang	0	10.50	0

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The moderating variable is fiscal support for agriculture, defined as the ratio of government spending on agriculture, forestry, and water affairs to total agricultural output, following Lu et al. (2023). This variable captures the scale of public investment supporting rural and agricultural development.

The threshold variable is land management scale, defined as the ratio of crop-sown area to the agricultural labor force, based on Tian and Zhang (2024). This indicator reflects changes in factor allocation efficiency and potential shifts in agricultural carbon emissions.

Control variables include six factors, selected with reference to Tian et al. (2024): Agricultural mechanization level: total agricultural machinery power per agricultural worker; Crop structure: share of grain-sown area in total crop-sown area; Agrochemical input intensity: fertilizer use per unit of crop-sown area; Natural disaster severity: ratio of disaster-affected crop area to total sown area; Rural education level: average years of schooling among rural residents.

Data sources

The panel data covers 31 provinces in China from 2012 to 2023. Data sources include the China Statistical Yearbook, China Rural Statistical Yearbook, EPS Database, Peking University Digital Finance Research Center, and various provincial yearbooks. Missing values are addressed via interpolation. Descriptive statistics are presented in *Table 2*.

Table 2. *Variable definitions and descriptive statistics*

Variable type	Variable name	Variable definition	Mean	Deviation
Explained variables	AC: agricultural carbon emissions	Production input emissions, soil emissions, and paddy field emissions (10^4 t)	355.7088	245.9196
Explanatory variables	DC: data capital	Measured using the entropy method	0.2062	0.1610
Control variables	C1: agricultural mechanization level	Total agricultural machinery power (10^4 kW) / Number of agricultural workers (10^4 persons)	5.9517	13.9263
	C2: crop structure	Grain-sown area (10^3 hm^2) / Total crop-sown area (10^3 hm^2)	0.6506	0.1429
	C3: agrochemical input intensity	Fertilizer usage (10^4 t) / Crop-sown area (10^3 hm^2)	0.0351	0.0133
	C4: natural disaster severity	Disaster-affected crop area (10^3 hm^2) / Total sown area (10^3 hm^2)	0.1217	0.1047
	C5: rural education level	Average years of education among rural residents (year)	7.7311	0.8401
	Agricultural FIXED asset investment	Agricultural fixed asset investment (CNY 100 million)	898.8990	901.4807
Moderating variable	EC: fiscal support for agriculture	Government expenditures on agriculture, forestry, and water affairs (CNY 100 million) / Agricultural output (CNY 100 million)	0.3050	0.3970
Threshold variable	SC: land management scale	Crop-sown area (10^3 hm^2) / Number of agricultural workers (10^3 persons)	0.8208	0.4351

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The descriptive statistics indicate that the log-transformed agricultural carbon emissions have a mean of 355.7088 and a standard deviation of 245.9196, highlighting significant potential for reduction. The data capital index exhibits a relatively low mean (0.2062) and moderate variation, suggesting suboptimal development with room for improvement. Control variables such as mechanization level, rural education level and agricultural fixed asset investment show considerable heterogeneity, while crop structure, input intensity, and natural disaster severity are relatively stable. Both the moderating and threshold variables exhibit substantial variation, pointing to potential influences on the relationship between data capital and carbon emissions.

Results

Analysis of baseline results

The baseline regression results are shown in *Table 3*: Columns (1) and (3) present baseline regression results without incorporating province and year fixed effects. In Column (1), without control variables, the coefficient of data capital is –0.6164, while in Column (3), after including control variables, it slightly increases in magnitude to –0.4432. Both coefficients are statistically significant at the 1% level. Columns (2) and (4) incorporate province and year fixed effects. In Column (2), the coefficient of data capital is –0.6340 without controls, remaining highly significant at the 5% level. When control variables are added in Column (4), the coefficient is –0.6343, still statistically significant. These results robustly confirm a significant negative relationship between data capital and agricultural carbon emissions. This finding supports Hypothesis H1, indicating that data capital effectively reduces agricultural carbon emissions. Through digital reconfiguration of production factors, data capital mitigates resource misallocation in traditional agricultural systems, thereby improving the efficiency of key inputs such as fertilizers and machinery. Additionally, precision agriculture technologies—such as remote sensing and intelligent algorithms—reduce carbon intensity per unit of land area, further con-attributing to emission reductions.

Regarding the control variables, the agricultural mechanization exhibit significantly positive coefficients, suggesting they contribute to increased emissions. This may be due to higher fossil fuel consumption and accelerated decomposition of soil organic matter. Conversely, natural disaster severity significantly reduces emissions, likely by leading to a significant reduction in sown area while prompting farmers to switch to low-carbon, climate-resilient crop varieties, directly decreasing carbon emissions from current-season agricultural production activities (e.g., farm machinery operation and irrigation energy consumption). Other control variables—such as crop structure, agrochemical input intensity, and rural education levels—do not have statistically significant effects. The lack of statistical significance may stem from homogeneous crop patterns, offsetting effects of different agrochemicals, and the delayed adoption of sustainable practices despite education.

Heterogeneity analysis

To assess regional heterogeneity in the impact of data capital on agricultural carbon emissions, provinces are grouped into major and non-major grain-producing regions. The regression results are presented in *Table 4*. In major grain-producing regions, the estimated coefficient of data capital is –0.7458 and is statistically significant at the 10% level. In

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contrast, in non-major grain-producing regions, data capital does not exhibit a statistically significant effect, indicating clear regional differences in its emission-reducing impact.

Table 3. *Estimation results of the baseline model*

Variable	(1)	(2)	(3)	(4)
DC	-0.6164*** (0.0383)	-0.6340** (0.3150)	-0.4432*** (0.0423)	-0.6343** (0.2917)
C1			0.0005* (0.0003)	0.0004*** (0.0001)
C2			-0.1597 (0.1055)	-0.2645 (0.3191)
C3			4.7652*** (0.9755)	2.2289 (3.6768)
C4			-0.0865*** (0.0158)	-0.0831*** (0.0257)
C5			0.0263 (0.0453)	0.0203 (0.0391)
Constant	5.5751*** (0.2115)	5.5396*** (0.0307)	6.1388*** (0.2658)	6.2558*** (0.2609)
Province FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
N	372	372	372	372
Pseudo R^2	0.4323	0.5421	0.5410	0.5860

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. Cluster-robust standard errors in parentheses

Table 4. *Heterogeneity analysis by grain production region*

Variable	Major grain-producing regions	Non-major grain-producing regions
DC	-0.7458* (0.3895)	-0.3335 (0.2121)
Constant	5.9884*** (0.3421)	6.4109*** (0.3134)
Control variables	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
N	156	216
Pseudo R^2	0.7319	0.6211

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. Cluster-robust standard errors in parentheses. The major grain-producing regions include 13 provinces: Heilongjiang, Henan, Shandong, Sichuan, Jiangsu, Hebei, Jilin, Anhui, Hunan, Hubei, Inner Mongolia, Jiangxi, and Liaoning. All other provinces are classified as non-major grain-producing regions

This heterogeneity can be attributed to the structural differences in agricultural production across regions. Major grain-producing areas are characterized by large-scale,

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intensive farming, which fosters the accumulation of data capital and facilitates the rapid development and adoption of agricultural digital technologies. These advancements help reduce carbon emissions by improving resource allocation and operational efficiency. Conversely, in non-major grain-producing regions, agricultural production tends to be more fragmented and small-scale, resulting in higher costs and coordination barriers for the implementation of digital technologies. Additionally, these regions often prioritize secondary and tertiary industries over agriculture, leading to less policy attention and investment in agricultural emission reduction. As a result, the scale and efficiency effects of data capital are significantly weakened.

Moderating effects test

As shown in *Table 5,* the regression coefficient of data capital on agricultural carbon emissions is –0.3088, significant at the 10% level. The interaction term between data capital and fiscal support for agriculture is –0.2943 and is statistically significant at the 1% level. These results suggest that increased fiscal support significantly enhances the carbon-reducing effect of data capital, thereby validating Hypothesis H2.

A likely explanation is that government funding reduces the financial barriers associated with the adoption of data-driven technologies in agriculture. Specifically, targeted subsidies for the acquisition of agricultural machinery, the development of data platforms, and related initiatives lower the entry threshold for farmers and agricultural enterprises, accelerating the integration of data capital into production processes. Furthermore, public investments in remote sensing networks and the deployment of IoT infrastructure across farmland significantly strengthen the environmental governance capabilities of data capital, further contributing to emission reductions.

Table 5. *Moderating effects of fiscal support on the impact of data capital*

Variable	AC	AC	AC
DC	-0.6343** (0.2917)	-0.4555** (0.1948)	-0.3088* (0.1763)
EC		-0.1982*** (0.0638)	
DC×EC			-0.2943*** （0.0458）
Constant	6.2558*** (0.2609)	6.0657*** (0.2123)	6.0870*** （0.2175）
Control variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	372	372	372
Pseudo R^2	0.5860	0.6447	0.6678

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. Cluster-robust standard errors in parentheses

Threshold test

Using 500 bootstrap replications, we conduct statistical inference on the threshold effect and determine the number of thresholds associated with land management scale.

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As presented in *Table 6,* a single threshold is statistically significant at the 1% confidence level, whereas the double threshold does not attain statistical significance. The identified threshold value is 0.4531, indicating that land management scale serves as a threshold variable in the relationship between data capital and agricultural carbon emissions. These findings provide empirical support for Hypothesis H3.

Table 6. *Threshold effect test*

Threshold variable	Model	P-value	F-statistic	10%	5%	1%	Threshold value
SC	Single threshold	0.0040	56.46	28.0508	36.1119	56.8957	0.4531
	Double threshold	0.1400	23.95	28.9572	38.3423	66.6572	-

Table 7 presents the results of the threshold regression. Based on the estimated threshold value (0.4531), the effect of data capital on agricultural carbon emissions is analyzed across two intervals. In the first interval (≤0.4531), the coefficient of data capital is −0.7282. In the second interval (>0.4531), the coefficient decreases in absolute value to −0.3775. These results indicate that data capital consistently reduces agricultural carbon emissions, thereby supporting Hypothesis H3. However, the degree of effectiveness varies notably across different scales of land management, echoing the findings of Ma et al. (2024).

A plausible explanation is that land management scale significantly influences agricultural operators' capacity to integrate and utilize data capital. At moderate scales, data capital facilitates the precise allocation of production factors through digital technologies such as precision fertilization and smart irrigation, effectively eliminating carbon inefficiencies. However, once land scale exceeds the critical threshold, the increasing complexity of production systems brings about challenges—including higher technical integration barriers and elevated coordination costs—that reduce the marginal benefits of data capital in emission reduction. Furthermore, large-scale farms of-ten reach a plateau in mechanization and face inflexibility in adjusting energy structures, which may partially offset the environmental gains brought by data capital.

Table 7. *Single threshold effect regression results*

Variable		AC
DC	Interval 1: (SC ≤ 0.4531)	-0.7282*** (0.0560)
DC	Interval 2: (SC＞0.4531)	-0.3775*** （0.0405）
Constant		5.9976*** (0.1512)
Control variables		Yes
Province FE		Yes
Year FE		Yes
N		372
Pseudo R2		0.6021

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. In parentheses are robust standard errors

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Robustness test

Lagged explanatory variable

To verify the robustness of the baseline regression results, the explanatory variable—data capital—is lagged by one period to account for potential time-delayed effects. As shown in *Table 8,* the coefficient of lagged data capital is −0.5051, which is statistically significant at the 5% level. This finding confirms that data capital continues to exhibit a significant negative effect on agricultural carbon emissions, consistent in both direction and significance with the baseline regression, thereby reinforcing the reliability of the results.

Trimmed sample

To mitigate the influence of exogenous shocks such as major policy changes and public health crises, data from the years 2013, 2020, and 2021 are excluded—an approach consistent with that of Li et al. (2024). The results, presented in *Table 8,* show that the coefficient of data capital remains at −0.6158, significantly negative at the 5% level. This is in line with the baseline estimates in both magnitude and significance, further demonstrating the robustness of the findings.

Additional control variables

To ensure robustness against omitted variable bias, two additional control variables are introduced: agricultural fixed asset investment (to control for the potential confounding effects of capital intensity on technological substitution) and effective irrigation rate (to capture the influence of water resource efficiency). The effective irrigation rate is defined as the proportion of effectively irrigated area to the total irrigated cropland area. As shown in *Table 8,* the coefficient of data capital is −0.5817 and re-mains significantly negative at the 5% level. These results further validate the robust-ness and stability of the emission-reducing effect of data capital.

Table 8. *Robustness test results*

Variable	Lagged DC	Trimmed sample	Additional control variables
DC	-0.5051**	-0.6158**	-0.5817 **
	(0.2416)	(0.2799)	(0.2572)
Control variables	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	341	279	372
Pseudo R2	0.6339	0.5922	0.6100

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. Cluster-robust standard errors in parentheses. Effective irrigation area refers to cultivated land with stable water sources, level terrain, and complete irrigation infrastructure that can achieve normal irrigation in typical years

Instrumental variable approach test

Despite the aforementioned robustness checks, potential endogeneity concerns—such as omitted variable bias and sample selection issues—may still affect the baseline results.

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To address this, an instrumental variable (IV) approach is employed, following the methodology of You et al. (2023). Specifically, the interaction term between the 1984 postal and telecommunications service volume and the one-period lagged internet penetration rate is constructed as the IV. The 1984 postal service volume reflects the historical foundation of regional communication infrastructure, which plausibly influences long-term data capital accumulation but bears no direct impact on contemporary agricultural carbon emissions. When interacted with the lagged internet penetration rate, the IV captures the path-dependent diffusion of digital technology while mitigating reverse causality concerns through temporal lagging. This design enhances both the relevance and exogeneity of the instrument, thereby meeting the key validity conditions of instrumental variable estimation.

Table 9 presents the two-stage least squares (2SLS) regression results. In the first stage, the IV demonstrates a significantly positive effect on data capital at the 1% level, confirming its strong relevance. The Lagrange Multiplier (LM) test rejects the null hypothesis of under identification, and the F-statistic exceeds the critical value threshold for weak instruments at the 10% maximal IV bias level, further affirming instrument strength and validity. In the second stage, the coefficient of data capital is estimated at −0.3228 and remains statistically significant at the 10% level. This confirms that, even after addressing potential endogeneity through a rigorous IV strategy, data capital continues to exert a significant negative impact on agricultural carbon emissions. The results thus provide further empirical support for Hypothesis H1.

Table 9. *Instrumental variable estimation result*

Variable	The first stage	The second stage
DC		-0.3228* (0.1664)
IV-DC	0.2544*** (0.0197)	
Constant	0.2723** (0.1448)	4.0239*** (0.2521)
Control variables	Yes	Yes
Province FE	Yes	Yes
Year FE	Yes	Yes
Kleibergen-Paap rk LM Statistic	39.29***	
Kleibergen-Paap rk Wald F Statistic	166.48	
N	341	341

***, **, * mean that the estimated results are significant at 1%, 5%, and 10%. In parentheses are robust standard errors

Discussion

The Chinese government explicitly proposed the strategic goal of “peaking carbon emissions by 2030 and achieving carbon neutrality by 2060” at the 75th Session of the United Nations General Assembly. As a fundamental industry in China, reducing agricultural carbon emissions is a crucial component of realizing this target. However, carbon emissions from the existing agricultural production system remain persistently high. With the quiet emergence of the digital economy, data has been designated as a new

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factor of production, presenting new opportunities for reducing agricultural carbon emissions.

The findings of this study reveal the role of data capital in reducing agricultural carbon emissions. Placing our discoveries within the broader literature enables a more nuanced understanding of the relationship between digital transformation and low-carbon agricultural development. The research on data capital presented here exhibits both consistencies and distinctions with existing studies on the digital economy. While our results align with research highlighting the environmental benefits of the digital economy, they diverge in critical aspects. Previous studies emphasize internet penetration rates and ICT adoption as drivers of emission reduction. In contrast, we position data capital as a distinct factor of production, underscoring that the value of data lies not only in connectivity but also in its capacity to optimize resource allocation—a dimension underexplored in prior research.

Compared with existing literature, this study makes two key contributions:

Theoretical contributions: This study enriches the literature on determinants of agricultural carbon emissions by elucidating the ecological impact of data capital. It also extends the discourse on the economic consequences of data capital allocation to include environmental externalities, offering new insights into the intersection of digital and green development.

Practical contributions: By empirically analyzing the relationships among data capital, fiscal support, land scale, and carbon emissions, this study provides policy-relevant insights. It proposes a differentiated, dynamic policy framework for promoting agricultural low-carbon transformation, which may guide future governance and investment strategies.

In addition, this study has certain limitations. First, there is the limitation of data coverage. Due to statistical constraints, carbon emission data from the livestock industry was not included, which may lead to an underestimation of the carbon reduction effects of data capital. Second, there are limitations associated with the panel data. For instance, constructing data capital indicators may fail to capture informal digital practices among small-scale farmers. Finally, due to space and time constraints, there are several areas that warrant further in-depth research. For example, the fiscal support indicators did not differentiate between types of subsidies (e.g., equipment purchase, technical training, or data services), resulting in less precise and detailed findings. Therefore, future research could conduct specialized analyses on livestock and poultry farming. Additionally, micro-level data could be obtained through surveys to enable more accurate and targeted exploration.

Conclusions and recommendations

Conclusions

Drawing on panel data from 31 Chinese provinces spanning 2012 to 2023, this study employs a two-way fixed effects model, a moderating effects model, and a threshold effects model to examine the impact of data capital on agricultural low-carbon development, while exploring the moderating role of fiscal support for agriculture and the threshold role of land management scale. The main findings are summarized as follows:

Data capital significantly contributes to agricultural low-carbon development. Its accumulation exerts a notable inhibitory effect on agricultural carbon emissions.

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Regional heterogeneity is evident in the effect of data capital. The emission-reducing effect is statistically significant in major grain-producing regions but becomes insignificant in non-major grain-producing regions.

Fiscal support for agriculture plays a dual role. It not only reduces agricultural emissions directly but also enhances the inhibitory effect of data capital on emissions.

Land management scale serves as a key threshold variable. A single statistically significant threshold (value = 0.4531) was identified. While data capital continues to suppress emissions on both sides of this threshold, the degree of effectiveness varies, indicating a non-linear relationship influenced by land scale dynamics.

Recommendations

Based on the above findings, the following policy recommendations are proposed:

Increase Investment in Data Capital to Maximize Synergistic Emission Reductions: Governments should expand targeted support for smart agriculture initiatives by systematically developing agricultural data resource systems and upgrading infrastructure, including sensor networks and blockchain-based traceability platforms. At the provincial level, agricultural big data-sharing platforms should be established to dismantle data silos. Additionally, comprehensive data collection systems spanning production and distribution chains should be promoted, with a focus on constructing agricultural carbon emission monitoring centers to enable real-time data exchange on soil moisture, machinery usage, and agricultural input application.

Innovate Fiscal Support Mechanisms to Strengthen Policy Synergies: Introduce differentiated ecological compensation mechanisms to incentivize the adoption of digital technologies for carbon reduction. Higher-tier compensation should be granted to projects that integrate digital and low-carbon benefits, thereby discouraging reliance on traditional economic subsidies. The development of carbon footprint tracking tools, green credit schemes, and agricultural education programs can further steer data capital toward synergistic low-carbon transformation, ensuring that technological advancements translate into ecological benefits.

Implement Differentiated Land Policies to Unlock the Potential of Scale: Establish carbon reduction pilot zones in major grain-producing regions, while designing adaptive strategies for non-major regions. Introduce a dynamic land management system by integrating digital evaluation tools into land transfer markets. Provide sub-threshold operators with precision agriculture toolkits, while encouraging above-threshold operators to implement real-time energy consumption monitoring. Furthermore, integrate digital emission reduction metrics into agricultural carbon accounting frameworks and performance evaluations to foster a digitally enabled, low-carbon agricultural development paradigm that balances productivity and environmental sustainability.

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