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Research article

A study on the potential of digital economy in reducing agricultural carbon emissions

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ABSTRACT

Agriculture is a significant source of carbon emissions, which have a substantial environmental impact. The digital economy plays a vital role in mitigating these emissions through innovative digital solutions. As a leading agricultural nation, China faces substantial pressure to reduce its agricultural carbon emissions(ACE). This paper aims to thoroughly examine the relationship between the growth of the rural digital economy and ACE. To achieve this, we utilize an extensive panel dataset covering China's provinces from 2011 to 2020, analyzing the dynamic and spatial effects of digital economy development on ACE. The key findings of this research are as follows: (1) The rapid expansion of the digital economy significantly reduces ACE. (2) The impact of digital economic development on lowering ACE varies spatially, with a clear progression from eastern to western regions. (3) The digital economy helps reduce ACE through three specific channels: fostering technological innovation, enhancing scale efficiency management, and providing agricultural financial incentives. Based on these findings, this study proposes policy recommendations to improve digital infrastructure, promote balanced regional development in the digital economy, and optimize the management of agricultural science and technology. These policy insights aim to transform agriculture and achieve the goal of reducing ACE, thereby contributing to broader environmental sustainability.

1. Introduction

Global warming poses a formidable challenge to human society, largely driven by the relentless rise in greenhouse gas emissions, with carbon dioxide being the primary contributor. This trend has precipitated a more frequent occurrence of extreme climatic events, including atmospheric pollution [1], bipolarization of drought and flood [2], and rising sea levels [3]. These phenomena collectively pose a grave threat to the biodiversity of our planet, disrupt the delicate balance of natural ecosystems, and give rise to a plethora of detrimental impacts on the livelihoods of human populations. In light of these circumstances, there has been a unanimous consensus across various sectors of society on the critical need to address these global climate challenges, underscoring the necessity for a transition towards low-carbon development practices [4]. Agriculture, a crucial component of the national economy, ranks as the second-largest contributor to greenhouse gas emissions, trailing only industrial production. Data released by the Food and Agriculture Organization of the United Nations (FAO) show that agricultural activities contribute to over 30 % of global anthropogenic greenhouse

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gas emissions, primarily through carbon dioxide [5]. This alarming trend has understandably drawn significant international attention towards the carbon emissions(CE) from agricultural practices. Nonetheless, it is necessary to acknowledge that agriculture remains exceedingly vulnerable to the impacts of climate change, and navigating the path towards emission reduction within this sector is fraught with complexity and challenges.

Within the conventional Chinese agricultural paradigm, several factors contribute, directly or indirectly, to elevated CE in the agricultural sector. These factors include the application of pesticides and chemical fertilizers [6], land irrigation [7], ploughing practices [7], resource allocation inefficiencies [8], and low production efficiency [9]. This situation hinders the pursuit of low-carbon agricultural evolution. China is the world's largest carbon emitter, China's agricultural carbon emissions(ACE) account for 17 % of the national total, making the reduction of these emissions crucial for achieving the "dual-carbon" objective [10]. In response to global climate change and the swift expansion of the DE, the Chinese government has introduced the "Opinions on Effectively Implementing the New Development Concept for Carbon Peaking and Neutrality" and the "2030 Peak Carbon Action Program." These initiatives aim to address the pressing environmental challenges and promote sustainable development [11]." These policy documents emphasize that there is an urgent need to reduce agricultural production costs through the use of agricultural digitalization and technological innovation [12], and that the digital transformation of agriculture can promote the improvement of traditional agricultural production and business structures, and ultimately promote low-carbon agriculture towards a sustainable development path.

In the contemporary era, the DE plays a crucial role in reshaping the global economic landscape and optimizing resource allocation through platformization, intelligence, and sharing [13]. The white paper "The Development of China" (2021) shows, the DE now makes up one-third of China's Gross Domestic Product (GDP) [14]. Its impact on rural development has been growing steadily, especially as digital technologies become more prevalent in rural regions. Advanced information technology has fostered the rise of new industries that digitize rural economic activities, enhancing efficiency, vitality, and quality. This shift has significantly supported the green transformation and revitalization of the rural economy [15]. Furthermore, the DE provides new opportunities for rural revitalization by reshaping production environments and creating innovative pathways for development. The DE offers innovative solutions for the greening of energy-intensive industries by both digital industrialization and industrial digitization. This process helps reduce the dominance of "high-pollution, high-energy-consumption, and high-emission" low-end industries. As a result, the DE plays a crucial role in decreasing ACE [16]. The rapid expansion of the DE is intricately connected to the rural economy, prompting scholars to explore the complex relationship between the DE and ACE. Can the DE significantly contribute to achieving the 'dual carbon' objectives? If so, what are the mechanisms behind its impact on lowering ACE? These questions are pivotal and remain a focus of current research. This study aims to explore novel approaches to reducing ACE and to provide a theoretical framework for advancing the DE.

This paper analyzes the impact of the DE on ACE using provincial panel data from China spanning 2011 to 2020. By constructing a panel data model, this paper discusses the development of rural digital economy across China and its impact on ACE. Additionally, a mediating effect model is established to elucidate the mechanisms linking the DE to ACE. Compared to previous studies, this paper offers several innovative contributions. Firstly, it validates the causal relationship between the DE and ACE from the perspective of the DE itself. Secondly, it integrates relevant DE data, providing a new foundation for understanding the interactions between DE development and ACE. Thirdly, it identifies and emphasizes mechanisms such as technological innovation incentives, scale efficiency management, and agricultural financial compensation in the relationship between the DE and ACE.

The paper is structured as follows: Section 2 presents the literature review. Section 3 explains the theoretical framework and hypotheses. Section 4 presents the data and variable selection for the study. Section 5 describes the empirical results. Section 6 presents the recommendations and limitations of the article.

2. Literature review

The evolution of the DE is significantly transforming and enhancing traditional agricultural production methodologies. By integrating with the DE, traditional agricultural practices benefit from the rapid dissemination of big data, fostering a shift towards a more efficient production paradigm. This synergy between conventional agriculture and digital innovations is driving substantial improvements in production efficiency and effectiveness. This culminates in the establishment of a digital agriculture model, characterized by a cooperation between government entities and businesses, thereby enhancing the productivity of agricultural operations and actualizing the high-quality development of the agricultural sector [17]. Additionally, the integration of agriculture and e-commerce has given rise to a novel paradigm in agricultural development, catalyzing the metamorphosis of the traditional industry into sectors that are technologically advanced and digital-intensive [18]. Present-day academic research into the DE's progression concentrate on two primary dimensions. Firstly, the growth of the DE profoundly impacts various societal aspects, such as employment, consumer behavior, trade, finance, and the industrial landscape. As a pivotal locational determinant for spatial economic configuration, the DE's ascension has led to an information revolution and a recalibration of factors, effectively dismantling geographical, temporal, and informational barriers. This not only offers positive stimuli for economic growth [19], industrial structure upgrading [20], regional innovation [21], and high-quality development of industries [22] but also propels the innovation in microenterprises and ensures the unimpeded circulation of production factors such as capital and technology [23]. Secondly, a group of scholars has begun exploring the environmental impacts of the DE. Although the expansion of the DE can increase overall output levels, it also raises concerns about the potential rise in energy consumption and CE associated with this growth. In the academic community, there appears a lack of consensus on this subject matter. A subset of scholars postulates that the DE possesses eco-friendly attributes and holds the potential to mitigate CE [24]. On one hand, the DE serves as an early catalyst for economic growth, offering extensive scale, scope, and long-tail effects that can create new industries and innovative business models [25]. This capacity underscores the "direct effect" of the DE in reducing CE. Additionally, by replacing traditional information technologies with advanced alternatives, the DE plays a crucial role in reducing energy consumption and lowering CE. This technological evolution enhances the allocation and utilization of resources, addressing the inefficiencies of previous development practices [26]. Through optimizing industrial energy consumption, the DE exhibits the "indirect effect" of CE reduction. However, some scholars contend that the relationship between the DE and CE follows a "unidirectional pathway." They argue that as the DE expands, it may increase resource consumption and result in higher CE [27].

ACE are the greenhouse gases released directly or indirectly from agricultural activities. These emissions stem from the use of fertilizers and pesticides, energy waste, and land tilling during the production process, specifically in plantation agriculture as discussed in this paper [28]. The data at hand reveal that approximately 70 % of the increased concentrations of atmospheric methane can be attributed to human production endeavors [29]. Agriculture stands out as the predominant contributor to methane emissions, and it is projected by some experts that, in the absence of efficacious interventions to reduce ACE, we may witness an additional 30 % surge in global ACE by the year 2050 [30]. Academic studies into the macro-level quantification and analysis of ACE were initiated by West and Marland, with their focus on variables such as seed cultivation, pesticides, fertilizers, energy wastage, and land tilling, specifically in the United States. They established a comprehensive index system for measuring ACE, spanning four critical dimensions: seed cultivation, pesticides, fertilizers, and agricultural irrigation, subsequently proceeding to perform calculations based on this framework [31]. Presently, China's agricultural GHG emissions constitute 17 % of the national total, placing the country at the forefront of ACE on a global scale. Currently, China is experiencing a continuous annual growth of 5 % in ACE, which constitute approximately 17 % of the nation's total greenhouse gas emissions [32]. Given this context, studying ACE within China's broader carbon footprint is essential. A significant portion of academic research in China has focused on understanding the regional distribution of these emissions and exploring the factors influencing their spatial patterns from various perspectives. Research in this domain has highlighted the pivotal role of agricultural carbon emission reduction, emphasizing the necessity of balancing economic efficiency with environmental sustainability. This research is crucial for achieving sustainable agricultural development [33]. Insights from these studies can inform and guide policy formulation, fostering region-specific low-carbon agricultural practices. These efforts also support the principles of green development in the agricultural sector.

Scholars, both domestically and internationally, have extensively discussed the intersection of the DE and CE, providing valuable insights into how the DE impacts carbon reduction mechanisms. However, a comprehensive review of existing literature reveals three main limitations. Firstly, while many studies have examined the correlation between the DE and CE, most have neglected the agricultural perspective, with only a few focusing on the relationship between the DE and ACE. Secondly, much of the existing literature has concentrated on identifying factors that influence ACE without exploring the underlying mechanisms [34]. Lastly, although the DE's impact extends beyond social employment, economic development, and industrial structure, its significant role in environmental enhancement is often overlooked. This paper aims to address these gaps and offers several potential contributions. Firstly, it shifts the research perspective from urban-level impacts of the DE on CE to analyzing the effects of the rural DE on ACEs, emphasizing the environmental ramifications attributed to the rural DE. Secondly, the study considers both spatial differences and the influence of DE characteristics on the results of the benchmark regression analysis, thoroughly examining the heterogeneous impacts of the rural DE on ACE through the lens of regional heterogeneity. In addition, the study delves into the mechanism of the rural DE's impact on ACE from three perspectives: technological innovation, scale of operation and financial compensation.

3. Theoretical analysis and hypotheses

3.1. The effect of DE advancement on ACE

Relying on digital resources such as knowledge and information, the DE has become a key factor of production. These resources are vital not only for the growth of the DE itself but also for the advancement of other industries. Unlike traditional production factors like capital and labor, digital resources stand out due to their virtual nature, high permeability, and instantaneous transmission capabilities [35]. This study employs a Cobb-Douglas production function incorporating labor, capital, and technology as inputs. Accordingly, a company's output level, denoted by Q, can be expressed as follows:

$$Q = D^{\theta} A^{\alpha} K^{\beta} L^{\gamma} \tag{1}$$

In this context, Q denotes a company's output level. D represents the components of the DE, A stands for exogenous technological progress, and K and L correspond to the inputs of capital and labor, respectively. The coefficients θ,α,β, and γ denote the output elasticities associated with each production factor.

Moreover, a specified portion of the total output, presumed to be a fraction ω, is allocated to emission reduction activities [36]. This allocation serves as the emission reduction output, culminating in the formulation of the company's net output equation and the equation for ACE.

$$Y = (1 - \omega)Q \tag{2}$$

$$CO_2 = (1 - \omega)^{\frac{1}{\mu}} Q \tag{3}$$

Wherein, Y represents the net output of a company, ω represents the proportion of the output used by the company for carbon reduction relative to the total output, μ represents the pollution elasticity of the company's net output, and CO_2 represents ACE. From equation (3), it is clear that ACE are positively correlated with both output and the pollution elasticity of net output, while they are negatively correlated with a company's efforts to reduce emissions. By solving for 1 - ω from equation (2) and integrating it into equation (3), along with equation (1), we can derive the relationship between ACE, pollution elasticity of net output, and various production factors:

$$CO_2 = Y^{\frac{1}{u}} * D^{\theta\left(1-\frac{1}{u}\right)} A^{\alpha\left(1-\frac{1}{u}\right)} K^{\beta\left(1-\frac{1}{u}\right)} L^{\gamma\left(1-\frac{1}{u}\right)} \tag{4}$$

To ensure that the model setup conforms to the linear characteristics required for parameter estimation and hypothesis testing, the logarithm of both sides of equation (4) is taken, resulting in the following model:

$$InCO_2 = \frac{1}{uInY} + \theta\left(1-\frac{1}{u}\right)InD + \alpha\left(1-\frac{1}{u}\right)InA + \beta\left(1-\frac{1}{u}\right)InK + \gamma\left(1-\frac{1}{u}\right)InL \tag{5}$$

Equation (5) demonstrates that ACE are influenced by the input of various factors and have a positive correlation with the pollution elasticity of net output, denoted as μ. When μ is within the range (0, 1), ACE show a negative correlation with the input of digital elements. In this case, the development of the DE can lead to an increased input of digital elements, which helps reduce ACE. Additionally, digital technology can be harnessed to transform and upgrade high-pollution industries. This process improves resource utilization efficiency and reduces the pollution elasticity of net output, thereby further decreasing ACE. Based on this, Hypothesis 1 is formulated in this paper:

Hypothesis 1. The advancement of the DE can substantially reduce ACE.

3.2. Mechanisms for mediating CE from agriculture in the DE

The DE generates substantial knowledge spillover effects that not only facilitate knowledge dissemination and diffusion but also diminish information asymmetry [37]. This economy augments the ease of accessing information resources for enterprises, expands market opportunities, and reveals latent profits. Moreover, it mitigates risks linked to agricultural technology innovation, encouraging enterprises to amalgamate both internal and external innovation resources and technological components [38]. From the perspective of market demand, the DE enhances innovation development strategies, increases production efficiency, and improves both the R&D process and business models. These advancements lead to improved total factor productivity and a reduction in ACE [39]. Therefore, Hypothesis 2 is formulated as shown in Fig. 1:

Hypothesis 2. The DE promotes technological innovation, thereby reducing ACE. Furthermore, a mechanism incentivizing technological innovation operates within the interaction between the DE and ACE.

Utilizing digital information technology, ED can alleviate the constraints of geographical resources and environmental conditions on industrial agglomeration. By fostering industrial agglomeration through collaborative production [37], it substantially lowers transaction costs, promotes agricultural collaborative and smart manufacturing, and drives innovation in agglomeration mechanisms, effects, and patterns, consequently facilitating online industrial aggregation [40]. Industrial agglomeration plays a crucial role in enhancing technological progress and diffusion, fostering competitive effects, and boosting production efficiency. Moreover, it leverages economies of scale to significantly reduce ACE [41]. In light of these findings, as depicted in Fig. 1, Hypothesis 3 is proposed:

Hypothesis 3. The DE intensifies industrial agglomeration, thus diminishing ACE, and establishes a management mechanism for economies of scale between the DE and ACE.

In agricultural development, the DE furnishes more accurate agricultural data. Under the impetus of the DE, financial institutions can extend loans and subsidies tailored to low-carbon agricultural technologies through diverse online platforms. Governments, similarly propelled by the DE, can leverage its financial channels to offer fiscal support, aiding farmers in managing uncertainties and risks [42]. By serving as a conduit for financial transactions, thereby bolstering information transparency and resource allocation efficiency, the DE effectively facilitates agriculture's transition toward low-carbon practices [43]. Hence, as depicted in Fig. 1, this

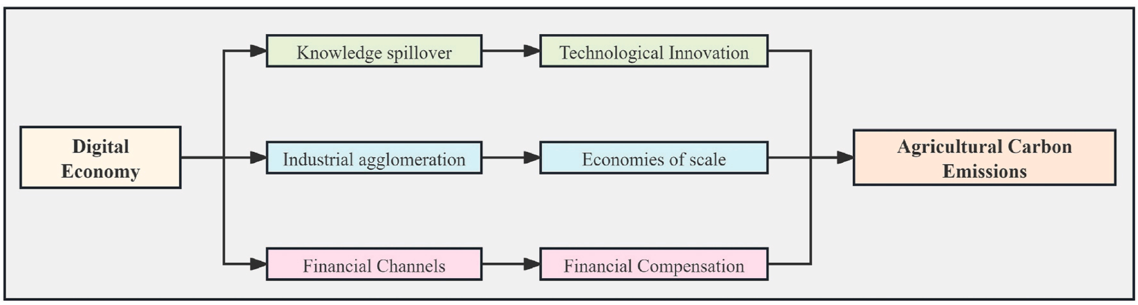

Fig. 1. Mechanistic analysis of the DE and ACE.

paper posits Hypothesis 4:

Hypothesis 4. The DE can employ financial channels to reduce ACE. This approach involves the creation of an agricultural financial offset mechanism that links the DE to the reduction of ACE.

4. Selecting variables and data source

4.1. Variables and data sources

4.1.1. Dependent variable

In this paper, the response variable is ACE. We calculate these emissions using the methodology recommended by the 2006 Guidelines for National Greenhouse Gas Inventories from the United Nations Intergovernmental Panel on Climate Change. This approach assesses the CE generated by the inputs of agricultural materials in farming practices [44]. The specific calculation method is detailed in Equation (6).

$$CE = \sum CE_i = \sum T_i \times \delta_i \tag{6}$$

In Equation (6), CE represents the total CE from agricultural activities. The term CE_i encompasses six types of agricultural materials, including fertilizers, pesticides, and agricultural films, which are referred to as carbon emission sources. T_i denotes the emissions from the i-th category of these sources, while δ_i signifies the emission coefficients for the respective category. The specific emission coefficients for each type of carbon emission source are detailed in Table 1.

4.2. Independent variable

The primary explanatory variable in this paper is the DE [46]. Given the wide scope of the DE, it is essential to consider multiple dimensions when assessing it. This paper selects five indicators to assess: Internet penetration, Internet-related outputs, the Digital Financial Inclusion Index, the number of users of the "accessible" Internet, and the number of relevant people working as Internet professionals [47]. The entropy method is employed to calculate these indicators, which together determine the digital rural consumption level for each province. We following the calculation method proposed by Jiang and other scholars [48], the data mentioned above are standardized, ensuring all indicators are positive, and the calculation results were shown in equations (7)–(12):

$$X'_{ij} = \frac{X_{ij} - min\{X_j\}}{max\{X_j\} - min\{X_j\}} \tag{7}$$

Calculate the weight Y_{ij} of the value of the jth indicator in year i:

$$Y_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{m} X'_{ij}} \tag{8}$$

Determine the entropy value of the ith indicator e_j:

$$e_j = -\frac{1}{In(m)\sum_{i=1}^{m}\left(Y_{ij} * InY_{ij}\right)} \tag{9}$$

Indicator weights W_i:

$$W_i = \frac{1 - e_j}{\sum_{i=1}^{m} X'_{ij}} \tag{10}$$

Single-indicator evaluation score S_{ij}:

$$S_{ij} = X'_{ij} W_i \tag{11}$$

Table 1
Carbon sources of ACE and their coefficients.

Carbon sources	Carbon emissions data	Reference sources
Fertilizer inputs	0.895 6 kg kg^{-1}	West et al. [31], Oak Ridge National Laboratory, USA
Pesticide application	4.934 1 kg kg^{-1}	Oak Ridge National Laboratory, USA
mulch	5.180 0 kg kg^{-1}	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
mechanical energy consumption	0.592 7 kg kg^{-1}	United Nations Intergovernmental Panel on Climate Change (IPCC)
Soil tillage	311.600 0 kg kg^{-2}	College of Biology and Technology, China Agricultural University
Electricity for irrigation	25.000 0 kg kg^{-2}	Dubey et al. [45]

Composite level score S_i in year i:

$$S_i = \sum_{j}^{n} S_{ij} \tag{12}$$

In this context, X_{ij} represents the value of the jth evaluation indicator for year i. m represents the number of years of assessment and n represents the total number of indicators.

4.2.1. Control variables

To account for the influence of extraneous factors on the explanatory variables, this study incorporates a set of control variables: rural consumption, agricultural labor productivity, agricultural production structure, population size, agricultural disaster rate, trade openness, population density, urbanization rate, and infrastructure. Rural consumption is expressed in terms of disposable income per rural resident [49]. Agricultural labor productivity is represented by the ratio of the total power of agricultural machinery to the number of people employed in the primary industry [50]. The agricultural production structure is defined by the ratio of the area sown with grain to the total cropped area [51]. Population size is indicated by the number of rural inhabitants [52]. The agricultural disaster rate is calculated as the proportion of the area affected by crop damage to the total cropped area [53]. Trade openness is expressed as the total volume of imports and exports relative to the Gross Regional Product (GRP) [54]. The ratio of resident population to area at the end of the year is used to calculate population density [55]. The ratio of urban population to total population was used to calculate the urbanization rate [56]. The natural pair quantification of regional road mileage is used to express infrastructure [57]. These variables are detailed in Table 2.

4.3. Model analysis

Examining the complex relationship between DE and ACE, developing a robust and targeted econometric model is essential. Building on the preceding theoretical analysis, this study employs a two-way fixed effects model.

$$ln\, ACE_{it} = \beta_0 + \beta_1 DE_{it} + \beta_3 control_{it} + \mu_i + \rho_t + \varepsilon_{it} \tag{13}$$

In equation (13), i represents the location, and t denotes the year. ACE_{it} indicates the ACE of region i at time t, while DE_{it} represents the DE of region ii at the same time. The term $control_{it}$ includes a set of control variables that may influence ACE, such as rural consumption, agricultural labor productivity, agricultural production structure, population size, agricultural disaster rate, trade openness, population density, urbanization rate, and infrastructure level. To address the issue of heteroskedasticity, a logarithmic transformation is applied to variables with significant value differences. μ_i denotes a locational fixed effect, serving to account for potential differences in ACE across diverse geographical terrains. ρ_t is a temporal fixed effect, offering a flexible mechanism to control for potential temporal differences, while ε_{it} constitutes a stochastic error term, encapsulating: (1) other influential factors of lesser significance, (2) observational inaccuracies, and (3) stochastic elements that elude control and precise quantification. The data in this paper come from the China Statistical Yearbook and the annual reports of provinces and cities, and summarize the balanced panel data of 30 provincial administrative divisions in China between 2011 and 2020. Tibet, Hong Kong, Macao, and Taiwan are excluded from the analysis due to data unavailability. To address any gaps in the dataset, linear interpolation and ARIMA modeling techniques are employed. As shown in Table 3.

4.4. Stylized fact

Fig. 2 showcases bubble diagrams depicting the correlation between the DE and ACE. The diagrams represent data from four different years: 2011 (top left), 2014 (top right), 2017 (bottom left), and 2020 (bottom right). To account for the substantial variations in ACE, these values have been logarithmically transformed. Each bubble's size represents the magnitude of rural consumption within the corresponding region. The charts clearly demonstrate that rural consumption significantly influences both the DE and ACE.

Table 2
Definitions and calculation methods of variables.

Definition	Variable	Symbol	Definition
DV	Agricultural Carbon Emission	ACE	Logarithm of total agricultural carbon emissions
IV	Digital Economy	DE	Standardized processing of the digital economy
CV	Rural Consumption	RC	Disposable income per rural inhabitant
CV	Agricultural Labor Productivity	ALP	Gross power of agricultural machinery/number of persons employed in the primary sector
CV	Structure of Agricultural Production	SAP	Area sown in grain/area sown in crops
CV	Size of Population	SP	Logarithm of rural population size
CV	Agricultural Disaster Rate	ADR	Area affected by crops/area sown with crops
CV	Trade Openness	TO	Total exports and imports/gross regional product
CV	Population Density	PD	Year-end resident population/area
CV	Urbanization Rate	UR	Urban Population/Total Population
CV	Level of Infrastructure	LI	Road mileage in logarithms

Table 3
Descriptive statistics of variables.

Variable	Obs	Mean	SD	Min	Max
ACE	300	5.47	1.02	2.66	6.90
DE	300	0.37	0.17	0.07	0.98
RC	300	9.35	0.41	8.27	10.46
ALP	300	4.47	2.05	1.55	12.59
SAP	300	0.64	0.14	0.35	0.97
SP	300	7.26	0.89	5.35	8.62
AD	300	0.14	0.11	0.01	0.61
TO	300	0.26	0.29	0.01	1.54
PD	300	8.20	0.74	6.34	9.44
UR	300	0.59	0.12	0.35	0.89
LI	300	11.68	0.84	9.39	12.88

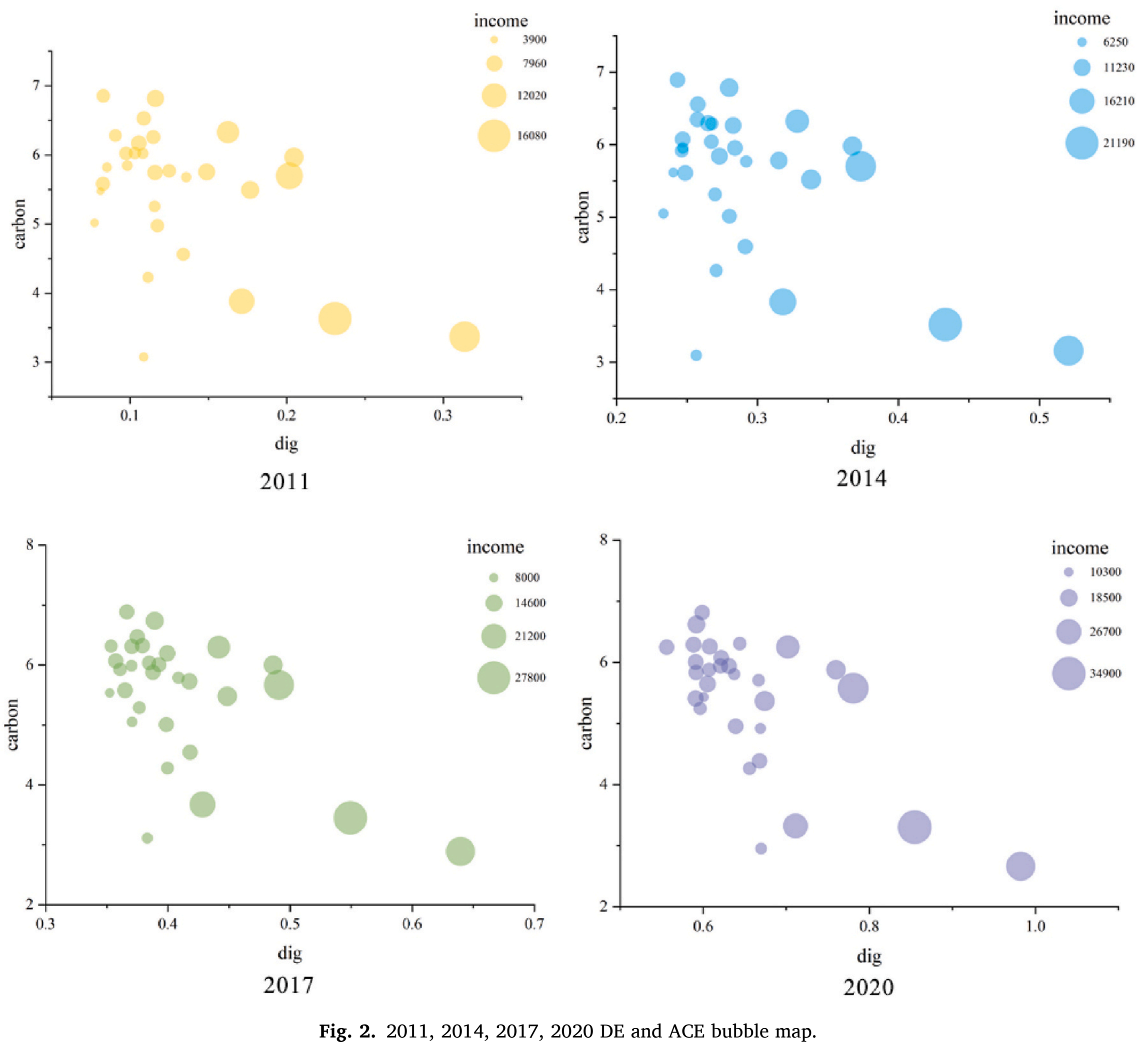

Fig. 2. 2011, 2014, 2017, 2020 DE and ACE bubble map.

Notably, regions with higher levels of rural consumption tend to have a robust DE while maintaining relatively low levels of ACE.

To further analyze the data, we computed the upper and lower quartiles, maximum and minimum values, and the median of ACE for each province annually from 2011 to 2020, covering 30 provinces nationwide. We then constructed a box plot to represent the distribution of ACE. As shown in Fig. 3, there are significant differences in ACE across provinces, highlighting the stark contrast in pollution levels between regions. Notably, there is a decreasing trend in ACE in each region post-2014, which may be attributable to shifts in policy. The year 2014 marks a pivotal moment, as big data was incorporated into China's central government work report for the first time, and the DE was elevated to a national strategy [58]. This qualitative transformation in 2014 actively facilitated changes

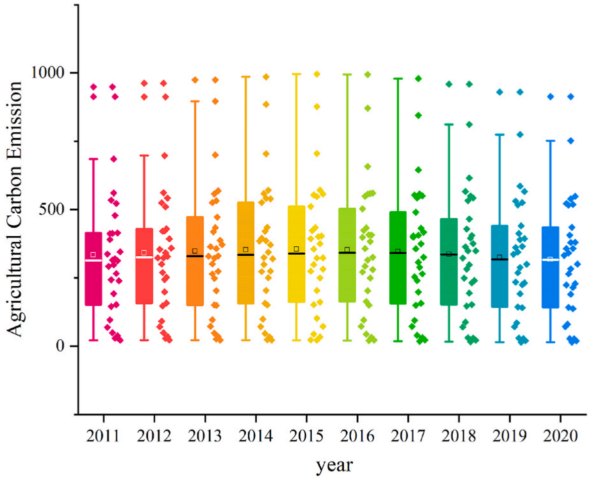

Fig. 3. Box-plot of ACE.

in agricultural production methods, contributing to a reduction in ACE [59].

5. Empirical analysis

5.1. Estimated results of fixed effects model

In this study, Stata 17 is employed to perform a Hausman test on the panel dataset. The results indicate a P value less than 0.01, leading to the rejection of the original hypothesis of random effects. Following this, annual dummy variables are included to test for individual time effects. The results reveal a P value below 0.01, compelling the rejection of the initial hypothesis of "no time effect." As a result, a two-way fixed-effects model is chosen to investigate the influence of the DE on ACE. This comprehensive model includes comparisons with both mixed-effects and random-effects models. Table 4 displays the regression outcomes for the mixed regression

Table 4
Regression.

Varible	OLS	RE	FE
	(1)	(2)	(3)
DE	−0.146	−0.161[c]	−0.236[c]
	(0.096)	0.017	(0.036)
RC	0.072	0.123[c]	0.077[a]
	(0.144)	0.035	(0.047)
ALP	0.169[c]	0.084[c]	0.066[c]
	(0.061)	0.022	(0.008)
SAP	−0.036	−0.041	−0.081[c]
	(0.085)	0.038	(0.017)
SP	2.132[c]	0.510[c]	0.358[c]
	(0.664)	0.112	(0.097)
ADR	0.010	0.013[c]	0.012[c]
	(0.036)	0.003	(0.004)
TO	−0.020	0.065[b]	0.056[b]
	(0.099)	0.027	(0.018)
PD	−1.089[b]	0.096	−0.016
	(0.457)	0.114	(0.113)
UR	0.525	0.133[a]	0.201
	(0.234)	0.076	(0.044)
LI	0.020[a]	0.135	−0.058
	(0.275)	0.107	(0.052)
Constant	−6.461	2.931[c]	−0.172[b]
	(0.062)	0.103	(0.067)
N	300	300	300
R^2	0.883	0.928	0.997

Standard errors are provided in parentheses. Significance levels are represented by symbols:
[a] for 10 %.
[b] for 5 %, and.
[c] for 1 %.

model (OLS), the random-effects model (RE), and the two-way fixed-effects model (FE).

As shown in Table 4, we observe that the mixed-effects model in Model (1) has an R2 of 0.883. In contrast, the random-effects model in Model (2) shows an R2 of 0.928, and the two-way fixed-effects model in Model (3) achieves a remarkable R2 of 0.997, indicating a superior overall fit for the fixed-effects model. Notably, the regression coefficient for the DE, the central explanatory variable in this study, is negative in column (3). This signifies a significant negative correlation between the DE and ACE. Specifically, a 1 % increase in the DE correlates with a 0.236 % decrease in ACE, a relationship that is statistically significant at the 1 % level. These empirical findings strongly suggest that the DE substantially suppresses ACE. Therefore, China can enhance agricultural production efficiency by advancing the DE, which in turn will reduce ACE and improve the ecological environment.

In the spectrum of control variables, the regression coefficient corresponding to the structure of agricultural production is manifestly negative, indicating a decrement in ACE as it ascends. Conversely, the regression coefficients pertaining to rural consumption, agricultural labor productivity, population magnitude, rate of agricultural disasters, and the openness of trade exhibit a positive orientation, leading to an enhancement in ACE concomitant with their increase.

5.2. *Heterogeneity analysis*

China's economic progression exhibits a phase-wise progression, initiating from the coastal regions in the east and gradually pervading the inland territories in the west. Crucially, the DE's influence is not uniform but varies significantly across diverse natural and human landscapes. Based on the regional categorization of the National Bureau of Statistics, this paper examines three regions: East, Central and West [60]. The regression analyses, as presented in Table 5, reveal an intriguing pattern. It becomes evident that the DE significantly impacts ACE in all three regions, with the western region exhibiting a notably stronger response. This discrepancy can be traced back to a variety of factors. The western region, in stark contrast to the eastern region which enjoys geographical advantages and a state of economic affluence, demonstrates an acute sensitivity in its agricultural labor productivity and production structure to the DE's fluctuations. This finding serves to highlight the transformative potential of DE advancements in mitigating ACE, especially in regions that are comparatively underdeveloped, such as the western part of the country.

5.3. *Tests for mediating effects*

The theoretical study above shows that the DE can reduce ACE through three main mechanisms: promoting technological innovation, enabling scale management, and providing agricultural financial compensation. First, the DE facilitates access to information, identifies market opportunities, diminishes technological innovation risks, and fosters enterprise innovation, consequently reducing ACE [61]. Second, the application of digital technology enhances industrial clustering, advances intelligent agricultural manufacturing, and boosts production efficiency, thereby curtailing ACE [62]. Third, the DE provides precise agricultural data, supports low-carbon technology loans and governmental financial backing, increases information transparency, and encourages a shift towards low-carbon agricultural practices [63]. To validate these theoretical mechanisms, this study employs a mediation analysis

Table 5
Heterogeneity analysis.

Varible	East	Middle	West
	(1)	(2)	(3)
DE	−0.079**	−0.136**	−0.242***
	(0.024)	(0.037)	(0.061)
RCL	0.034**	0.021*	0.084***
	(0.087)	(0.026)	(0.096)
ALP	0.069*	0.132**	0.157***
	(0.072)	(0.018)	(0.043)
SAP	−0.027**	−0.041**	−0.069***
	(0.085)	(0.024)	(0.038)
SP	1.872***	0.478***	0.612***
	(0.569)	(0.237)	(0.148)
ADR	0.009	0.014***	0.013***
	(0.013)	(0.002)	(0.005)
TO	−0.018*	0.059**	0.082***
	(0.076)	(0.034)	(0.027)
PD	−0.791	0.128	−0.027
	(0.236)	(0.175)	(0.182)
UR	0.347	0.276*	0.218
	(0.271)	(0.142)	(0.163)
LI	0.014*	0.027	−0.039
	(0.156)	(0.034)	(0.029)
Constant	−1.871	1.587***	−1.356**
	(0.089)	(0.167)	(0.084)
N	300	300	300
R^2	0.914	0.958	0.981

approach inspired by Baron [64] and Hayes [65], utilizing a fixed effects model. Within this framework, we introduce three recursive equations as shown in Eqs. (14)–(16):

$$\ln ACE_{it} = \alpha_{it} + \beta_1 DE_{it} + \beta_3 control_{it} + \mu_i + \rho_t + \varepsilon_{it} \tag{14}$$

$$W_{it} = \alpha_{it} + \gamma_1 DE_{it} + \varphi control_{it} + u_i + \varrho_t + \varepsilon_{it} \tag{15}$$

$$\ln ACE_{it} = \alpha_{it} + \beta_2 DE_{it} + \theta W_{it} + \mu control_{it} + u_i + \varrho_t + \varepsilon_{it} \tag{16}$$

In this model, $lnACE_{it}$ represents the logarithmic ACE of region i at time t, while DE_{it} denotes the DE of region i at the same time. $control_{it}$ includes many control variables that affect ACE, e.g. rural consumption, agricultural labor productivity, the structure of agricultural production, population size, agricultural disaster rate, trade openness, population density, urbanization rate, and infrastructure state. Additionally, W_{it} serves as a mediating variable, including (1) scientific and technological innovation, measured by the number of patents related to agricultural science and technology [66]; (2) scale of operation, indicated by the expanse of arable land under family contracting operations [67]; and (3) financial compensation, reflected by the level of financial support allocated to agriculture [68].

The procedure for assessing the mediating effect is carried out as follows [69]: First, model (1) is estimated to assess the impact of the DE on ACE. A significantly negative β_1 would indicate a suppressive influence of the DE on ACE, which is already supported by the data presented in the table. Next, estimate model (2) to analyze the relationship between the DE and the mediating variables. A significantly positive coefficient would suggest that the DE facilitates the intermediary variable, whereas a negative coefficient would imply a restraining effect. Finally, estimate model (3). If either γ_1 or θ is non-significant, proceed to the next phase of testing. Conversely, if both γ_1 and θ are significant, an intermediary effect is established. At this point, a significant regression coefficient β_2 would indicate a partial intermediary effect, while a non-significant β_2 would suggest a complete intermediary effect.

Table 6 presents the findings derived from the evaluations of the second-stage and third-stage mediated effects. Columns (1), (3) and (5) show the important impact of the development index on DE, scale of operations and economic compensation. This observation necessitates further exploration through mediated effects tests. Meanwhile, Columns (2), (4), and (6) of the same table showcase the third-stage estimation results relevant to the mediation effect model, assessing the impacts of scientific and technological innovation, operational scale, and financial compensation on ACE. Notably, the coefficients for scientific and technological innovation, operational scale, and financial compensation all demonstrate a significant negative correlation with ACE. This indicates that the DE continues to play a crucial role in reducing ACE. It underscores the existence of mediating mechanisms associated with technological innovation, business operation scale, and financial compensation. In summary, the findings confirm that scientific and technological innovation, the scale of business operations, and financial compensation each serve as partial mediators. Thus, the DE emerges as a crucial tool for reducing ACE, facilitated by the relationship of three distinct mechanisms: the incentive for technological innovation, the management of scale efficiency, and the mechanism for agricultural financial compensation.

Building on the preceding theoretical analysis, the DE influences ACE through three main mechanisms: technological innovation, operational scale factors, and financial compensation. As shown in columns (1) and (2) of Table 6, confirm that the DE promotes technological innovation, which in turn reduces ACE. This highlights an incentive mechanism for technological innovation between the DE and ACE. For Hypothesis 3, the results in Columns (3) and (4) demonstrate that the DE enhances industrial clustering, thereby decreasing ACE. This underscores a mechanism of scale efficiency management. Furthermore, the results for Hypothesis 4 in Columns (5) and (6) indicate that the DE effectively utilizes financial channels to reduce ACE, emphasizing a financial compensation mechanism. Thus, all hypotheses are validated, confirming that the DE, through these three mechanisms, plays a crucial role in mitigating ACE.

Table 6
Results of the intermediary effect test.

varible	Incentives for technological innovation		Management of economies of scale		Agricultural financial compensation	
	(1)	(2)	(3)	(4)	(5)	(6)
	Technological innovation	Carbon	Scale of operations	Carbon	Financial compensation	Carbon
DE	0.176**	−0.182*	0.281*	−0.213**	0.098**	−0.182*
	(0.091)	(0.117)	(0.175)	(0.057)	(0.074)	(0.078)
Technological innovation		−0.259***				
		(0.038)				
Scale of operations				−0.092***		
				(0.034)		
Financial compensation						−0.164***
						(0.057)
Constant	0.234	−0.549***	−0.348	−1.411***	−1.723***	−1.867***
	(0.241)	(0.187)	(0.244)	(0.361)	(-0.207)	(0.214)
Control	YES	YES	YES	YES	YES	YES
Time FE	YES	YES	YES	YES	YES	YES
Province FE	YES	YES	YES	YES	YES	YES
N	300	300	300	300	300	300
R^2	0.918	0.929	0.857	0.839	0.984	0.891

6. Conclusion and recommendations

6.1. Conclusions of the study

This paper investigates the impact of the rural DE on ACE using panel data from 30 Chinese provinces from 2011 to 2020. The analysis is conducted through a fixed-effects model. Additionally, it evaluates the internal mechanisms by which the DE contributes to the reduction of ACE. The primary findings are as follows: Firstly, a higher level of rural consumption correlates with a more robust DE, which is associated with relatively lower ACE. However, there are differences in ACE across provinces, highlighting significant regional variations in pollution levels. Secondly, a clear downward shift in ACE is observed post-2014, closely linked to policy adjustments in that year. The year 2014 is remarkable for integrating big data into China's central government work report, marking the DE's elevation to a national strategic priority. This transformation has been pivotal in changing agricultural production, significantly reducing ACE. Thirdly, there is a strong negative correlation between the DE and ACE. Specifically, a 1 % increase in the DE results in a 0.236 % reduction in ACE, a finding that is statistically significant at the 1 % level. Fourthly, the DE has a significant impact on ACE across China's eastern, central, and western provinces, with the most pronounced effects observed in the western region. Finally, the study demonstrates through a mediation effect model that the DE reduces ACE via three mechanisms: incentivizing scientific and technological innovation, managing scale efficiency, and providing agricultural financial compensation.

6.2. Policy recommendations

Premised on the insights obtained from the preceding analysis, it becomes unequivocally clear that the evolution of the DE, propelled by its foundational elements of digital technology and data, harbors the potential to catalyze a comprehensive metamorphosis including the dimensions of production factors, productivity, and the relationships in production, subsequently exerting a direct impact on carbon reduction in the agricultural domain. In light of these findings, the following policy recommendations are proffered:

Firstly, establishing a robust DE infrastructure in rural areas is essential. Strengthening the research, development, and dissemination of digital agricultural technologies can empower farmers to modernize their equipment and adopt energy-efficient practices, ultimately reducing greenhouse gas emissions. The government can significantly contribute by boosting financial support to facilitate the adoption of innovative technologies, enhance agricultural production efficiency, and establish a carbon market. This approach would incentivize the agricultural sector to reduce ACE through carbon trading mechanisms.

Secondly, fostering balanced progress in the development of the rural DE across various regions is of paramount importance. Given the significant disparities in ACE between different areas, it is essential to tailor policies to the unique conditions of each region. This strategy ensures that local needs are met while also minimizing unnecessary ACE. In addition, there is an urgent need to amplify the adoption of innovative digital agricultural technologies, alongside providing comprehensive training that supports practices such as organic farming, diversified cultivation, and the enhancement of farming methodologies. These initiatives play a pivotal role in reducing dependence on chemical fertilizers and pesticides, as well as in reducing greenhouse gas emissions, ultimately contributing to the overarching objective of lowering ACE. Moreover, there is a call for a unified and vigorous approach towards education and awareness-raising campaigns within rural communities. The goal here is to elevate the environmental awareness of rural inhabitants, fostering their enthusiastic involvement in projects designed to mitigate ACE.

Thirdly, is necessary to strengthen mechanisms that promote scientific and technological innovation, enhance scale efficiency management, and offer fiscal recompense for the agricultural sector. This enhancement plays a vital role in driving forward technological progress and nurturing environmentally sustainable farming practices. The governmental bodies should allocate additional funds for research and development to stimulate innovation in digital agricultural technology, while also protecting the intellectual property rights of innovators. Moreover, there appears a necessity to offer comprehensive training and guidance in managing large-scale agricultural operations, and to simultaneously encourage farmers to adopt a cooperative model of operation, which would serve to amplify production efficiency. Moreover, establishing suitable financial compensation frameworks for agriculture is of utmost importance. This could involve fostering active participation of the agricultural sector in the trading of carbon emission rights, providing agricultural producers with an opportunity to gain additional income through emission reduction initiatives. Such incentives are poised to inspire farmers to adopt agricultural practices that are more environmentally friendly.

6.3. Limits and Future research

This paper examines the impact of DE on ACE in China, focusing on technological innovation, business scale, and fiscal compensation. However, several limitations are present. Firstly, the study does not account for long-term trends or seasonal variations, even though both the DE and ACE are dynamic. Consequently, longer-term data is necessary. Additionally, China's agricultural production varies significantly by region, with large-scale plantations in the north and small-scale diversified agriculture in the south, making it challenging to generalize the findings nationwide. Secondly, on a theoretical level, studying the DE and ACE spans multiple disciplines, including economics, environmental science, and information technology. Differences in theoretical approaches and methods among these disciplines may limit the research perspectives and explanatory frameworks. Furthermore, existing economic development and environmental impact models may not fully explain the specific effects of digital technology on ACE. Thirdly, from a methodological point of view, it is more difficult to build an accurate model to assess the impact of DE on ACE. It requires comprehensive consideration of factors such as technological innovation, market dynamics, and policy changes. Lastly, in terms of argumentation, this study establishes certain assumptions, and the uncertainty of these assumptions may affect the reliability of the results. Additionally, interpreting the results often depends on specific geographical, economic, and socio-cultural contexts.

Future research should aim to conduct more geographic information system (GIS) studies to analyze the relationship between digital economic development and ACE across different regions. Additionally, studying the impact of policy and institutional factors on this relationship is crucial to understanding how policies may affect ACE reduction or increase. The influence of policy regimes on the DE and ACE also requires deeper investigation, as government policies and regulations can significantly shape this dynamic. Overall, this area of research is still developing, and more in-depth studies are necessary to better understand the impacts of the DE on ACE. This understanding will be vital for supporting more sustainable agricultural practices and economic development.

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CRediT authorship contribution statement

Zijun Wang: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Jialong Zhang:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Yuanhang He:** Writing – review & editing, Conceptualization. **Hancheng Liu:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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