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Impacts of the Digital Economy on Agricultural Carbon Emissions: Empirical Analyses from 31 Provinces in China

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Greenhouse gas emissions from global agrifood production systems have increased by 17 % over the past 30 years. In China, the goal of achieving carbon neutrality presents new challenges and requirements for all sectors, especially agriculture, which is a major source of carbon emissions. The emergence of the digital economy (DE) offers an opportunity to advance this goal. This study utilized longitudinal data from 31 provinces in China from 2011 to 2021 and constructed a fixed-effects regression model to analyze the impact of DE on agricultural carbon emissions (ACE) and its performance variations under different environmental regulatory intensities. The main findings of this research are: (1) The development of DE can significantly reduce ACE, with more pronounced effects in regions having stricter environmental regulations. (2) Research and development (R&D) investment significantly mediates the relationship between DE and ACE, accounting for 9.7 % of the effect. (3) A heterogeneity analysis indicates regional variations in the carbon emission reduction effects of DE, with non-Yangtze River Economic Belt (NYREB) regions exhibiting stronger effects than those within the Yangtze River Economic Belt (YREB). This study elucidates the mechanisms and impacts of DE on ACE and provides theoretical support for the low-carbon sustainable development of agriculture, as well as for the creation of regionally differentiated policies.

1. Introduction

As global climate change becomes increasingly serious, governments and international organizations are paying greater attention to achieving the carbon neutrality target (Tan et al., 2022). Agriculture, a major contributor to the world's emissions of greenhouse gases (GHGs), plays a crucial role in the effective control of carbon emissions, which is essential for meeting this goal (Liu et al., 2024). In China, not only is agriculture a fundamental base for food production, but it also serves as a significant source of GHG emissions (Dar et al., 2024). According to the White Paper on the Development of China's Digital Economy (2022), DE in China was valued at 45.5 trillion RMB in 2021, accounting for 39.8 % of the Gross Domestic Product. The 14th Five-Year Plan for Economic and Social Development declares that DE will be one of the key pillars for China to achieve the carbon neutrality goal.

Existing research on the impact of DE on carbon emissions has primarily focused on urban areas(Bai et al., 2023). In contrast, few studies have linked DE to ACE, largely due to the complexity and variability of sources in agriculture. Although a small number of scholars have begun to explore the potential effects of DE on ACE, they have mainly focused on mediated effects analyses (Wang et al., 2024). This study integrates both mediating and moderating effects to provide an in-depth exploration of the complex relationship between DE and ACE. Furthermore, by subdividing the study area into YREB and NYREB, this research also details regional differences, an innovative approach that offers a new perspective for understanding the complex dynamics in this field. The research gap emerges when potential positive impacts of DE on ACE have been initially recognized. However, specific impacts and how they vary across different regions and under varying intensities of environmental regulation have not been sufficiently researched. This study aims to examine the impact of DE on ACE by conducting an empirical analysis of longitudinal data from 31 provinces in China. The research questions are: How does the development of DE affect ACE in Chinese provinces? What are the mediating and

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moderating effects of this impact? Additionally, what are the regional differences in the impact of DE on ACE between YREB and NYREB? The significance of this study lies not only in providing a scientific basis for the government to formulate relevant policies in agriculture, the environment, and the digital economy, but also in offering a technical pathway for achieving sustainable agricultural development. Furthermore, it holds great importance for the transformation and upgrading of the rural economy. Following the introduction, the second chapter will provide a detailed theoretical background and literature review. The third chapter will explain the research methods and data sources, the fourth chapter will present the empirical results and analysis, and the final chapter will summarize the entire paper and offer policy recommendations.

2. Literature Review

The White Paper on the Development of China's Digital Economy (2022) defines DE as a new type of economy that utilizes digitized knowledge and information as key production factors. It is driven primarily by digital technology and relies on modern information networks as a crucial conduit. This economy achieves a comprehensive integration of digital technology with the actual economy, consistently enhancing digitalization, networking, and intelligence within the economic society. This represents a new economic form that significantly transforms the reconstruction of economic development and governance models. ACE refers to carbon emissions resulting from the utilization of agricultural land in the process of production and cultivation. These emissions arise from the direct or indirect release of carbon elements through the use of farming petrochemicals such as fertilizers, plastic sheeting, pesticides, mechanical energy, land tilling, and the process of agricultural irrigation. This study adopts the Ecological Modernization Theory, which argues that environmental problems can be resolved through technological innovation, economic growth, and institutional reforms. This research employs empirical analysis, a method based on a large amount of data that reduces the interference of subjective judgment and provides more objective and quantifiable findings.

Hypothesis 1. The development of DE can significantly reduce carbon emissions in agriculture.

There are two main pathways to reduce ACE: adjusting the ratio of inputs of factors of production and enhancing the effectiveness with which these production elements are utilized (Fei and Lin, 2017). Zhou and Li (2020) have confirmed that continuous improvements in technology levels can significantly decrease ACE. Agricultural technology, depending on its role during the farming process, can be divided into two categories: one that increases the technological sophistication of agricultural production without altering the factor input structure, and the other optimizes the original input factor structure by utilizing agricultural production technology. Currently, DE constituted by digital components and information technology, is increasingly penetrating the agricultural field. The gradual integration of DE with farming production has become an essential direction for high-quality development in agriculture. On one hand, the use of DE as an emerging technology in agricultural production enhances efficiency (Zhang et al., 2023); on the other hand, it is a technical component that influences agricultural output by altering both the efficiency of factor use and the structure of inputs.

Hypothesis 2. Technological innovation (TI) plays a mediating role in DE empowering ACE reduction.

TI promotes DE development through the construction of digital information technology platforms, improving research and development of key technologies and innovation capabilities, and supporting the construction of agricultural digitalization (Fielke et al., 2019). TI facilitates the agricultural sector's integration with DE by using geographic information systems, remote sensing, and other new technologies to timely understand crop production situations. This enables online communication with experts to address challenges encountered in planting, rationalize the inputs of agricultural materials, and ultimately promotes the reduction of ACE (Obiahu et al., 2021). Furthermore, TI can enhance the scientific and technological content of seeds, machinery, and other related agricultural input elements, which can directly reduce carbon emissions (CE) per unit in agriculture. The development of agricultural information networks and e-commerce can reduce the cost of sales, broaden the commerce channels for agriculture-related products, and encourage producers to improve quality and increase income, thus freeing up more funds to invest in TI and realize the reduction of ACE.

Hypothesis 3. Environmental regulation (ER) can moderate the emission reduction effect of DE in agriculture.

The technical efficiency of pollution control investments can be improved through DE interventions (Huang et al., 2023). Accurate soil and weather data analysis, based on digital technologies, can optimize pollution control systems and reduce the overuse of pesticides and fertilizers, thereby minimizing the environmental impact of chemicals. Real-time data analysis and smart algorithms can help adjust and optimize energy use and reduce unnecessary waste, thereby increasing the cost-effectiveness of pollution control equipment (Papadopoulos et al., 2024). Government departments can utilize the vast amount of real-time data collected from various digital sources to more accurately understand and assess regional variations and specific needs for ER, thereby designing more targeted and effective environmental protection measures.

3. Methodology

The econometric model is formulated to regress the influence of DE on ACE, using longitudinal data from the 31 provinces of China spanning from 2011 to 2021. Principal component analysis was adopted to calculate the composite index of DE. The operational steps include calculating eigenvalues and eigenvectors, selecting principal components, computing scores for each observation, and constructing a composite index for DE. The carbon emission coefficient method was employed to quantify ACE.

3.1 Variables

The explanatory variable is DE. The system of DE development indicators is extensive; based on Chang et al. (2023), this study utilizes the digital financial inclusion index, Internet broadband access users, mobile phone subscribers, computer services and software employees, and the total volume of telecommunications business to create a comprehensive system of development indicators for DE (Table 1).

Table 1: System of indicators for the digital economy

Primary Indicator	Secondary Indicator	Indicator Measurement	Unit
Digital Economy	Digital finance	Digital Financial Inclusion Index	%
	Mobile telephone user	Mobile telephone penetration	%
	Internet broadband access	Internet broadband access users	10^6
	Computer services and software employees	Information services and software industry employees	10^6
	Telecommunication services	Total telecommunication services	10^8 RMB

ACE is the dependent variable. The Intergovernmental Panel on Climate Change (IPCC) of the United Nations recommends a methodology widely used by scholars to measure ACE. This method involves quantifying CE from various agricultural inputs (Table 2) and aggregating them to determine the total CE. ACE is calculated using Eq(1):

$$C = \sum C_C = \sum T_C \times \delta_c \tag{1}$$

where Tc represents the amount of each carbon source, Cc stands for the carbon emissions from various carbon sources, and δc denotes the carbon emission factors. C is the total ACE.

Table 2: Emission factors of agricultural carbon emission sources (Yao et al., 2024)

Carbon Emission sources	Carbon Emission Coefficient	References
Chemical Fertilizer	0.8956 kg CO_2-eq/kg	Oak Ridge National Laboratory, USA
Pesticide	4.9341 kg CO_2-eq/kg	Oak Ridge National Laboratory, USA
Agricultural diesel oil	0.5927 kg CO_2-eq/kg	IPCC
Agricultural plastic sheeting	5.18 kg CO_2-eq/kg	Nanjing Agricultural University
Irrigation	266.48 kg CO_2-eq/hm^2	(Duan et al., 2011)
Ploughing	312.6 kg CO_2-eq/hm^2	China Agricultural University

There are four control variables, selected based on those commonly used by scholars studying similar problems. Agricultural machinery is measured by its total power (Chi et al., 2021); the level of government intervention is defined by the share of fiscal expenditure in GDP; the demographic factor is expressed by the number of the resident rural population (Xu et al., 2024); and urbanization is determined by the proportion of the total population that is urban. The selection of mediating and moderating variables is based on the theory of ecological modernization, which suggests that environmental problems can be resolved through technological innovation, economic growth, and institutional reform. This study also draws upon related research examining the impact of DE on urban CE. The mediating variable, TI, is measured by R&D investment (Xia et al., 2024). The moderating variable, ER, is determined by the investments in environmental pollution control as a share of GDP (Zhang & Wei, 2014). The conceptual framework is illustrated in Figure 1.

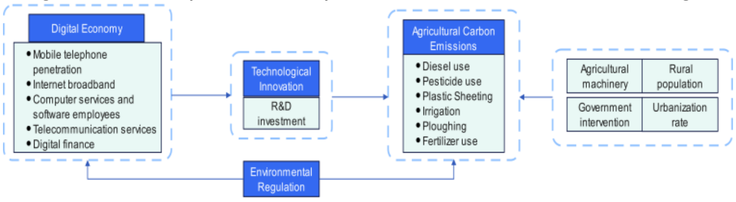

Figure 1: Conceptual framework

3.2 Data Sources and Model Construction

The China Statistical Yearbook of Rural, Environmental, Energy, and Electronic Information Industry for 2011–2021 are the primary data sources, covering 31 provinces in China. Data from Peking University's Digital Finance Research Centre were provided to calculate the level of digital financial inclusion. According to the study by Cheng and Qu (2023), the basic regression model, mediation model, and moderation model are presented in Eq(2) to (5):

$$CE_{\mathrm{it}} = \alpha_i + \beta_1 DE_{it} + \beta_2 \sum X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

$$TI_{\mathrm{it}} = \alpha_i + \beta_3 DE_{it} + \beta_2 \sum X_{\mathrm{it}} + \mu_i + \lambda_t + \varepsilon_{it} \tag{3}$$

$$CE_{it} = \alpha_i + \beta_1 DE_{it} + \beta_4 TI_{\mathrm{it}} + \beta_2 \sum X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$CE_{it} = \alpha_i + \beta_1 DE_{it} + \beta_5 (DE_{\mathrm{it}} \times ER_{it}) + \beta_2 \sum X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{5}$$

Where i and t are the provinces and years, i = 1, 2,..., 31, t = 1, 2,…, 11. $\mathrm{CE_{it}}$ represents ACE of the i province in the t year. $\mathrm{DE_{it}}$ denotes the composite index of DE in year t of the i province. $\sum \mathrm{X_{it}}$ is a collection of control variables. β_1 indicates the direct impact coefficient of DE on ACE. β_2 represents the coefficient of control variables on ACE. β_3 indicates the coefficient of DE on TI. β_4 measures the coefficient of TI on ACE, β_5 indicates the coefficient of the interaction term. The error term $\varepsilon_{\mathrm{it}}$, which represents the random variation that the model fails to explain. μ_i stands for the fixed effect of the area, λ_t represents the fixed effect over time.

4. Empirical Analysis

Taking into account the effect of time trends on ACE, the study incorporates both individual and time effects, and builds the fixed-effect model to investigate the impact of DE on ACE. According to columns (1) of Table 3, The F-statistics are large and their corresponding p-values are less than 0.05, indicating that at least one independent variable significantly affects ACE. A Single-variable t-test shows that the regression coefficient of DE is -3.310, with a t-statistic of -4.74, whose absolute value is greater than 1.96, with a p-value is less than 0.05, indicating a significant negative impact on ACE. When the DE level increases by one unit, ACE decreases by 3.310 units, thus verifying Hypothesis 1. Regarding control variables, increases in the total power of agricultural machinery and the level of urbanization significantly enhance ACE. This effect is attributed to the precise control over the use of fertilizers and pesticides facilitated by digital technology, thus reducing CE associated with these inputs. Agricultural machinery, which requires large amounts of fossil fuels, directly increases fuel consumption and thus GHG emissions. During urbanization, a significant amount of agricultural land is converted to building land, which not only reduces the land’s carbon absorption capacity but also entails high CE from construction activities.

The study employs a three-step approach to validate whether DE can serve as a pathway through R&D inputs to subsequently influence ACE. According to columns (2) and (3) of Table 3, the regression results for R&D investment on DE show a coefficient of 3.165 and a t-statistic of 1.98, whose absolute value is greater than 1.96, indicating that DE has a significant positive impact on R&D inputs. The regression analysis of ACE on R&D inputs and DE demonstrates a significant negative effect. The coefficient for R&D inputs, acting as the mediating variable, indicates that a 1 % increase in R&D inputs leads to a 0.101 % decrease in ACE. Consequently, the mediating effect is calculated at -0.32, and the direct effect at -2.987. The mediating effect accounts for 9.7 %, while the direct effect constitutes 90.3 %. Hypothesis 2 is supported. This significant shift results from the application of new technologies that have made agricultural production more reliant on data and automation rather than on traditional human and fossil-fuel-driven machinery, directly impacting CE levels. Furthermore, TI has drastically reduced the carbon footprint of the entire agricultural production chain by improving the efficiency of each link.

To distinguish between strong and weak ER, the study sets the mean values of ER measures across provinces and above as the strong ER group, and defines the group below the mean as the weak ER group. To investigate whether ER has a moderation effect on the impact of DE on ACE, the study includes an interaction term between this dummy variable and DE. According to column (4) of Table 3, after adding the interaction term, DE continues to have a significant negative effect on ACE. Furthermore, the coefficient of the interaction term is significantly negative, indicating that ER further strengthens the emission reduction effect of DE. Compared with stronger environmental regulation, DE leads to an additional 0.0427 reduction in ACE. This validates Hypothesis 3.

Because stringent ER measures require agricultural producers to comply with specific environmental standards, making them more inclined to invest in efficient, low-carbon technologies and management practices to reduce CE.

To compare the differences in the impact of DE on ACE between Yangtze River Economic Belt (YREB) and non-Yangtze River Economic Belt (NYREB), the study performs group regressions. According to columns (5) and (6) of Table 3, the coefficients are -1.695 and -3.556, both significantly negative for YREB and NYREB, indicating that DE has a significant negative effect on ACE. However, since the absolute value of the coefficient is larger in NYREB, this indicates regional differences in the impact of DE on ACE. NYREB starts from a lower baseline in terms of technology and management practices, which means that even modest technological improvements or management optimizations can lead to larger environmental benefits. Relative rates of change tend to be higher, resulting in more significant reductions in emissions.

Our findings are consistent with those of Wang et al. (2024), who observed that the rapid expansion of DE significantly reduces ACE. The impact of DE development on reducing ACE exhibits a clear progressive trend from the eastern to the western regions. However, our results differ slightly from those of Jin et al. (2024), who identified a nonlinear relationship between rural DE and ACE. This discrepancy may stem from the multidimensional nature of DE. Different studies may focus on different components, leading to slight variations in the results.

Table 3: Summary of benchmark regressions, mediation effects, moderation effects and heterogeneity test.

	Benchmark regressions	Mediation effects		Moderation effects	Heterogeneity test	
	(1) ACE	(2) TI	(3) ACE	(4) ACE	(5) YREB	(6) NYREB
DE	-3.310***	3.165*	-2.987***	-3.281***	-1.695***	-3.556***
	(-4.74)	(1.98)	(-4.48)	(-4.71)	(-2.79)	(-3.35)
Mac	0.174**	-0.0159	0.173***	0.179**	0.0309	0.240**
	(2.44)	(-0.12)	(2.77)	(2.71)	(0.91)	(2.40)
Urban	1.862**	5.098***	2.399***	2.151***	1.116**	2.357***
	(2.60)	(3.97)	(3.22)	(3.30)	(2.39)	(2.97)
Pop	-0.0446	1.135	0.0719	0.0597	-0.491**	-0.144
	(-0.17)	(1.69)	(0.29)	(0.24)	(-2.55)	(-0.57)
Gov	0.298	-2.033***	0.103	0.353	0.205	-0.0749
	(1.16)	(-4.01)	(0.37)	(1.58)	(0.84)	(-0.24)
TI			-0.101* (-1.89)			
Env_DE				-0.0427**		
				(-2.29)		
_cons	5.118**	-7.125	4.365**	4.146*	9.497***	5.155**
	(2.15)	(-1.26)	(2.09)	(1.86)	(5.41)	(2.12)
N	312	311	308	312	116	196
F	26.32	149.1	29.35	28.06	29.74	29.34
p	0.000	0.000	0.000	0.000	0.0000	0.0000
r2	0.679	0.914	0.695	0.698	0.832	0.674

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5. Conclusions

This research analyzes the influence of DE on ACE. The findings reveal that: a) The development of DE significantly reduces ACE, with a 3.31 unit reduction in ACE for every unit increase in DE. b) TI plays a mediating role between DE and ACE, accounting for 9.7 % of the effect. c) ER enhances the reduction effect of DE on ACE. In regions with strong ER, the abatement effect of DE on ACE is more significant. d) There are regional differences in the impact of DE on ACE, with a stronger abatement effect in NYREB than YREB. This study confirms the direct and indirect impacts of DE on ACE, providing a new perspective for understanding and promoting a low-carbon transition in agricultural production. Based on these findings, it is recommended that the government consider the synergistic effects of DE and ER when formulating relevant policies, and further stimulate the potential of DE in agricultural emission reduction by strengthening support for TI and optimizing ER. For agribusinesses, the adoption of more digital technologies is recommended to optimize production processes and improve energy efficiency. Future research could focus on the spatiotemporal analysis of the impact of DE development on ACE to identify spatial dependencies and dynamic interactions.

References

Bai L., Guo T., Xu W., Liu Y., Kuang M., Jiang L., 2023,. Effects of digital economy on carbon emission intensity in Chinese cities: A life-cycle theory and the application of non-linear spatial panel smooth transition threshold model, Energy Policy, 183, 113792.

Chang H., Ding Q., Zhao W., Hou N., Liu W., 2023, The digital economy, industrial structure upgrading, and carbon emission intensity: empirical evidence from China's provinces, Energy Strategy Reviews, 50, 101218.

Cheng S., Qu G., 2023, Research on the effect of digital economy on carbon emissions under the background of “double carbon”, International Journal of Environmental Research Public Health, 20(6), 4931.

Chi Y., Zhou W., Wang Z., Hu Y., Han X., 2021, The influence paths of agricultural mechanization on green agricultural development, Sustainability, 13(23), 12984.

Dar A.A., Chen Z., Rodríguez-Rodríguez S., Haghighat F., González-Rosales B., 2024, Assessing greenhouse gas emissions in Cuban agricultural soils: Implications for climate change and rice (Oryza sativa L.) production, Journal of Environmental Management, 353, 120088.

Duan H., Zhang Y., Zhao J., Bian X., 2011, Carbon footprint analysis of farmland ecosystem in China, Soil Water Conserv, 25(5), 203-208.

Fei R., Lin B., 2017, The integrated efficiency of inputs–outputs and energy–CO2 emissions performance of China's agricultural sector, Renewable Sustainable Energy Reviews, 75, 668-676.

Fielke S.J., Garrard R., Jakku E., Fleming A., Wiseman L., Taylor B.M., 2019, Conceptualising the DAIS: Implications of the ‘Digitalisation of Agricultural Innovation Systems’ on technology and policy at multiple levels, Wageningen Journal of Life, Sciences, 90(1), 1-11.

Huang Y., Chen Z., Li H., Yin S.J.S.R., 2023, The impact of digital economy on green total factor productivity considering the labor-technology-pollution factors, 13(1), 22902.

Jin M., Feng Y., Wang S., Chen N., Cao F., 2024, Can the development of the rural digital economy reduce agricultural carbon emissions? A spatiotemporal empirical study based on China's provinces, Science of the Total Environment, 939, 173437.

Liu L., Hu X., Li L., Sun Z., Zhang Q., 2024, Understanding China's agricultural non-carbon-dioxide greenhouse gas emissions: Subnational insights and global trade dynamics, Environmental Impact Assessment Review, 106, 107487.

Obiahu O.H., Yan Z., Uchenna U.B., 2021, Spatiotemporal analysis of land use land cover changes and built-up expansion projection in predominantly dystric nitosol of Ebonyi state, Southeastern, Nigeria, Environmental Challenges, 4, 100145.

Papadopoulos G., Arduini S., Uyar H., Psiroukis V., Kasimati A., Fountas S.J.S.A.T., 2024, Economic and Environmental Benefits of Digital Agricultural Technologies in Crop Production: A review, Smart Agricultural Technology, 8, 100441.

Tan X., Wang Y., Gu B., Kong L., Zeng A., 2022, Research on the national climate governance system toward carbon neutrality—A critical literature review, Fundamental Research, 2(3), 384-391.

Wang Z., Zhang J., He Y., Liu H., 2024, A study on the potential of digital economy in reducing agricultural carbon emissions, Heliyon, 10(11), e31941.

Xia Y., Guo H., Xu S., Pan C., 2024, Environmental regulations and agricultural carbon emissions efficiency: Evidence from rural China, Heliyon, 10(4), e25677.

Xu Y., Li H., Zhang R., Wang T., Sui P., Gao W., Chen Y., 2024, Balancing the development and carbon emissions in rural areas of China, Journal of Cleaner Production, 454, 142338.

Yao Y., Bi X., Li C., Xu X., Jing L., Chen J., 2024, A united framework modeling of spatial-temporal characteristics for county-level agricultural carbon emission with an application to Hunan in China, Journal of Environmental Management, 364, 121321.

Zhang H., Wei X., 2014, Green Paradox or Forced Emission Reduction: The Dual Effects of Environmental Regulation on Carbon Emissions, 24(9), 21-29.

Zhang Y., Ji M., Zheng X., 2023, Digital economy, agricultural technology innovation, and agricultural green total factor productivity, Sage Open, 13(3), 21582440231194388.

Zhou H., Li C., 2020, Relationship between Agricultural Technological Progress and Carbon Emission Intensity - Empirical Analysis under Different Influence Pathways, Journal of China Agricultural University, 25(11), 162-171.