THE IMPACT OF THE DIGITAL ECONOMY ON AGRICULTURAL CARBON EMISSIONS--EMPIRICAL EVIDENCE FROM CHINA

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BY

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With the rapid advancement of the digital economy, its influence on agricultural carbon emissions has garnered growing scholarly interest. Drawing upon panel data from 30 provinces in China over the period 2012–2022, this research investigates the linkage between digital economic development and agricultural carbon emissions, while also exploring the internal transmission pathways. The empirical findings demonstrate that the digital economy plays a significant role in curbing total agricultural carbon emissions, and this conclusion remains consistent across a range of robustness checks. Importantly, the emission reduction effects vary by region, with stronger impacts identified in key grain-producing areas. The principal transmission channels identified include farmland scale expansion, the proliferation of digital financial inclusion, and progress in agri-technological innovation. Based on these insights, this paper proposes several policy recommendations: advancing digital infrastructure in rural areas, improving digital financial systems tailored for agriculture, cultivating a workforce skilled in digital agriculture, and encouraging the adoption of innovative digital agriculture models.

Keyword : Digital economy, Agricultural carbon emissions, Scale effect, Financial effect, Technological innovation effect

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INTRODUCTION

1.1 Background of the Study

(1) Agricultural carbon emissions constitute approximately 14% of China's total carbon emissions, underscoring the critical importance of emission reductions in the agricultural sector.

According to IPCC's report, the year-on-year increase in atmospheric CO_2 concentrations over the past century has led to an estimated rise of 0.78°C in the Earth's surface temperature. Observations from NASA further reveal that global concentrations of greenhouse gases have increased by 1.2°C relative to the 19th century baseline. Over the past 170 years, atmospheric CO_2 concentrations have surged by 47%, triggering resource depletion, biome degradation, falling water tables, shrinking rivers and lakes, and destabilizing terrestrial and marine ecosystems. These environmental shifts have, in turn, resulted in biodiversity loss, declining agricultural yields, and adverse human health impacts. The accelerating pace of carbonization and its consequences highlight that climate change, driven primarily by anthropogenic greenhouse gas emissions, has become a major threat to ecological integrity and the sustainable development of human society. Addressing carbon emissions has thus emerged as a priority for both the international community and the global research agenda.

Agriculture continues to be a crucial economic activity for human society. In China, a country with a significant agricultural sector, greenhouse gas (GHG) emissions from agriculture activities releases between 5.5 and 7.5 billion tonnes of carbon dioxide equivalent (CO_{2e}) annually. In agricultural GHG emissions, CO_2, CH_4, and N_2O account for roughly 80% of total anthropogenic emissions. According to the International Fertilizer Assohly 10–20% of the nation's total emissions. Globally, it is estimated that soil disturbance from agciation (IFA), China accounts for roughly 30% of global fertilizer consumption, significantly exceeding the world average (about 130 kilograms per hectare) and standing at 2.6 times and 2.5 times the usage rates of the USA and the EU, respectively.

Amid global climate warming, China, a major source of agricultural carbon emissions, has a crucial role in reducing emission. At the 2021 COP15 Conference, China targeting to top out carbon emissions by 2030 and achieve a balanced sustainable development strategy. Since the agricultural sector significantly contributes to the nation's total carbon emissions, speeding up its low-carbon transformation has become particularly pressing. While ensuring food security and agricultural product supply, exploring a coordinated mechanism to balance carbon peaking and neutrality remains one of the key challenges that must be addressed.

(2) Rapid Development of China’s Digital Economy

As a new economic style, the digital economy boasts substantial growth potential and distinct advantages, drawing broad public interest through its swift expansion, superior service quality, extensive market reach, and unique conveniences. The annual growth rate of the added value of China's digital industry was about 15%. By the end of 2023, the "China Urban Digital Economy Development Report" showed that the nationwide digital economy had exceeded 50 trillion yuan, representing about 41.5% of GDP. In such situations, central government bodies and the State Council have released several policy documents to promote the progress of ‘digital villages.’ It specifically demands that by 2025, digital economy in agriculture should exceed 20%, and mandates that internet usage in rural areas should expand annually by more than 10.5%. By the end of 2021, China's digital rural development index reached 39.1%. By the end of 2022, rural areas had largely established their network infrastructure, with an internet penetration rate reaching 58.8%. Data indicates that in that year, the total transaction value of rural e-commerce surpassed 2.17 trillion yuan, with more than 80% of villages achieving complete coverage of delivery services.

(3) Digital Economy as a New Approach to Enhancing Agricultural Carbon Emission Efficiency

The digital economy, known for its high level of innovation, acts as a crucial driving force and practical approach to improving carbon emission efficiency. Its key features are deep penetration and wide coverage. President Xi Jinping has clearly emphasized: 'Our industries should towards high-end, intelligent, and green goals, fully harness vast data resources, broaden various application scenarios, advance the deep integration of digital technology with the real economy, expedite the transformation and upgrading of traditional sectors, and foster new momentum for emerging industries and new drivers for economic growth.'

The digitalization, intelligentization, and green transformation of traditional industries are crucial for carbon emission control and essential for the digital economy. The 'Energy Digital Transformation White Paper' suggests that utilizing advanced technologies can effectively achieve energy conservation and emission reduction, enhance operational efficiency, and promote innovations in decarbonization and negative carbon technologies. The report calls for speeding up the digital transformation in the energy sector to offer technical support for reaching regional carbon neutrality. Both theoretical research and practical applications highlight the significant value and strategic importance of using digital economy tools to improve the efficiency of agricultural carbon emissions management.

1.2 Research Objectives

Committing to green innovation and realizing green transformation stand as the main approaches for China to advance ecological civilization development and carbon neutrality objectives. To achieve the peak carbon emissions target in advance, it is crucial to fully utilize innovative elements like digital technology to comprehensively tap the latent emission reduction potential within agriculture. Current research findings show that when examining how the digital economy affects agricultural carbon emissions and its transmission mechanisms, there is a significant lack of relevant academic studies in this field. This becomes a critical issue that both academia and industry need to tackle. Against this backdrop, the study examines the impact of the digital economy on agricultural carbon emissions. It uses empirical methods to analyze the specific mechanisms of influence and assess the emission reduction effects in all provincial regions nationwide, aiming to offer some support and guidance for the agricultural carbon neutrality. With this goal in mind, the article will explore the following aspects:

(1) Building an indicator framework, while analyzing their spatio-temporal distribution patterns quantitatively.

(2) In what ways does the digital economy affect agricultural carbon emissions? Can it break away from the traditional agricultural model reliant on resource depletion and environmental degradation, achieving simultaneous progress in economic growth and ecological conservation, thereby contributing to the formation of a modern economic system and advancing ecological civilisation?

(3) Can the role of the digital economy be systematically examined through the lenses of scale economies, financial support impacts, and technological innovation influences? This topic is extensively explored.

1.3 Research Significance

The digital economy, as a crucial subject in academic research, has produced substantial outcomes. The existing literature often exhibits scattered and superficial traits, posing challenges in forming a theoretical framework with broad guiding significance. This offers significant opportunities for innovation and advancement in this area.

This research introduces an innovative assessment system that integrates both the digital economy and agricultural carbon emission intensity. It performs a comprehensive quantitative analysis of the current development status from various angles, examines the spatial distribution features and temporal evolution trends, and uses empirical methods to explore the relationship between the two, including whether significant linear or non-linear connections exist. It further analyzes how the digital economy specifically impacts agricultural carbon emissions and establishes corresponding transmission pathways and intrinsic operational mechanisms. Policy recommendations are offered to advance the digital economy and enhance carbon emission efficiency. This study carries theoretical innovation and offers practical operational guidance.

(1) Theoretical Significance

This study expands the theoretical viewpoint on the connection between the digital economy and carbon emissions, performing a systematic analysis. The digital economy serves as a crucial driver of contemporary economic growth, and the inherent link between it and agricultural carbon emissions warrants further investigation. This study enriches the relevant theoretical framework, updates research paradigms, and provides new insights for refining the carbon emissions theoretical framework by dissecting the mechanisms, while also deepening understanding of the driving factors behind carbon emissions.

This study has important academic implications for improving the theoretical framework of the digital economy. As a potent driver of global economic growth, the digital economy has profound impacts across various industries, necessitating further exploration and systematic explanation. It broadens the scope of theoretical discussions and innovatively introduces fresh perspectives.

(2) Practical Significance

This study is practice-based and seeks to offer theoretical support for enhancing China's agricultural carbon emissions management policies and implementation approaches. As an agricultural powerhouse, China faces substantial pressure to cut emissions within global climate governance. A careful examination of how the digital economy impacts agricultural carbon emissions can aid in forming a scientific and systematic framework for emission reduction strategies. This also promotes green agricultural development and drives the agricultural economy towards sustainable transformation.

This study seeks to identify practical pathways for closely integrating the digital economy with green development. Amid the swift advancement of the digital economy, its innovative role in fostering simultaneous economic growth and environmental protection grows ever more significant. Through a detailed analysis of the mechanisms by which the digital economy affects agricultural carbon emissions, this article clarifies the inherent logic of their interaction and offers policy suggestions to foster coordinated development and high-quality growth, thus providing theoretical and empirical support for sustainable development goals.

1.4 Scope of the Study

1.4.1 Research Subjects

The study focuses on 30 provinces in mainland China from 2012 to 2022 as sample objects. The data for the Tibet, Taiwan, Hong Kong and Macau are mostly unavailable, thus they are excluded from this sample. A standard panel data model is utilized to systematically examine the dynamic impact of the digital economy on agricultural carbon emissions, with empirical analysis conducted to validate the results.

This study selects 30 regions in China as sample units, including Guangdong, Jiangsu, Beijing, Zhejiang, Shandong, Shanghai, Fujian, Sichuan, Anhui, Henan, Hubei, Jiangxi, Hunan, Hebei, Shaanxi, Tianjin, Chongqing, Liaoning, Guangxi, Shanxi, Gansu, Yunnan, Guizhou, Jilin, Xinjiang, Inner Mongolia, Heilongjiang, Hainan, Ningxia, and Qinghai.

1.4.2 Research Methodology

(1) Literature Review Method

Thoroughly organize literature, examine the academic value and limitations of these documents, and thereby identify the key issues and starting points for this research. Additionally, discuss the innovative importance, offering theoretical backing for future studies and directing the course of practical applications.

(2) Statistical Analysis Method

This study uses a multi-dimensional research framework. Through the systematic collection and analysis of data from various provinces and regions in China between 2012 and 2022, along with detailed validation analyses, it was revealed that the level of the digital economy shows specific dynamic trends in both geographical space and temporal progression. Quantitative methods were used to estimate total agricultural carbon emissions and their temporal changes, while further examining the relationship between them.

(3) Integration of Theoretical Analysis and Empirical Testing

This study gives a theoretical framework for the digital economy's impact on agricultural carbon emissions, explores the underlying mechanisms, and proposes relevant research hypotheses. Through a mediation effect model, it empirically analyzes and verifies the relationship between them, ultimately summarizing the key findings.

1.5 Definition of Key Concepts

To better grasp the impact mechanism of the digital economy on agricultural carbon emissions, it is essential to first define the key concepts involved in this research clearly.

1.5.1 The Connotation of the Digital Economy

(1) Definition of the Digital Economy Concept

As research continues to expand and enrich, scholars have defined it from various perspectives. In terms of factor resource allocation, the digital economy denotes a range of economic activities or forms where data generation enhances the interaction among existing production factors, leading to profound shifts in production methods and economic structures. From an input-output viewpoint, the digital economy represents the overall economic output produced by digital inputs, such as skills, equipment, and diverse digital products In terms of Organisational structure, the digital economy denotes the process of attaining global connectivity via digital technologies like the internet and big data, creating a multi-layered and intricate framework composed of a growing number of interconnected nodes.

Therefore, the digital economy is not separate from traditional industries. Instead, it integrates and spreads across sectors, continually offering new knowledge, products, and services to conventional fields, while enhancing communication and collaboration among entities .

In general, the agreement on the core of the digital economy centres on the notion that data plays a crucial role, with digital products and services being delivered via information technologies. Drawing on prior research and the definition in the 2021 Digital Economy and Its Core Industry Statistical Classification by China's National Bureau of Statistics, this study characterizes the digital economy as "an emerging economic form where data serves as the central production factor, digital technology innovation propels growth, the internet functions as a critical platform, digital industrialization and industry digitalization act as primary drivers, and digital governance offers fundamental support." In this system, data, via information technology, boosts productivity, transforms traditional industry models, creates digital goods and services, and fosters significant improvements in economic quality, efficiency, and momentum.

1.5.2 The Connotation of Agricultural Carbon Emissions

(1) Carbon Emissions

The idea of carbon emissions arose from the demand for low-carbon economic growth and pertains to global climate shifts triggered by greenhouse gas discharges. At present, the sources of carbon emissions in the industrial sector are relatively well-defined, whereas agricultural carbon emissions, given their multiple stages and varied mechanisms, represent a significant research focus. Agricultural carbon emissions encompass crop cultivation, livestock farming, forest management, and fisheries production, among other activities. Their emission pathways are varied and show distinct temporal dynamics.

(2) Agricultural Carbon Emissions

This study defines agricultural carbon emissions as greenhouse gas releases from activities associated with agricultural land use. The main sources of agricultural carbon emissions are the use of fertilizers, pesticides, and agricultural films in farming, the substantial energy usage linked to agricultural machinery, and the energy consumed from burning fossil fuels during farmland management and crop irrigation. The Intergovernmental Panel on Climate Change (IPCC) has identified and detailed prevalent agricultural greenhouse gases in its reports, including major atmospheric gases like CO_2, NO_2, CH_4, SF_6, PFCs, and HFCs. Agricultural carbon emissions are typically grouped into categories such as land-use changes, energy use, rice production, and livestock rearing. Throughout the crop growth cycle, greenhouse gas emissions mainly occur as CO_2, N_2O, and CH_4 under varying land use conditions.

These emissions can be classified as follows: Agricultural inputs represent the main carbon sources, primarily seen in greenhouse gas emissions from pesticide, agricultural film, and fertilizer use during farming. These also include carbon emissions from fuel combustion in agricultural machinery, soil carbon imbalances and organic matter breakdown due to ploughing or rotary tilling for soil fertility enhancement, and greenhouse gas releases during irrigation processes.

1.6 Technical roadmap

Based on a review of existing domestic and international research, this paper delves into the academic frontiers of the digital economy and agricultural carbon emissions, constructs a theoretical research and analysis framework. The specific research framework is illustrated in the figure below:

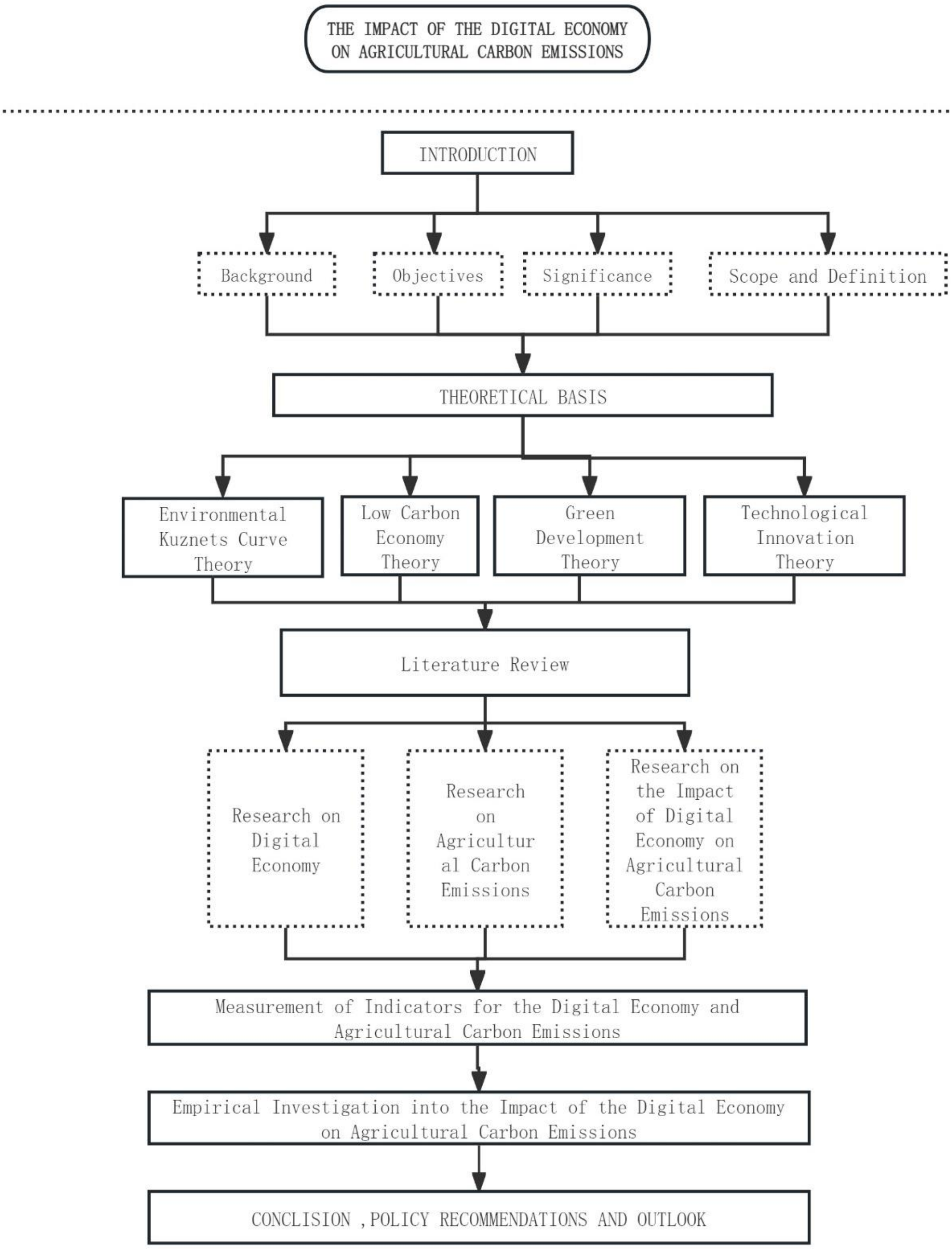


Figure 1 Technical roadmap

CHAPTER 2

THEORETICAL BASIS AND LITERATURE REVIEW

2.1 Theoretical basis

2.1.1 Environmental Kuznets Curve Theory (EKC)

The EKC theory examines the dynamic relationship between economic and environmental. Initially introduced by economist Simon Kuznets in 1992, this theory seeks to reveal the fundamental patterns influencing changes in environmental quality throughout a nation's economic development. Based on the EKC model, in the early stages of economic growth, expanding output levels lead to a notable rise in environmental pollution. However, as an economy advances to a higher stage of development, environmental pollution initially rises and subsequently declines. The root cause of this phenomenon is that early economic growth often entails excessive resource extraction and a swift rise in pollutant emissions. With the enhancement of societal environmental awareness and progress in technological innovations, the conflict between economic growth and environmental conservation gradually eases, resulting in the realization of synergistic advancement and improvement.

Agriculture, a major economic sector, is closely linked to the EKC theory, especially concerning agricultural carbon emissions. In numerous developing nations, agriculture serves as a significant economic pillar and is also among the leading sources of carbon emissions. Most studies confirm that in the early stages of agricultural development, carbon emissions tend to increase, consistent with the initial rise in environmental pollution as described by the Environmental Kuznets Curve (Atasel et al., 2022; Khan et al., 2023; Mengke et al., 2023).

However, with economic growth and increasing societal awareness of environmental concerns, the agricultural sector has started to recognize these issues and has adopted measures to cut carbon emissions and promote sustainable agricultural development. These measures involve smart agricultural technologies, including modern tools, to enable precision fertilization and targeted irrigation, thus cutting down on fertilizer and water use, which helps lower emissions. The implementation of organic farming, which cuts down on chemical pesticides and fertilizers, enhances soil health, and reduces carbon emissions, is included among these measures. As these measures have been widely applied, agricultural carbon emissions have gradually decreased. This is mirrored in the EKC by the decline after the peak of agricultural carbon emissions. The smart agricultural technologies and new farming practices often stems from national economic development. Thus, it is reasonable to expect that as the national economy improves, agricultural carbon emissions will stabilize or even decrease. This is due to technological innovation and increased environmental awareness, leading the agricultural sector to increasingly prioritize environmental protection and steadily diminish its negative environmental impact.

From the standpoint of marginal utility, the EKC suggests a declining marginal impact of carbon reduction, point that the marginal benefits of integrating the digital economy in agriculture are most significant in the early stages of carbon mitigation. Regarding heterogeneity, this observation also aids in explaining the varying impacts of digital economy empowerment between more developed eastern regions and less developed western regions. It offers a theoretical basis for including heterogeneity robustness checks in this study.

2.1.2 Low Carbon Economy Theory

The central idea of low-carbon economy theory is to foster the parallel advancement of economic growth and environmental preservation while markedly decreasing greenhouse gas emission levels. In the present global scenario of increasing temperatures and significant ecosystem challenges, the 'low-carbon economy' has emerged as a strategic concern shared by countries worldwide. This concept was initially introduced by Kinzig and later expanded upon by the British government as a novel approach to achieving high-quality growth through enhanced resource allocation. China has made substantial efforts in this field, implementing policies and regulations to foster a resource-efficient and environmentally protective society. In recent years, the Chinese government has increasingly reinforced its strategic plans for green and low-carbon transformation, deeply embedding the concept of ecological civilization. It has explicitly introduced the development philosophy that "green mountains and clear waters equate to mountains of gold and silver" and formally pledged to achieve the dual carbon objectives.

The issue of achieving sustainable development in both social production and the ecological environment has long been a key concern both in China and globally. Against the backdrop of the escalating ecological degradation and climate crisis caused by the traditional "high-carbon economy", investigating fresh approaches to the harmonious growth of the economy and the environment has become especially urgent. Markard and Rosenbloom (2022) point out that high-carbon pathways in energy systems not only exacerbate climate change but also limit the possibility of transitioning to sustainable development. Therefore, transitioning to a low carbon economy is a crucial strategic step toward achieving net-zero goals. In this context, low carbon economy theory has gradually become a core concept guiding green development. This theoretical framework spans multiple levels, from macroeconomic policy formulation to micro-level business behavior, emphasizing that green transformation drives the sustainable development of the economy and society.

Thus, a deeper understanding of the theoretical essence of the low-carbon economy holds significant practical importance for achieving coordinated development between ecological environmental protection and socio-economic progress. Although a unified definition of the low carbon economy concept remains elusive, several scholars have achieved consensus on specific aspects. For example, it is widely accepted that a low-carbon economy should feature "three lows" include "five aspects," encouraging energy-saving technologies, advancing green energy, and reaching sustainable development objectives. It achieves this by enhancing technological innovation, promoting large-scale green energy development, and establishing regulatory mechanisms and environmental protection systems. These efforts minimize greenhouse gas emissions and foster coordinated development between ecological environments and socio-economic progress.

2.1.3 Green Development Theory

Green development serves as the central strategic framework for enacting sustainable development principles, striving for the balanced coexistence of economic progress and environmental preservation. In 2009, the Organisation for Economic Co-operation and Development (OECD) outlined the core of green development, highlighting the significance of ecological protection in fostering economic growth. In 2011, the United Nations Environment Programmeme (UNEP) further refined the theoretical framework of green development, describing it as a model that promotes social progress by substantially reducing environmental risks and ecological resource pressures. In 2012, China integrated green development into the national strategic framework, indicating that this concept had started to develop a systematic theoretical structure. Although its meaning is still under exploration, it has already shown the government's strong emphasis on ecological civilization construction, aiming to achieve a dynamic balance between economic transformation and environmental protection, and thus developing and enforcing policies and measures to advance green development.

Overall, green development theory encompasses Marxist ecological thought, ecological economics, circular economy theory, sustainable development theory, and Xi Jinping's green development philosophy. Marxist ecological thought emphasizes that nature is the fundamental premise for human survival and development, and that humans must coexist harmoniously with nature (Wei, 2021). Ecological economics focuses on the fundamental contradiction between humanity's unlimited needs and the limited supply of resources. Røpke (2004) explored how to integrate ecological constraints into economic growth. Circular economy theory advocates extending the productive life of resources and promoting their recycling to reduce environmental burdens and foster sustainable resource management by Blomsma and Brennan (2017). Imperatives (1987) proposed sustainable development theory posits that we should "meet the needs of the present without compromising the ability of future generations to meet their own needs," and in many contexts, green development is seen as synonymous with sustainable development. Xi Jinping's green development philosophy, as one of China's "Five Development Concepts," centres on the "Two Mountains Theory" (i.e., "green mountains and clear waters are as valuable as mountains of gold and silver") and provides a systematic framework for green development strategy and policy, aiming to achieve a unity of economic construction and ecological protection, pointed by Hu et al. (2018). While these theories emerged in different historical periods and social contexts, they fundamentally share a common emphasis on the need to ensure the sustainability of the ecological environment while promoting economic growth.

As an important guiding principle for agricultural green development, the theory of green development provides clear directional guidance for practice. As a key pathway for promoting agricultural green transformation, agricultural green development become a central role in implementing the ‘dual carbon’ strategic goals. Its essence lies in practising the concept of green development, systematically improving traditional extensive production models, and driving agriculture toward sustainable development.

2.1.4 Theory of Technological Innovation

The theory of technological innovation can be traced back to Schumpeter (1934), in which he first systematically proposed the core role of innovation in driving economic dynamic changes. Although Schumpeter’s views did not attract widespread attention at the time, by the mid-to-late 20th, the rapid development of technology, scholars began to recognize the profound impact and foresight of his theory, (Fagerberg, 2006). In subsequent research, innovation was further refined and classified. For example, Dosi (1982) proposed the theory of path dependency in technological innovation, emphasizing that innovation is constrained by existing technological trajectories.

During the evolution of technological innovation theory, Robert Solow

developed the famous economic growth model and, through empirical analysis, confirmed for the first time the pivotal impact of technological advancements on economic expansion, particularly highlighting the importance of technological progress in agricultural output growth (Solow, 1957). Subsequently, scholars such as Schmookler (1966) and Griliches (1979) deepened the understanding of technological innovation from various perspectives, including economics, industrial Organisation, and technological diffusion. Their work expanded the application of technological innovation theory in economic growth and industrial transformation.

In the era of the digital economy, the theory of technological innovation provides crucial support for understanding the link between them. The application of new generation information technologies not only promotes research and development innovation within enterprises and enhances production efficiency but also fosters new business models, structures, and Organisational forms through platform economies (Brynjolfsson & McAfee, 2014).However, it is important to note that technological innovation itself may also trigger countervailing effects. For example, the production processes of certain high-tech products, such as data centres and the semiconductor industry, can lead to significant energy consumption (Andrae & Edler, 2015). Therefore, the impact is dualistic, necessitating systematic research and appropriate guidance.

2.2 Literature Review

2.2.1 Research on Digital Economy

(1) Concept and Characteristics of Digital Economy

The digital economy, as an integral part of the modern economic system, has seen its scope continuously expand and evolve alongside advancements in information technology. Tapscott (1996) initially presented the idea, defined as economic activities carried out through digital computing technology. Its defining feature is the use of emerging technologies to reshape how businesses, consumers, and governments interact. Tapscott systematically articulate the concept of the digital economy; however, his definition of it remains somewhat unclear. Later, the World Bank (2016) broadened the scope of the digital economy, describing it as the complete process of production, distribution, and consumption carried out through digital networks, while highlighting the role of digital technology in driving economic growth and social equity. As defined by the Organisation for Economic Co-operation and Development (OECD, 2019), data, knowledge, and information are identified as critical components of economic transactions, with significant attention given to privacy protection, data security, and market concentration. This definition shows that the digital economy includes technological innovation, economic operational mechanisms, social management frameworks, and policy regulatory measures, clearly reflecting its strategic role and impact in the modern economic system.

Network effects are one of the fundamental characteristics of the digital economy. In the digital economy, the worth of a product or service rises with an increase in user count. Shapiro and Varian (1999) discussed how network effects influence product strategies and market structures, emphasizing that companies that successfully harness network effects often thrive in the digital economy. Mayer-Schönberger and Cukier (2013) identified data as a core asset in the digital economy. Their research explored how big data transforms decision-making, innovation, and forecasting, noting that companies that own and can analyze data gain a competitive advantage. Innovation and rapid iteration are other significant features of the digital economy. Christensen's theory defined by Christensen (2015) of disruptive innovation emphasizes how emerging technologies can disrupt existing markets and industries. In the digital economy, businesses can quickly iterate products and services, constantly adapting to and shaping market demand. Additionally, the platform economy has become a major characteristic of the digital economy. Pan et al. (2022) define the key features of the digital economy in terms of infrastructure, industrial scale, and the value of spillover effects.

(2) Measurement of Digital Economy

In recent years, scholars have conducted numerous studies on measuring the digital economy. Based on the focus, these studies are divided into two primary methodologies: indicator construction and scale estimation.

Countries have started to establish numerous research institutions that progressively enhance their analysis of global or regional digital economy development levels, creating various indicator systems for measurement. Examples include the China Urban Digital Economy Index by H3C Technologies, the China Digital Economy Index (CDEI) by Caixin Think Tank, Tencent's “Internet+” Digital Economy Index, and the Global Digital Economy Development Index jointly issued by Alibaba Research Institute and KPMG.

In addition, some scholars have attempted to construct digital economy indicator systems to calculate the digital economy index. Bukht and Heeks (2017) measured from multiple dimensions such as digital infrastructure, digital services and content, and digital trade, aiming to provide a more comprehensive and accurate method for measuring the digital economy, thus better capturing its development status and trends and providing strong support for policymaking and strategic planning. Li and Wang (2022) developed an indicator system based on metrics such as output and employment in the internet industry, internet penetration rate, mobile communication coverage, and digital financial development. Ma and Zhu (2022) focused on dimensions such as industry digitalization, digital sustainability, and the integration of digital industries. Yi et al. (2022) referred to the digital economy and its core industries statistics released by the CAICT and the National Bureau of Statistics. Shahbaz et al. (2022) constructed a index based on four sub-indices.

The digital economy in societal development continues to rise, the issue of measuring the scale has gained significant attention from various institutions and the academic community. These studies cover the application of the production approach and explore innovative applications, such as cloud platforms, and principal component analysis, in digital economy scale measurement. Machlup (1962) studied the measurement of value-added in knowledge and information economies. The U.S. Bureau of Economic Analysis calculated the scale of the U.S. digital economy in its report "Defining and Measuring the Digital Economy" using supply-use tables, (Barefoot et al., 2019). The New Zealand Statistics Bureau adopted BEA's measurement approach to estimate the digital economy scale in New Zealand, Millar and Grant (2019), and Ahmad and Ribarsky (2018) using the OECD as a research sample, assessed the overall level and internal structure (Yang & Li, 2021), combining macroeconomic models and dynamic analysis, proposed a more accurate method to measure the scale of the digital economy and forecast its development trends. They provide a new measurement method for the digital economy's scale, constructing empirical equations to predict inflationary pressure and using dynamic coefficients to analyze the growth trends of China's manufacturing industry over time.

Yuan (2023) emphasized the use of quantitative analysis of multidimensional data in the context of big data to comprehensively assess the scale and benefits of the digital economy. Chinoracky and Corejova (2021) introduced a composite indicator method for key areas such as the economy, labor, and skills, designed to measure the scale and potential of the digital economy, offering quantitative analytical tools for policymaking and growth strategies. Zhao and Zhou (2022) explored the use of cloud platforms for measuring the scale of the digital economy. This approach not only considers the direct output of the digital economy but also accounts for the application and efficiency of digital technologies in traditional industries, providing a comprehensive and dynamic measurement method.

Novikova et al. (2020) developed a set of methodological tools, which includes a comprehensive evaluation system with twelve individual indicators, to measure the digital economy in a regional context. This system covers digital infrastructure construction and digital services applications. Zaicev et al. (2021) combined traditional national accounting systems (UN SNA, European System of National and Regional Accounts (ESA), and OECD) with innovative hedonic method techniques to measure the scale of the digital economy and its impacts. Ziming and Kharchenko (2023) used new models incorporating subjective and objective weighting methods such as principal component analysis, Analytic Hierarchy Process (AHP), cluster analysis, standard deviation, entropy methods, and extreme methods to analyze biases caused by human factors in the results. These approaches offer a multi-dimensional evaluation and analysis of the digital economy's scale.

(3) Research on the Economic and Social Effects

As a key engine driving global economic transformation and social change, the digital economy’s effects have increasingly attracted widespread attention from both academia and policymakers. Existing literature explores the multifaceted impacts of the digital economy from various perspectives, including economic growth, labor market restructuring, globalization, environmental impacts, and technological innovation.

In recent years, the digital economy has become a pivotal force in driving economic transformation and social change. Scholars have examined its effects on economic growth, labor market restructuring, globalization, and its environmental and social implications from diverse angles. Pang et al. (2022) and Ding et al. (2021) highlighted through empirical analysis the critical role of digital tools and information and communication technologies (ICT) in enhancing supply-demand efficiency, optimizing resource allocation, and promoting high-quality growth. Likewise, Schreyer (2000) and Jorgenson et al. (2008) confirmed the foundational role of information technology in enhancing productivity and stimulating economic recovery, through case studies of G7 countries and the United States. Although these studies differ in methodology and perspective, they all provide strong empirical evidence of the digital economy’s contribution to macroeconomic growth, while revealing shortcomings in cross-country comparisons and regional data integration. This lays the foundation for further exploration of the underlying mechanisms of digital economic effects.

In the fields of labor markets and globalization, scholars have also delved into the structural changes brought about by the digital economy. Autor et al. (1998) pointed out that the widespread adoption of information technology has reshaped the skill demand structure in the labor market, driving the expansion of high-skilled jobs while exerting pressure on low-skilled jobs, thereby having profound impacts on income distribution (Acemoglu & Autor, 2011), further explored the dynamic relationship between technological change, employment structures, and income inequality. Baldwin (2016) emphasized the role of information technology in driving global resource flows and cross-border industrial chain reorganisation. Stallkamp and Schotter (2021) found that the digital economy has spurred the multinational businesses. Chatterjee and Kar (2020) concluded that the digital economy benefits the smart management of enterprise supply chains, adding momentum to corporate growth. However, the regional implementation bottlenecks described by Chatterjee and Kar (2020) indicate significant disparities in the performance of different economies during their digital economic transformation. Moreover, Tukhtabaev et al. (2022) warned of the potential risks of the digital economy concerning energy consumption and carbon emissions, while Aly (2022) and Yoo et al. (2010) provided new perspectives on the application in green transformation and resource optimization.

In summary, existing literature not only systematically discusses the impact of the digital economy on various social and economic phenomena but also highlights the limitations of methodologies and data applications. It suggests that future research should further integrate macro and micro data from an interdisciplinary perspective to develop a more comprehensive and systematic theoretical framework, thereby providing a solid theoretical basis for policy formulation.

2.2.2 Research on Agricultural Carbon Emissions

The study of carbon emissions can be traced to Grossman and Krueger (1991), who analysed the effects of economic growth on variations in carbon emissions and proposed the existence of three major effects: scale, structure, and technology. Since then, research into the factors influencing carbon emissions has expanded substantially, encompassing dimensions such as technological advancement, industrial structural transformation, population aging, trade development, and foreign direct investment (Esmaeilpour Moghadam & Dehbashi, 2018; Hanif, 2018; Li & Li, 2020; Sun & Huang, 2020; Ye et al., 2019). The shift toward examining carbon emissions specifically within the agricultural sector emerged slightly later, with early studies focusing primarily on agricultural production processes, including crop varieties, cultivation patterns, input materials, and waste management (Johnson et al., 2007; Vleeshouwers & Verhagen, 2002).

Given the complex and multifaceted nature of factors influencing agricultural carbon emissions, considerable heterogeneity exists in the methodologies employed by scholars for its estimation. For example, West and Post (2002) measured agricultural carbon emissions based on agricultural material inputs. Johnson et al. (2007) refined the assessment by categorizing emissions across crop cultivation, livestock production, energy inputs, waste management, and biomass combustion, thereby providing a comprehensive estimation of agricultural carbon emissions in the USA Yun and Zhang (2014) applied a similar multi-faceted approach to estimate China's agricultural carbon emissions, examining energy consumption, rice cultivation, livestock farming, and unconventional waste disposal, while also analyzing the underlying mechanisms driving these emissions. Furthermore, Xiaowen et al. (2015) use the Kaya decomposition method to disentangle the multidimensional factors influencing agricultural carbon emissions, using differential factor decomposition analysis to determine the directional effects of these variables on agricultural emissions in China.

2.2.3 Research on the Impact of Digital Economy on Agricultural Carbon Emissions

Yang et al. (2023) studied how the digital economy reduces carbon emissions, focusing on digital industrialization and digitization. Zhou and Wang (2023) explained how the digital economy can change farming practices, looking at market politics. Wolfert et al. (2017) reinforced the argument that digital-tech are changing agricultural production paradigms through a comprehensive review of big data in smart agriculture.

At the empirical level, someone found that the digital economy promotes agricultural structural upgrading, technological innovation, and large-scale management. This conclusion aligns with the development trends revealed by Sørensen et al. (2010), constructed for future agricultural management information systems.

Kaila and Tarp (2019) found digital economy improve agricultural productivity is becoming increasingly significant. Research shows that the digital economy not only significantly enhances agricultural productivity through technological innovation and factor flows, Fabregas et al. (2019), empowering high-quality agricultural development, but also unveils new opportunities and challenges in agricultural and environmental analysis through the application of big data technologies (Weersink et al., 2018). These technologies provide substantial support for precision and intelligent agricultural production, improving resource allocation efficiency (Guo et al., 2013; Kamilaris et al., 2017), significantly reducing agricultural carbon emissions, and effectively promoting the transformation of agricultural green production modes. Low-efficiency sectors or enterprises that cannot adapt to new production conditions or lag behind in production capabilities are gradually marginalized and eventually eliminated (Acemoglu & Autor, 2011).

Furthermore, some scholars explored optimizing the spatial layout of the agricultural industry through the digital economy from the perspective of industrial agglomeration, enhancing the collaborative development capabilities of regional agriculture. Elijah et al. (2018) evaluated the application and environmental benefits of Internet of Things (IoT) technologies in modern agricultural production, revealing the multi-dimensional mechanisms of IoT in resource optimization, precision production, and carbon reduction through a meta-analysis of 50 typical agricultural cases worldwide. Sylvester presented a global perspective from the United Nations Food and Agriculture Organisation (FAO), systematically discussing the strategic implications of digital agricultural transformation for climate change mitigation. The study deeply analysed the crucial role of digital technologies in agricultural decarbonization and climate adaptability enhancement, providing innovative pathways for developing countries to address climate change.

2.3 Literature Overview

While China has been actively promoting the deep integration of digital technologies with economic and social life, with a particular emphasis on aligning these developments with current ecological and environmental governance issues. Scholars both domestically and internationally have conducted extensive analysis from multiple perspectives and dimensions. These studies have yielded a wealth of research outcomes. The research findings related to the digital economy or carbon emissions provide a solid theoretical, methodological. However, there are still areas that warrant further expansion, as detailed below:

Although there are already numerous digital economy evaluation systems in place, the fragmented understanding of statistical categories has led to significant challenges in existing research. This limitation prevents the selection of indicators and the allocation of weights from achieving uniform standards, resulting in assessment outcomes exhibiting diverse characteristics.

Based on the theoretical framework mentioned earlier, this study pioneers the establishment of a statistical system for the digital economy across all provinces and regions in China, and designs a comprehensive evaluation model covering multiple aspects. It precisely calculates the primary digital economy indicators for each region, conducts a detailed analysis of the distribution of these indicators in rural areas, and employs empirical methods to explore the internal connection mechanisms and driving factors between the two.

CHAPTER 3
METHODOLOGY

3.1 Research Hypotheses

3.1.1 Direct Effects

The digital economy directly affects agricultural costs, resource utilization efficiency, supply chains, and environmental management, influencing agricultural carbon emissions.

First, the digital economy cuts agricultural costs and promotes the digitization of farming practices. Traditional agricultural inputs are converted into data-driven resources. For example, the incorporation of digital technologies transforms traditional machinery into intelligent systems, boosting production efficiency while cutting labor costs and energy consumption. Studies show that a 1% rise in digital economy development correlates with a 0.595% decrease in agricultural carbon emissions.

Second, the digital economy greatly improves resource utilization efficiency via precision agriculture technologies. The advancement of digital framework facilitates the widespread implementation of digital tools in networked, intelligent, and refined agricultural practices. By employing smart machinery, sensors, drones, and data analytics , enabling precise fertilization and irrigation ,said by Subeesh and Mehta (2021). This targeted approach reduces fertilizer and water consumption, thereby decreasing agricultural carbon emissions and contributing to climate change mitigation, pointed by García-García and Parra-López (2024).

Third, the digital agricultural supply chain facilitates the transformation of traditional agricultural practices towards intelligent, value-driven, and efficient development, ultimately improving the overall efficiency of sustainable agricultural production, pointed by Tzachor et al. (2022) and Zhu et al. (2023) . Digital technologies enable producers to respond more effectively to market demand fluctuations, achieving a dynamic alignment between production and market needs.

This adaptability allows for better management of energy consumption during agricultural production, resulting in reduced greenhouse gas emissions (Ji et al., 2024).

Finally, the role of the digital economy in environmental management is noteworthy (Fankhauser, 2013). Based on this, the author proposes the following hypotheses for further verification:

H_1: The digital economy can directly and effectively reduce agricultural carbon emissions.

3.1.2 Indirect Effects

(1) Scale-Mediated Effects of the Digital Economy on Agricultural Carbon Emissions

Digital technology serves as a pivotal catalyst for contemporary agricultural reform, facilitating the reconfiguration of traditional small-scale business models. In an agroecological context dominated by smallholder operations, production is often constrained by high unit cultivation costs, low levels of mechanisation, and inefficient management practices. The introduction of digital technology has enabled the integration of advanced agricultural machinery and digital management systems, gradually replacing conventional fragmented and decentralized production models with more standardized and scalable approaches.

This transformation not only boosts mechanisation and digital management capabilities but also enhances information flow. Digital technology facilitates the efficient exchange of market and technical information among agricultural producers via information platforms, tackling problems related to information asymmetry. This improved information exchange boosts resource allocation efficiency and aids the shift from traditional decentralized operations to moderate-scale farming. Moreover, digital platforms lower the financial costs of land transfers, facilitating smoother and quicker transactions. This promotes the efficient allocation of agricultural resources and aids in the growth of large-scale operations.

Studies show that moderate-scale operations can improve land use efficiency and lower agricultural carbon emissions, addressing issues of operational fragmentation and resource waste. The incorporation of digital technology fosters the efficient allocation of land resources, enhancing agricultural production by accurately matching supply with demand. Scaling up agricultural operations has been found to enhance production efficiency, reduce resource waste, and alleviate pollution (Fan Guohua and Han Jianmin, 2024). This shift reduces the costs of rural pollution management and cuts agricultural carbon emissions. Additionally, large-scale operations are typically associated with greater mechanisation and automation, significantly lowering carbon emissions per unit of output. This shift directly cuts energy use and carbon emissions commonly linked to small-scale farming. Based on this analysis, the following hypothesis is proposed for the study:

H_{2a}: The digital economy can effectively reduce agricultural carbon emissions through the scale effect of land use.

(2) Financial Intermediation Effects of the Digital Economy on Agricultural Carbon Emissions

The digital economy has greatly expanded the boundaries of traditional finance, lowering service costs and increasing access to inclusive financial services, which in turn boosts the overall efficiency of the financial system. Traditionally, high costs have kept many "long-tail groups" from accessing financial services. However, the swift advancement of digital finance has reduced these costs, enhancing access for underserved groups and generating positive effects on economic growth, income, consumption, innovation, and entrepreneurship.

The Guide to Digital Finance in Agriculture, published by the United States Agency for International Development (USAID, 2016), emphasizes that digital finance successfully broadens access to the formal financial system by utilizing advancements in digital and mobile infrastructure, as well as the expansion of branchless banking. This evolution has increased the accessibility of financial services for rural households. In China, the restricted coverage of traditional financial institutions in rural regions frequently leads to substantial time and travel expenses for farmers in need of financing, posing obstacles to easy access.

Through the use of internet technology and mobile payment systems, digital finance has broken down the long-standing exclusive connection between rural agriculture and financial capital. It offers services like online agricultural loans and microcredit, effectively tackling the financing challenges faced by farmers. This shift allows agricultural producers to access funding for sustainable development and prompts research institutions and enterprises to secure financial backing, thereby driving innovation in green agricultural technologies. This, in turn, enhances agricultural production efficiency and product quality. An empirical study by Zhao et al. (2021), utilizing a series of exogenous events and difference-in-differences methodology, confirmed that digital finance significantly contributes to carbon emission reductions. In light of this analysis, we propose the following hypothesis:

H_{2b}: The digital economy can effectively reduce agricultural carbon emissions through financial intermediation effects.

(3) The Mediating Effect of Technological Innovation Between the Digital Economy and Agricultural Carbon Emissions

Salahuddin and Alam (2015) and Hamdi et al. (2014) said technological innovation serves as a fundamental driver of economic progress, playing a pivotal role in enhancing environmental quality and fostering sustainable development. It strengthens interactions, collaboration, and knowledge exchange among key stakeholders, facilitating the pervasive adoption of digital technologies that significantly contribute to carbon emissions reduction.

By leveraging advanced digital tools, such as multidimensional sensors, enterprises can monitor production processes with precision, obtaining real-time data on various inputs and activities. This capability enables Organisations to identify inefficiencies within their production systems and implement incremental improvements that enhance operational efficiency, thereby reducing carbon emissions (Kohli & Melville, 2019). Empirical evidence provided by Dietz and Rosa (1994), utilizing an IPTA model that incorporates stochastic elements, underscores the critical influence of technological advancements on the mitigation of carbon emissions. Moreover, Yin et al. (2015) demonstrate that technological innovation exerts a positive influence on carbon reduction performance, contributing to decreased carbon dioxide emissions. Research conducted by Cole et al. (2013) among Japanese firms indicates that increased investment in research and development effectively catalyzes technological innovation and leads to substantial reductions in corporate carbon emissions. Supporting this, studies by Haseeb et al. (2019) and Shobande (2021) affirm that technological innovation can diminish carbon emissions over the long term. The digital economy has facilitated the integration of technological innovation with agricultural production. By leveraging advanced technologies, stakeholders can gain timely insights into crop growth, mitigate losses from natural disasters, and connect with experts to address challenges in cultivation. This enables the rational adjustment of agricultural inputs and fosters reductions in carbon emissions from agricultural practices.

Based on this analysis, we propose the following research hypothesis:

H_{2c}: The digital economy can reduce agricultural carbon emissions through technological innovation.

3.2 Measurement of Rural digital economy

3.2.1 Rural digital economy indicator system

As a novel and intricate economic form, it exhibits a variety of fundamental attributes. Owing to the complexity of its meaning, a single indicator cannot fully capture its development level. Thus, current studies mainly use indicator-based methods for quantitative analysis to assess its development level.

Now, there is minimal study on the quantitative evaluation of rural digital development. The "2021 National County-Level Agricultural and Rural Informationized Development Level Evaluation Report" outlines a comprehensive evaluation system. It designed to reflect the overall state of digital agriculture and rural modernisation at the county level. introduced more precise evaluation criteria from three dimensions: digital infrastructure development, intelligent agricultural practices, and the digital economic shift in rural areas.

In 2022, the Central Cyberspace Administration of China, working with the Ministry of Agriculture and Rural Affairs and other relevant departments, released a document. This document outlined 30 key tasks targeting crucial areas like rural network infrastructure, agricultural digital transformation, intelligent rural governance, and enhancing farmers' digital literacy.

This study aiming to develop a digital economy evaluation framework tailored to rural regional features. When designing indicators, the primary considerations are data availability, reasonableness, and comprehensiveness. At present, China has essentially set up a relatively comprehensive quantitative evaluation framework for the digital economy. The rural digital economy constitutes a vital part of the national economy, and its evaluation framework should align with the current statistical system(Wang et al., 2024) . Based on the 'Statistical Classification of the Digital Economy and Its Core Industries (2021)' document and referencing the research findings of Wang and Chen (2024), this study comprehensively analysed the reliability and applicability of data to select nine core indicators across three key dimensions. Finally, the EMW was used to calculate the rural digital economy across China's provinces, with detailed results shown in Table 1.

Table 1 Rural digital economy indicator system

Primary Indicator	Secondary Indicator	Indicator Description
Rural Digital Foundation	Rural Internet Penetration Rate	Users of broadband internet in rural areas / rural population
	Computer Penetration Rate	Average number of computers owned per hundred households
	Communication Service Level	Population Served per Kilometer of Rural Delivery Route.
	Mobile Phone Penetration Rate	Number of mobile phone users per hundred individuals
Rural Industry Digitization	Rural Digital Transformation Model	Total Agricultural Machinery Power / Total Output Value of Agricultural, Forestry, Animal Husbandry, and Fishery Industries
	Digital Talent Investment	Number of personnel in information technology and software services (ten thousand)
Rural Digital Industry	Information Transmission Level	Number of Taobao Villages.
	E-commerce Sales Volume	Total e-commerce sales revenue
	Digital Finance Index	Index for digital financial services

3.2.2 Measurement Method of Rural Digital Economy – Entropy Weight Method

Numerous comprehensive evaluation methods exist both domestically and internationally. Objective weighting methods are extensively used in multi-indicator comprehensive evaluation research because they determine weights based on inherent data differences, effectively minimizing human subjectivity. To address the limitations of subjective weighting methods, which often include arbitrary weight allocation and vulnerability to bias, this study uses the EWM to establish the rank of each evaluation indicator. The EWM is rooted in the entropy concept from information theory, which suggests that greater differences in indicators among various evaluation objects result in more information and consequently higher weights. By computing the information entropy of each indicator and handling redundancy, the Entropy Weight Method objectively mirrors the data's internal structure, effectively minimizing subjective influences and boosting the scientific and rational quality of comprehensive evaluation outcomes. This, together with subsequent comprehensive evaluation models, can further enhance the accuracy of indicator ranking and the reliability of results, offering robust data support for high-quality, multi-dimensional analysis. The Entropy Weight Method employs the range method for data convergence and dimensionless processing, as illustrated in the formula below:

$$Y_{ij} = \begin{cases} \frac{X_{ij} - minX_{ij}}{maxX_{ij} - minX_{ij}}, & X_i \text{ is a negative indicator} \\ \frac{maxX_{ij} - X_{ij}}{maxX_{ij} - minX_{ij}}, & X_i \text{ is a positive indicator} \end{cases} \quad (1)$$

Where i represents the province, j represents the indicator, max and min represent the maximum and minimum values of X_{ij}, Y_{ij} represents the value of the indicator after standardization.

This paper intends to collect data of China's 30 provincial administrative regions from 2012 to 2022. This paper uses Stata software to assign weights to all index data after standardization. The weights of the indicators calculated according to formula (2) are.

$$W_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} X_{ij}} \quad (2)$$

The each indicator is calculated according to equation (3) as. (3)

$$e_j = \frac{\sum_{i=1}^{n} W_{ij} \ln W_{ij}}{\ln n} \quad (3)$$

Calculate the information entropy redundancy according to equation (4)d_j:

$$d_j = 1 - e_j \quad (4)$$

where is the evaluation year and the weights of the indicators are calculated according to formula (5) C_j:

$$C_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \quad (5)$$

The level of rural digital economy development is derived by objectively assigning weights to each indicator in the rural digital economy evaluation index system based on the entropy value method and calculating the composite index, which is calculated by the formula (6):

$$digital_i = \sum_{j=1}^{m} C_j \times w_{ij} \quad (6)$$

3.2.3 Analysis of the weight of the rural digital economy

(1) Analysis of the Weight Results of Rural Digital Economy

Table 2 Rural igital economy weighting results

First-level indicator	Second-level indicator	Entropy value	Indicator weight (%)		Ranking
			First-level indicator	Second-level indicator	
Digital Foundations of the Countryside	Internet penetration rate	0.947	7.163	17.627	4
	Computer penetration rate	0.968	4.239		6
	Level of communications services	0.976	3.270		7
	Cell phone penetration rate	0.978	2.955		8
Digitalization of Rural Industries	Scale of digitization in agriculture	0.964	4.802	18.535	5
	Digital talent investment	0.897	13.733		3
Digital Industrialization of the Countryside	E-commerce penetration	0.670	44.189	63.839	1
	Digital trading levels	0.874	16.877		2
	Digital Inclusive Finance	0.979	2.773		9

The dimensional weight of the rural digital economy is shown in Table 2. The swift advancement of the digital economy has made digitalization a central force and crucial driver in revitalizing rural areas and enhancing the environment. The main task in promoting the rural digital economy involves speeding up the development of information infrastructure, broadening and deepening the use of information technology in rural sectors, fostering the integration of information technology with agricultural equipment, and continually driving innovation and enhancement in digital services, thus leading to new forms of digital villages. Specifically, in terms of indicators, e-commerce penetration, digital transaction levels, and digital talent investment rank in the top three positions. This reflects that new business models and economies, such as e-commerce, serve as effective avenues for rural digital economies to achieve breakthroughs. Building digital villages and establishing a "digital ecosystem" requires comprehensive strategies that focus on both hardware infrastructure construction and software service enhancement. The government needs to actively nurture digital talent in rural regions to boost agricultural productivity, refine resource allocation, and strengthen the market competitiveness of agricultural goods. Moreover, e-commerce platforms should be leveraged to expand sales channels and boost farmers' incomes. Moreover, rural digitalization can aid in advancing precision agriculture, minimizing resource waste, and utilizing information technology to attain sustainable agricultural growth, thus enhancing the living standards of rural inhabitants and encouraging a balanced relationship between rural economies and the natural environment (Jin et al., 2024).

(2) Trend analysis of changes in the rural digital economy index by province

This study employs the entropy method to quantitatively assess the growth of the rural digital economy across China's 30 provinces from 2012 to 2022, with the findings shown in Table 3. It has been confirmed that during this period, China's rural digital economy exhibited a significant overall growth trend. In comparison to 2012, the scale of China's rural digital economy in 2022 expanded by roughly 2.5 times, with most regions experiencing relatively slight shifts in rankings. Typical regions like Guangdong Province and Zhejiang Province are particularly notable.

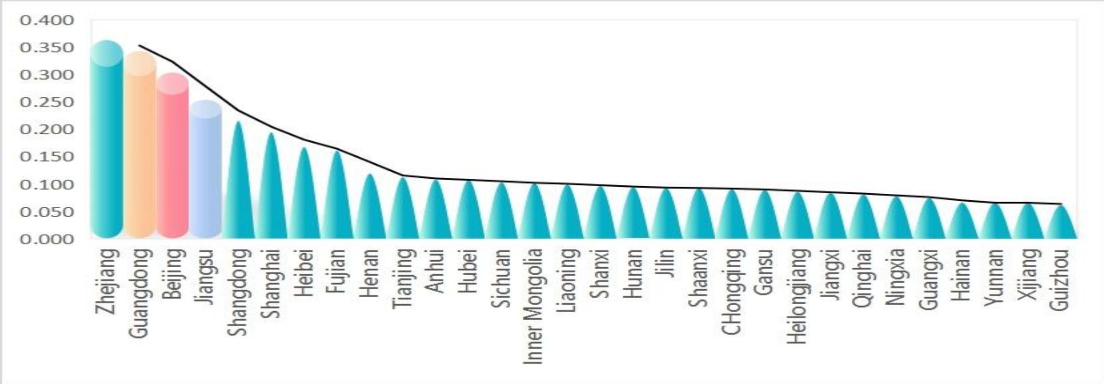
Table 3 2012-2022 Development Levels of Rural Digital Economy in Each Province

Region	pro	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
East	Beijing	0.200	0.228	0.249	0.256	0.261	0.296	0.305	0.330	0.366	0.414	0.431
	Tianjin	0.085	0.085	0.088	0.096	0.099	0.107	0.107	0.124	0.137	0.151	0.151
	Hebei	0.086	0.098	0.109	0.121	0.125	0.145	0.168	0.201	0.235	0.266	0.286
	Liaoning	0.064	0.075	0.084	0.096	0.099	0.108	0.108	0.105	0.105	0.117	0.127
	Shanghai	0.085	0.114	0.148	0.150	0.171	0.185	0.195	0.223	0.247	0.282	0.335
	Jiangsu	0.106	0.147	0.149	0.181	0.202	0.233	0.284	0.330	0.355	0.381	0.418
	Zhejiang	0.125	0.133	0.145	0.199	0.247	0.315	0.411	0.508	0.543	0.641	0.715
	Fujian	0.070	0.081	0.094	0.110	0.117	0.148	0.173	0.213	0.223	0.253	0.288
	Shandong	0.090	0.108	0.118	0.141	0.165	0.214	0.248	0.258	0.296	0.343	0.381
	Guangdong	0.107	0.150	0.175	0.202	0.246	0.310	0.382	0.445	0.500	0.592	0.658
	Hainan	0.028	0.036	0.042	0.050	0.056	0.067	0.072	0.080	0.084	0.095	0.113
	Average	0.095	0.114	0.127	0.146	0.163	0.193	0.223	0.256	0.281	0.321	0.355
Central	Shanxi	0.087	0.090	0.094	0.103	0.082	0.087	0.095	0.097	0.101	0.106	0.116
	Jilin	0.060	0.071	0.081	0.087	0.090	0.101	0.104	0.104	0.103	0.106	0.111
	Heilong jiang	0.055	0.063	0.068	0.076	0.079	0.091	0.099	0.105	0.102	0.098	0.102
	Anhui	0.057	0.067	0.075	0.084	0.089	0.099	0.123	0.130	0.141	0.154	0.167
	Jiangxi	0.060	0.047	0.054	0.065	0.066	0.080	0.091	0.099	0.111	0.122	0.129
	Henan	0.064	0.078	0.086	0.097	0.103	0.116	0.127	0.137	0.152	0.168	0.179
	Hubei	0.057	0.069	0.078	0.082	0.085	0.101	0.115	0.133	0.141	0.152	0.164
	Hunan	0.053	0.062	0.068	0.075	0.079	0.091	0.105	0.112	0.120	0.131	0.137
	Average	0.061	0.068	0.076	0.084	0.084	0.096	0.107	0.115	0.121	0.130	0.138
West	Inner Mongolia	0.063	0.076	0.082	0.092	0.094	0.105	0.115	0.116	0.121	0.123	0.128
	Guangxi	0.037	0.043	0.050	0.055	0.057	0.069	0.082	0.090	0.101	0.111	0.121
	Chongqing	0.041	0.049	0.060	0.067	0.074	0.088	0.097	0.104	0.112	0.131	0.169
	Sichuan	0.035	0.056	0.063	0.078	0.086	0.102	0.116	0.128	0.141	0.152	0.172
	Guizhou	0.036	0.043	0.045	0.046	0.048	0.057	0.066	0.070	0.074	0.086	0.101
	Yunnan	0.039	0.049	0.054	0.059	0.055	0.061	0.069	0.075	0.081	0.087	0.092
	Shaanxi	0.058	0.064	0.072	0.077	0.083	0.093	0.099	0.104	0.110	0.119	0.138
	Gansu	0.062	0.068	0.074	0.081	0.073	0.083	0.099	0.101	0.106	0.112	0.120
	Qinghai	0.043	0.039	0.044	0.070	0.073	0.077	0.094	0.099	0.102	0.115	0.130
	Ningxia	0.060	0.064	0.068	0.068	0.058	0.068	0.082	0.089	0.094	0.101	0.102
	Xinjiang	0.038	0.044	0.046	0.055	0.056	0.064	0.073	0.079	0.079	0.088	0.099
	Average	0.047	0.054	0.060	0.068	0.069	0.079	0.090	0.096	0.102	0.111	0.125

From 2012 to 2021, the total digital economy in Guangdong Province increased nearly 6.15 times, achieving a compound annual growth rate of 19.92%, solidifying its top position nationwide. Zhejiang Province utilized its advanced data infrastructure and high degree of industrial digitization to achieve a growth rate of nearly 5.73 times during this period, with an annual compound growth rate of 19.07%, also placing it among the top ranks. Provinces like Anhui and Sichuan have consistently focused on development in this sector and stayed within the top ten for a long time. Regarding Chongqing, its initial performance was not especially notable, but it started to climb from 2018 onward, reaching the 11th position nationwide by 2022.This resulted from the execution of infrastructure enhancement plans, resource integration approaches, and the introduction of incentive-driven support policies. Certain resource-rich areas, such as Shanxi, Liaoning, and Gansu, have seen a significant reduction in their influence within the digital economy sector. Shanxi's overall ranking declined from 6th in 2012 to 23rd in 2022, while Liaoning's position dropped from 11th in 2012 to 20th in 2022. Similarly, Gansu's ranking fell from 14th in 2012 to 22nd in 2022. This could stem from their prolonged overdependence on traditional resource-based industries, resulting in structural rigidity and impeding economic transformation. Innovation-driven growth, infrastructure enhancement, market environment optimization, and high-level talent development have all encountered substantial challenges. Moreover, their disadvantageous geographical positions and elevated logistics expenses have intensified these challenges, rendering the difficulties in digital economy element aggregation, technological R&D advancements, and industrial upgrading more pronounced in these areas.

Figure 2 reveals significant regional disparities in the comprehensive development levels of the digital economy among China's provinces, municipalities, and key cities. Zhejiang Province tops the list with a total score of 0.362, followed by Guangdong Province and Beijing Municipality, scoring 0.343 and 0.303 respectively. These regions exhibit robust competitiveness and development potential, particularly in digital infrastructure construction, technological innovation capabilities, and industrial integration.

Jiangsu, Shandong, Shanghai, Hebei, Fujian, and other areas, despite showing considerable potential for development in the digital economy, still trail behind more developed regions in terms of overall digital economy levels. This suggests that these areas have significant potential for improvement and urgently require enhancing their competitive advantage to close the gap with more developed regions.



Pro	Zhejiang	Guangdong	Beijing	Jiangsu	Shangdong	Shanghai	Heibei	Fujian	Henan	Tianjing
Digital level	0. 362	0. 343	0. 303	0. 253	0. 215	0. 194	0. 167	0. 161	0. 119	0. 112
Pro	Anhui	Hubei	Sichuan	Inner Mongolia	Liaoning	Shaanxi	Hunan	Jilin	Shanxi	CHongqing
Digital level	0. 108	0. 107	0. 103	0. 101	0. 099	0. 096	0. 094	0. 093	0. 092	0. 09
Pro	Gansu	Heilongjiang	Jiangxi	Qinghai	Ningxia	Guangxi	Hainan	Yunnan	Xijiang	Guizhou
Digital level	0. 089	0. 085	0. 084	0. 08	0. 078	0. 074	0. 066	0. 066	0. 066	0. 061

Figure 2 Average Level of Digital Economy Development

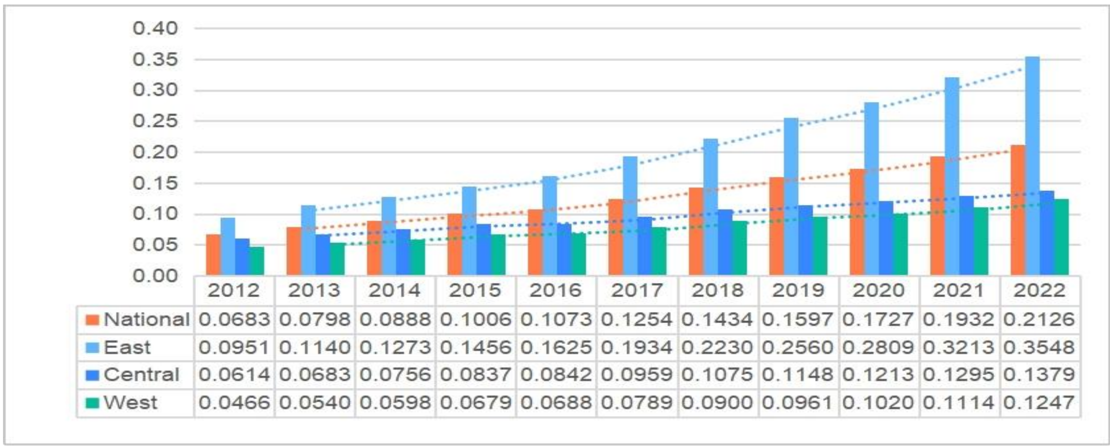
Regions in the intermediate development stage, like Hubei and Shaanxi Provinces, show a balanced distribution of the digital economy, with infrastructure development starting to exhibit scale effects. However, substantial room for improvement remains in technological innovation capabilities and the depth of industrial integration. Regions in the underdeveloped stage, from Chongqing Municipality to the Ningxia Hui Autonomous Region, are in the early phases of digital economy development and urgently need policy guidance and resource allocation to achieve leapfrog growth.

Some underdeveloped areas, like the Guangxi Zhuang Autonomous Region and Guizhou Province, exhibit relatively low levels of digital economy development. There are clear deficiencies in infrastructure development, technological innovation implementation, and industrial upgrading and transformation. To achieve comprehensive breakthroughs in all aspects of the digital economy, it is essential to enhance policy guidance and build a more robust technical support and resource protection system.

Looking ahead, it is essential to strengthen the policy support system and increase resource allocation, with a particular focus on providing development support to low- and middle-income regions. It is crucial to fully harness the technological spillover benefits and resource allocation strengths of high-tech industrial clusters through regional collaborative development strategies, thereby driving the swift rise of the digital economy in neighboring areas. Additionally, it is essential to focus on strengthening talent reserves, improving the digital literacy and professional skills of workers in the digital economy sector, promoting entrepreneurship and innovation, fostering new business models, and fully utilizing development potential to achieve balanced economic growth and comprehensive transformation across regions.

(3) Average Level and Dynamic Evolutionary Features of Regional Digital Economy Development

China is divided into three areas: eastern, central, and western. Assessing the development status of rural digital economies across these regions using this criterion, as depicted in Figure 3 statistical data reveals that from 2012 to 2022, China's digital economy showed notable spatial disparities. Generally, it follows a pattern of 'the eastern region leading, with the central and western regions trailing behind.' The eastern region, leveraging its solid economic base, advanced technological infrastructure, and strong innovation drive, has sustained a high digital economy index, reaching 0.3548 by 2022. In contrast, the central and western regions have seen relatively slow growth in their digital economies due to limited economic development potential and a lack of technological R&D capabilities. The eastern regions have established a distinct advantage in the digital economy. In contrast, the central and western regions, hindered by weaker economic foundations and insufficient innovative momentum, have experienced slower development. Although the digital economy in the central and western regions has expanded in recent years, its growth rate still lags far behind that of the eastern regions. To foster regional coordination and reduce developmental disparities, it is essential to enhance policy direction and boost resource allocation, speeding up the high-quality growth of the digital economy in less developed areas to attain nationwide balanced digital economic progress.



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
National	0.0683	0.0798	0.0888	0.1006	0.1073	0.1254	0.1434	0.1597	0.1727	0.1932	0.2126
East	0.0951	0.1140	0.1273	0.1456	0.1625	0.1934	0.2230	0.2560	0.2809	0.3213	0.3548
Central	0.0614	0.0683	0.0756	0.0837	0.0842	0.0959	0.1075	0.1148	0.1213	0.1295	0.1379
West	0.0466	0.0540	0.0598	0.0679	0.0688	0.0789	0.0900	0.0961	0.1020	0.1114	0.1247

Figure 3 Comparison of Regional Average Digital Economy Development Levels

To better understand the temporal changes across three regions of China and nationwide, then analyze the temporal dynamic evolution characteristics, a non-parametric kernel density estimation method was employed. The kernel density estimation plots of the digital economy levels for the entire country and for the eastern, central, and western regions are presented in Figure 4.

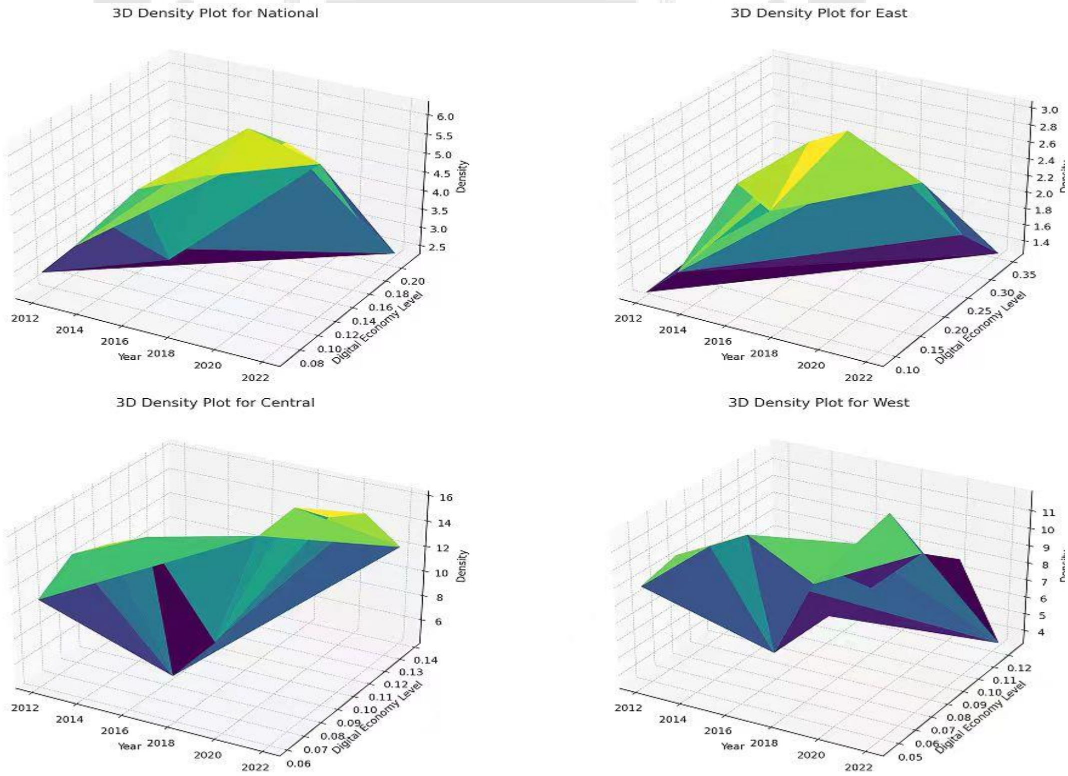


Figure 4 Kernel Density Estimations of National and Regional Digital Economy Level

From a macro perspective, China's digital economy experienced continuous growth from 2012 to 2022. The statistical characteristics of the annual distribution centre of the kernel density curve show minimal fluctuation and a steady upward trend, reflecting a development path of continuous improvement in core indicators. Exploring the patterns of changes in the main peak's height reveals short-term fluctuations, yet the overall level stays consistently high. This suggests that the development of the digital economy shows no significant regional disparities nationwide, reflecting robust stability.

The distribution of peaks shows clear phased features. From 2012 to 2015, the national digital economy level curve showed a double-peak structure, where the main peak was notably higher than the secondary one. However, this trait started to diminish from 2016 and had shifted to a single peak by 2019. It means in the early step of digital economic growth, China encountered notable regional disparities. But, the enhancement of the macroeconomic environment and the strengthening of policy regulation efforts, its development model is progressively shifting towards a more balanced direction.

Analysis of the curve's tail characteristics shows that the distribution of digital economy levels across provinces and municipalities nationwide displays a left-tail exceeding the right-tail pattern, indicating that regions with lower development levels significantly outnumber those with higher development levels. Although differences exist at both ends, the gaps are small, suggesting that regional imbalances in China's digital economy do indeed exist. However, overall, the development level stays relatively low, showing a pattern of balanced growth across the board.

During the study period, the digital economy in the eastern region showed a pattern of slight fluctuations. The kernel density estimation curve's centre of gravity consistently shifted to the right with fluctuations, suggesting that the region's overall digital economy level is relatively high but shows some variability. The changes in the main peak height indicate that the disparities in the digital economy within the eastern region experienced a dynamic process of initial contraction followed by subsequent expansion.

The eastern region has consistently shown a single peak, suggesting no significant bipolarization in its digital economy during the study period. The curve's shape shows a notably longer left tail compared to the right, suggesting varying development levels among eastern provinces. Provinces at the forefront exhibit a more advanced digital economy, while those lagging behind display a lower and less evenly distributed digital economy.

The digital economy in the central region shows more distinct dynamic features compared to other areas. Analysis through kernel density estimation shows that the trajectory of the centre of gravity followed a pattern of initially shifting rightward and then leftward during the study period. This suggests that the digital economy in the central region underwent a period of rapid growth, eventually transitioning into a phase of steady development. The peak height hit its highest point in 2013, stayed at a relatively low level with a stable trend from 2014 to 2017, and then continued to decline, remaining low for an extended period.

The statistical analysis of peak numbers revealed a double-peak structure in the central region during 2013–2014, which subsequently transformed into a single peak. This change reflects the stage-specific fluctuations and internal structural variations in the development of the digital economy in the central region over the study period. The curve's right-hand tail is slightly elevated compared to the left, suggesting a greater number of economically developed provinces than less developed ones, with an overall trend toward concentration.

The development path of the digital economy in western regions has shown a relatively stable dynamic trend. According to the distribution curve plotted with the kernel density estimation method, the centre of gravity shows no significant shift, suggesting that the digital economy in this region sustained a relatively stable growth trend throughout the study period. The main peak's height peaked in 2013 and has gradually declined since, staying at a low level.

The digital economy in the western region shows a clear single-peak distribution pattern, indicating that the overall development status remained relatively stable throughout the study period, without notable fluctuations. In terms of distribution, it exhibits a left-tail-heavy, right-tail-narrow pattern, with the number of provinces having lower overall levels far exceeding those with higher levels. Although the overall level is still relatively low, regional balance is robust, with negligible differences.

An examination of the dynamic evolution in the spatial distribution of China's digital economy uncovers clear spatial heterogeneity and temporal trends. In general, the national digital economy keeps expanding, and regional development disparities are gradually decreasing. While the eastern region boasts a solid foundation, its internal structural optimization is still incomplete. The central region has experienced a slowdown in growth rates following a period of rapid expansion. The western region, despite its later start, shows relatively balanced development and steady growth. These research findings offer crucial theoretical support and practical references for devising regional digital economy strategies and advancing coordinated regional economic growth.

3.3 Measurement of agricultural carbon emission

3.3.1 Agricultural carbon emission indicator system

Due to the wide range of agricultural carbon sources, data and information are difficult to obtain, making it difficult to accurately measure agricultural carbon emissions. This paper adopts the coefficient measurement method of Zhu and Huo (2022) to divide the agricultural land use carbon emission sources of agriculture (this paper refers to the planting industry) into four categories. The specific measurement model of total agricultural carbon emissions is as follows.

$$T = T_k + T_g + T_u + T_j \tag{7}$$

In equation (7): T denotes the total agricultural carbon emissions, and T_k, T_g, T_u, T_j denote the agricultural carbon emissions from agricultural inputs, agricultural land plowing, agricultural irrigation, and mechanical diesel fuel, respectively.

Table 4 Emission factors of agricultural carbon emission sources

Input Elements	Carbon Emission Coefficient	Data Selection	Reference Sources
Fertilizer	0.8956 kg C/kg	Application of Agricultural Fertilizer (Adjusted Amount)	Oak Ridge National Laboratory (ORNL)
Pesticide	4.9341 kg C/kg	Pesticide Application Quantity	Oak Ridge National Laboratory (ORNL)
Agricultural Film	5.18 kg C/kg	Usage of Agricultural Film	College of Resources and Environmental Sciences,Nanjing Agricultural University
Irrigation	20.476kg/hm²	Effective Irrigated Area	Dubey
Ploughing	3.126 kg /hm²	Total Area Under Crop Cultivation	Faculty of Biological Science and Technology, China Agricultural University

Carbon emissions from agricultural land are estimated by the equation:

$$TAC = \sum TAC_i = \sum F_i \times \sum Y_i \tag{8}$$

TAC_i represents the carbon emissions from the i-th type of carbon source; F_i represents the absolute amount of the i -th type of carbon source; Y_i represents the carbon emission coefficient of the i -th type of carbon source.

3.3.2 Analysis of agricultural carbon emission measurement results

(1) Trend analysis of changes in agricultural carbon emissions

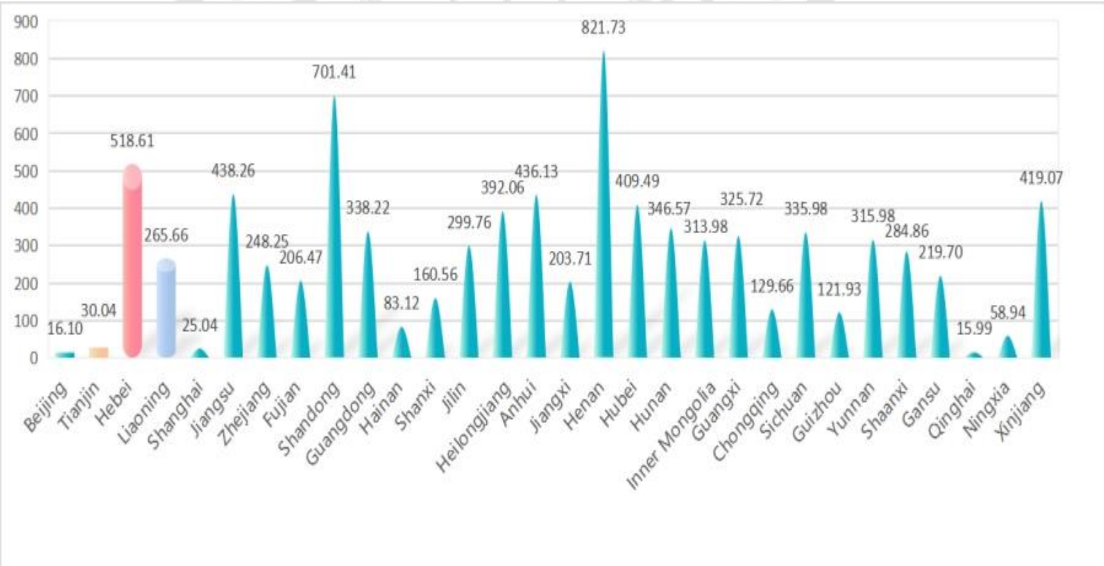


Figure 5 Changes in Average Agricultural Carbon Emissions Across Provinces

Table 5 Calculation Results of Agricultural Carbon Emissions(10,000 tons)

Region	pro	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
East	Beijing	23.51	22.35	20.15	18.32	17.05	15.15	13.43	11.94	11.67	11.72	11.81
	Tianjin	40.57	40.09	38.82	36.64	36.37	31.93	22.92	21.70	20.45	20.55	20.38
	Hebei	587.12	595.64	597.17	597.03	549.03	536.52	506.86	477.38	430.41	417.87	409.70
	Liaoning	283.25	289.00	289.34	286.35	277.61	268.56	259.26	248.62	243.54	241.14	235.56
	Shanghai	30.36	30.42	29.38	28.82	27.61	26.90	24.99	23.06	23.20	15.41	15.27
	Jiangsu	467.52	466.71	462.80	458.32	451.21	442.78	431.35	423.34	416.26	405.41	395.15
	Zhejiang	265.89	268.38	265.62	265.08	258.78	254.86	248.01	234.73	230.11	222.50	216.81
	Fujian	220.53	221.16	222.93	224.21	224.01	214.07	205.63	198.27	187.15	179.83	173.39
	Shandong	791.44	783.20	766.98	756.75	745.98	718.94	684.68	646.39	623.07	606.79	591.28
	Guangdong	349.08	346.20	353.91	361.62	365.44	361.54	333.72	323.43	315.49	306.61	303.35
	Hainan	85.22	90.07	92.82	95.73	88.40	87.09	80.93	77.79	73.29	72.49	70.51
	Average	285.86	286.65	285.45	284.44	276.50	268.94	255.62	244.24	234.06	227.30	222.11
Central	Shanxi	166.56	169.74	169.64	168.01	166.73	161.51	157.18	154.50	153.17	150.53	148.54
	Jilin	284.82	295.13	305.10	312.17	313.24	310.96	303.47	298.75	295.33	290.92	287.45
	Heilong jiang	394.86	403.01	411.44	411.75	410.95	409.35	398.65	363.99	363.42	374.30	370.88
	Anhui	456.33	465.45	465.21	463.64	450.17	439.90	431.32	418.72	409.12	401.90	395.70
	Jiangxi	224.13	225.93	224.56	225.33	221.84	214.77	199.07	184.51	173.60	173.57	173.49
	Henan	838.30	856.65	863.26	870.48	867.97	852.35	831.21	801.33	781.22	752.69	723.61
	Hubei	464.76	459.44	457.40	441.90	433.30	419.75	394.97	368.85	360.50	355.45	348.10
	Hunan	357.26	360.04	359.57	358.59	356.69	354.94	351.80	334.69	327.84	342.22	308.68
	Average	398.38	404.42	407.03	406.48	402.61	395.44	383.46	365.67	358.03	355.20	344.56
West	Inner Mongolia	267.06	286.50	312.42	325.99	331.80	328.68	317.79	311.95	301.40	340.07	330.15
	Guangxi	318.64	327.24	333.08	336.89	344.56	335.21	323.32	320.46	316.04	315.86	311.66
	Chongqing	130.58	133.06	134.26	134.54	133.00	132.48	129.67	126.28	124.56	124.12	123.69
	Sichuan	357.66	356.52	355.84	356.54	355.59	347.53	333.93	322.06	307.16	303.47	299.43
	Guizhou	128.05	128.53	132.59	135.32	136.34	129.26	124.37	112.26	108.32	104.72	101.46
	Yunnan	319.79	332.80	344.56	351.79	355.63	354.69	303.10	290.37	284.83	271.89	266.35
	Shaanxi	294.06	301.79	291.42	294.60	296.33	295.97	292.99	269.65	268.79	266.77	261.07
	Gansu	220.32	233.38	243.59	250.78	248.98	221.09	206.96	198.78	196.17	196.70	199.97
	Qinghai	16.46	17.52	17.67	18.22	17.29	17.42	16.59	14.73	13.77	13.35	12.83
	Ningxia	59.05	60.64	59.28	59.85	60.26	59.95	57.46	57.68	57.81	57.63	58.68
	Xinjiang	332.22	356.81	422.30	437.05	439.36	433.07	448.02	445.83	429.73	425.63	439.73
	Average	222.17	230.44	240.64	245.60	247.19	241.40	232.20	224.55	218.96	220.02	218.64

The data shows that Henan Province has the highest agricultural carbon emissions at 821.73, markedly exceeding other provinces. Shandong Province comes next, with agricultural carbon emissions reaching 701.41. Hebei and Anhui Provinces rank high with carbon emissions of 518.61 and 436.13, respectively. The high carbon emissions in these provinces might be closely linked to their extensive agricultural production, diverse crops, and frequent farming activities.

Moreover, the agricultural carbon emissions in Jiangsu Province and Guangdong Province were 438.26 and 338.22, respectively, indicating a moderate level of carbon emissions. This suggests that agricultural production is more active in these regions, yet carbon emission control measures might be more effective. Moreover, Heilongjiang Province, Hubei Province, Inner Mongolia Autonomous Region, and Xinjiang Uygur Autonomous Region have carbon emissions of 392.06, 409.49, 313.98, and 419.07, respectively, also indicating the significant contribution of their agricultural activities to carbon emissions.

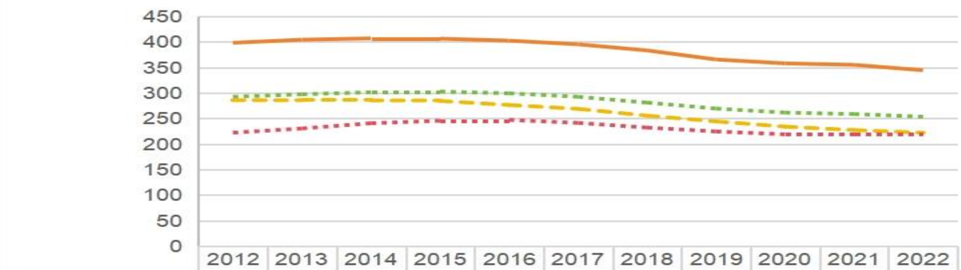
Other provinces with moderate carbon emissions include Jilin, Shanxi, Guangxi Zhuang Autonomous Region, Sichuan, Hunan, Jiangxi, Fujian, Yunnan, Shaanxi, and Gansu. The carbon emissions of these provinces are 299.76, 160.56, 325.72, 335.98, 346.57, 203.71, 206.47, 315.98, 284.86, and 219.70, respectively, suggesting that agricultural production in these areas is relatively active and that carbon emission control measures are starting to show results.

Provinces with low carbon emissions are primarily located in highly urbanized areas with minimal agricultural production. For instance, the agricultural carbon emissions in Beijing, Tianjin, and Shanghai are 16.10, 30.04, and 25.04, respectively, significantly lower than those in other provinces. Carbon emissions in Hainan Province, Chongqing Municipality, Guizhou Province, Qinghai Province, and Ningxia Hui Autonomous Region are also relatively low, standing at 83.12, 129.66, 121.93, 15.99, and 58.94, respectively.

Overall, provinces with high carbon emissions are primarily found in major agricultural production areas and key grain - producing regions, where agricultural activities contribute significantly to carbon emissions. Provinces with medium carbon emissions are more dispersed, showing active agricultural operations and initial success in carbon emission control measures. Provinces with low carbon emissions are mostly highly urbanized areas with limited - scale agricultural production. Each province should implement effective carbon emission reduction measures based on its own actual conditions to advance the green and low-carbon development of agriculture. By enhancing agricultural production methods and applying low-carbon technologies, each region can effectively control carbon emissions while maintaining agricultural productivity. This analysis offers a crucial reference for further research and the development of regional carbon emission control policies.

(2) Trend of Regional Average Agricultural Carbon Emissions and Its Time-Series Dynamic Evolution Characteristics

This study, using data from 2012 to 2022, thoroughly examines the spatiotemporal evolution of agricultural carbon emissions across China's regions and carefully contrasts the notable differences and trends between the national level and the eastern, central, and western regions. As illustrated in the statistical data of Figure 6, during this time, total agricultural carbon emissions in different regions all showed a downward trend, though the extent and rate of decline differed considerably. At the national level, agricultural carbon emissions fell from 2.925 million tons in 2012 to 25,340 tons in 2022, averaging an annual reduction of 1.8%. Despite fluctuations in 2013-2014, emissions have steadily declined since 2015, highlighting the notable progress in China's agricultural low-carbon transition. The eastern region experienced the most significant reduction in carbon emissions, averaging a yearly decrease of 2.6%. The central region displayed a typical inverted U-shaped curve, reaching its peak around 2015 before gradually declining. The western region, although starting with a lower initial value, also exhibited an inverted U-shaped trajectory, peaking around 2016 and declining to about 2.2 million tons of carbon dioxide equivalent by 2022. A systematic analysis of regional differences reveals that China's agricultural carbon emissions show a complex dynamic spatial pattern. The central region has consistently exhibited high carbon emission intensity, largely due to the prevalence of large-scale farming models, the ongoing use of traditional agricultural methods, and the swift expansion of agricultural mechanisation. This underscores the significant challenges encountered by the central region in its emissions reduction initiatives, while also offering valuable insights for enhancing reduction strategies in this area. The eastern region has achieved significant results in carbon emission reduction by utilizing scientific and technological innovations, detailed management practices, and the improvement and optimization of industrial structures. This experience offers valuable reference for other regions. The western region adopts a distinctive development trajectory. The rise in carbon emissions from 2012 to 2016 might be linked to the expansion of agriculture driven by the Western Development Policy. The decline since 2016 suggests that the region is progressing toward sustainable development and has ramped up efforts in ecological conservation. It is especially noteworthy that the trend in national agricultural greenhouse gas emissions reveals a distinct consistency between the eastern and central regions, highlighting the crucial role and central position these two regions hold in executing national agricultural emission reduction policies.



	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
National	292.5	297.4	301.4	302.7	299.3	292.5	281.1	269.4	261.5	258.7	253.4
East	285.8	286.6	285.4	284.4	276.4	268.9	255.6	244.2	234.0	227.3	222.1
Central	398.3	404.4	407.0	406.4	402.6	395.4	383.4	365.6	358.0	355.1	344.5
West	222.1	230.4	240.6	245.5	247.1	241.3	232.1	224.5	218.9	220.0	218.6

Figure 6 Regional Average Agricultural Carbon Emissions

A systematic analysis of the spatial distribution and temporal characteristics of China's agricultural carbon emissions, utilizing nuclear density estimation methods, shows that from 2012 to 2022, carbon emissions nationwide and in the eastern, central, and western regions displayed notable spatial disparities and dynamic variations. The study findings suggest that China's agricultural carbon emissions show clear phased evolutionary trends and regional variations.

From a macro perspective, although national agricultural carbon emissions have fluctuated and declined, the centre of gravity of the kernel density curve has continuously shifted leftward, showing that the cumulative impacts of carbon reduction policies are becoming more apparent, especially after 2016. This indicates that national-level emission reduction measures have started to show results. The change in the peak position from a double peak to a single peak suggests that the gap in carbon emissions among different regions is decreasing, illustrating the coordinated impact of national carbon emission control policies. The continuous extension of the left tail also indicates that the proportion of low-carbon emission years is rising, reflecting the long-term nature of implementing these relevant policies and measures.

Carbon emissions in the eastern region have shown a declining trend, with a single-peak kernel density distribution and a notable left-tail extension. This clearly illustrates the remarkable progress achieved by the eastern region in technological innovation for energy conservation and emissions reduction, along with the optimization and upgrading of its industrial structure. This situation not only underscores the eastern region's early lead in modern agricultural transformation but also offers other regions a viable example for reaching green and low-carbon development goals.

The carbon emissions in the central region show a clear inverted U-shaped development trend, illustrating the dynamic equilibrium between agricultural growth and ecological conservation. By examining the shifts in the centre of gravity and the changes in the peak amplitude of the nuclear density curve, one can thoroughly discuss the phased changes faced by the central region during the expansion of agricultural production scale and the innovation of emission reduction technologies. This highlights the intricate contradictions encountered by the central region, a crucial national grain-producing area, in balancing food security and carbon peaking goals.

Carbon emissions in the western region show a significant level of stability. Although the centre of gravity of the kernel density curve exhibits slight fluctuations, it stays in a single-peak state. This reflects, to some extent, the backward state of agricultural development and the potential for emission reduction. The small protrusion on the left tail indicates that this area is progressively advancing towards modern agricultural development, provided that low-carbon targets are met.

This study employs a systematic analytical approach to conduct a comprehensive survey of the spatiotemporal evolution patterns of agricultural carbon emissions nationwide and in the eastern, central, and western regions. It focuses on analyzing the spatial differences and temporal trends in these emissions. The survey results indicate that the total volume of agricultural carbon emissions across the country is gradually declining, with regional disparities slowly diminishing. The eastern region retains its advantage in carbon reduction, the central region achieves notable emission cuts via structural reforms, and the western region sustains a relatively low and stable emission level.

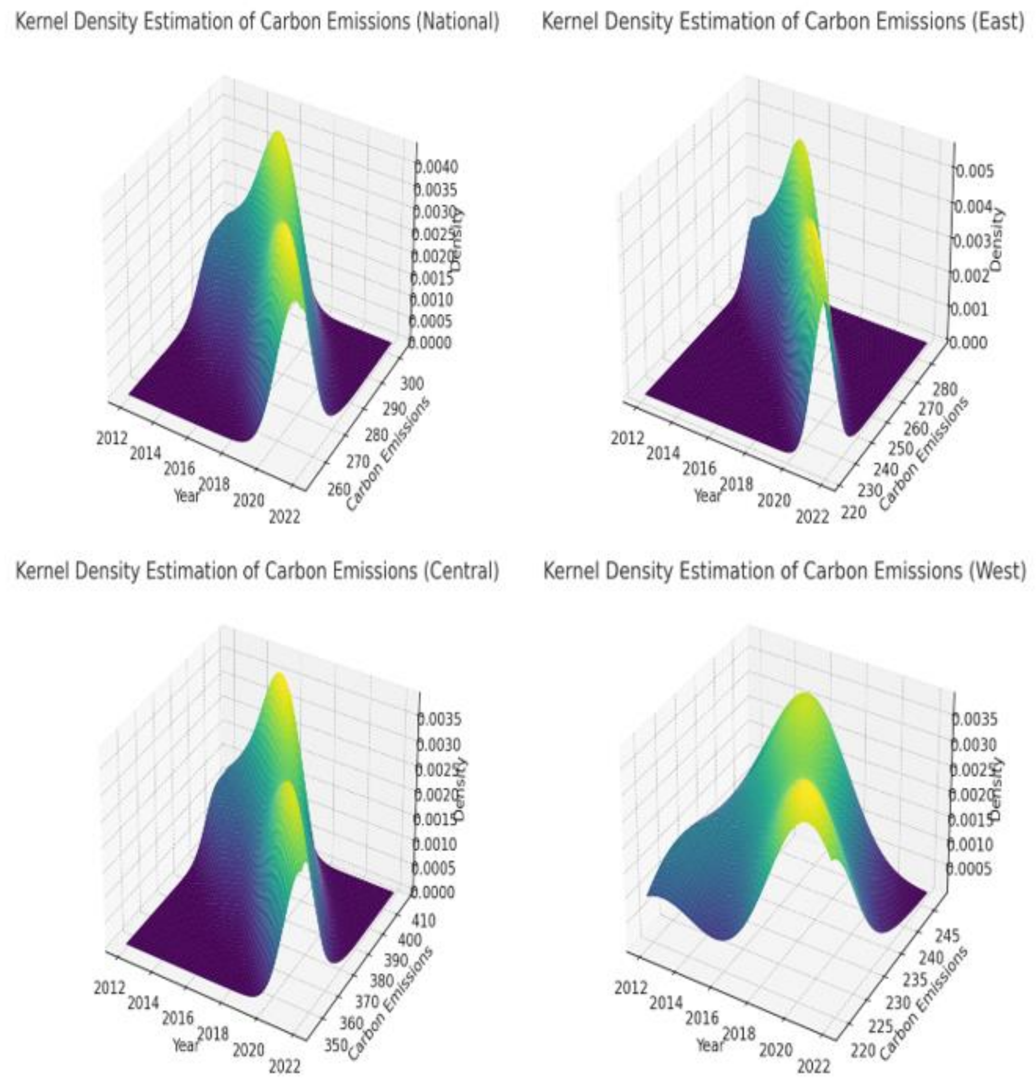
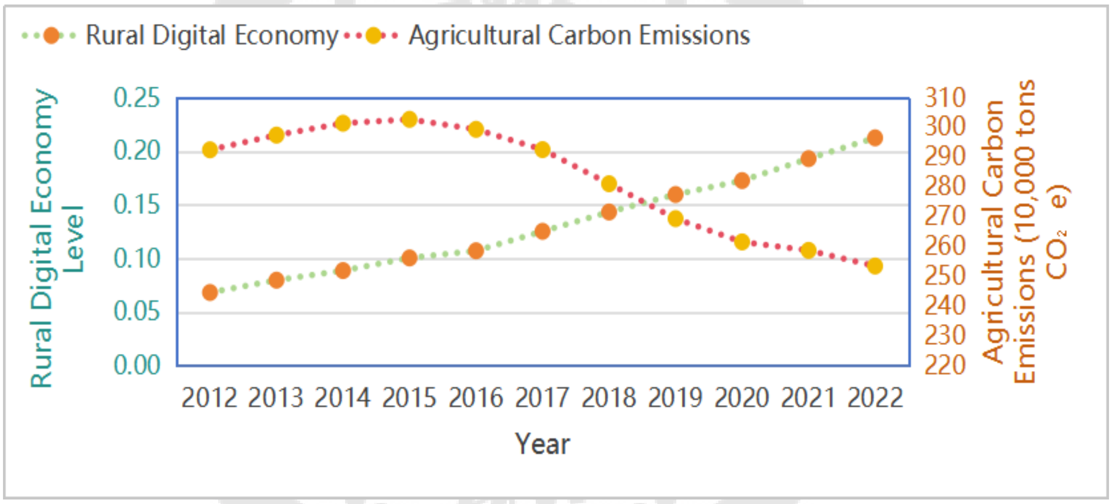


Figure 7 Kernel Density Estimations of National and Regional Agricultural Carbon Emissions

3.4.The Spatial-Temporal Characteristics of digital economy development and agricultural carbon emissions

Figure 8 shows the growth of China's rural digital economy from 2012 to 2022 and its connection to agricultural carbon emissions. Statistical data indicates that the rural digital technology application index rose from 0.06 in the base period to 0.22, marking a growth rate of 367%. Meanwhile, the agricultural sector's total carbon emissions fell from roughly 295 million tons of CO2 equivalent to about 250 million tons, marking a 14.8% decrease. This implies that the swift expansion of the digital economy could substantially suppress agricultural carbon emissions, underscoring its significance in promoting low-carbon agriculture.



data sources : Table 3 and Table 5

Figure 8 Temporal Trends of Agricultural Carbon Emissions and Rural Digital Economy Level

As illustrated in Figure 9-10, distinct spatial heterogeneity features are observed across different regions. Provinces like Beijing, Qinghai, and Ningxia exhibit carbon emissions under 50×10^{4} tonnes of CO_{2e}, potentially due to their smaller agricultural scales or significant carbon reduction impacts. In contrast, Henan (723.61), Shandong (591.28), and Xinjiang (439.73) display notably high emissions, suggesting that agricultural production is heavily concentrated in these regions. Provinces like Jiangsu, Heilongjiang, and Guangdong exhibit medium-high to high emission levels

($150–450 \times 10^4$ tonnes of CO_{2e}). This difference in distribution illustrates that the stage of regional economic development and the level of technological application significantly influence carbon emission characteristics. This situation underscores the need for developing targeted emission reduction strategies that account for local emission patterns.

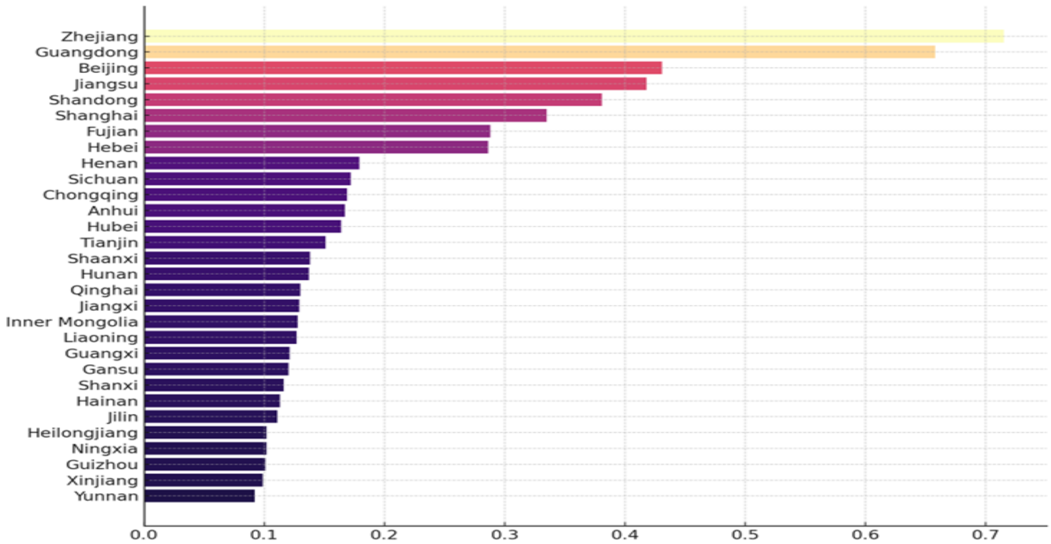


Figure 9 Spatial Distribution of Agricultural Carbon Emissions (2022)

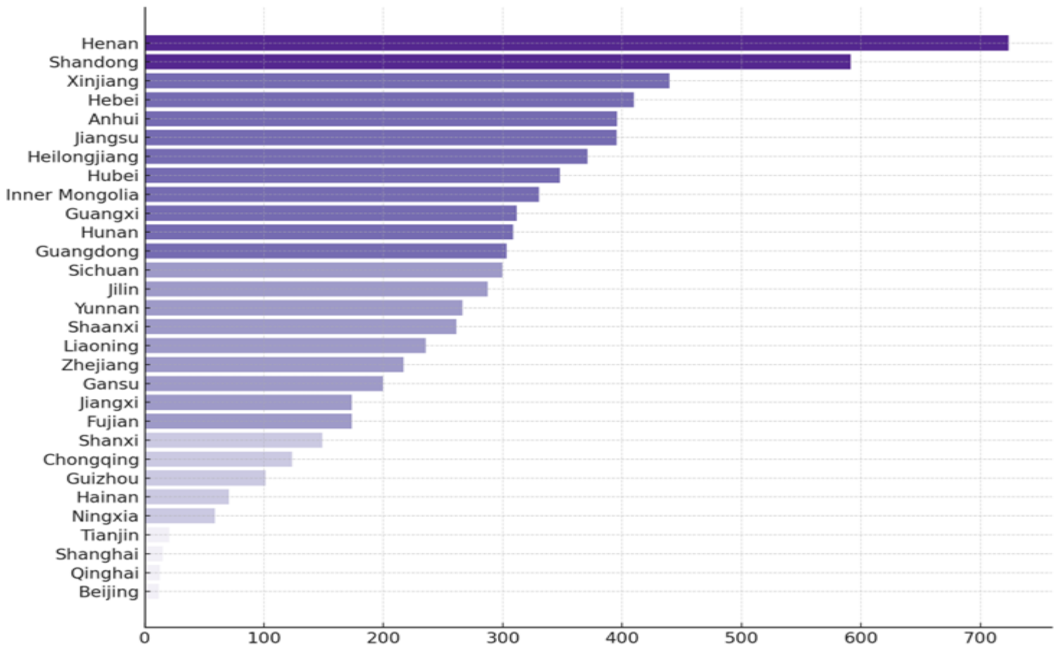


Figure 10 Spatial Distribution of Agricultural Carbon Emissions (2022)

3.5. Model Construction

Model construction forms a vital basis for ensuring the success of empirical research. The first three chapters offer an initial examination of the research background, theory, and current features of agricultural carbon emissions and the digital economy. This section details the model, variables, and data for testing the research hypotheses, divided into three parts: model construction, variable selection, data sources, and variable descriptive statistics.

3.5.1 Benchmark Regression Model

To investigate the impact of the digital economy on agricultural carbon emissions, we formulated the fixed effects model, drawing on the methodology established by Chen and Li (2024):

$$TAC = \partial_0 + \partial_1 \mathrm{ADIG}_{it} + \partial_2 \mathrm{X}_{it} + \delta_{it} + \tau_{\mathrm{it}} + \mu_{it} \quad (9)$$

In equation (9) , TAC represents total agricultural carbon emissions; $ADIG_{it}$ represents the level of digital economic development; X_{it} represents the relevant control variables; ∂_0 is a constant term; δ_{it} represents region effects and τ_{it} represents time effects, and μ_{it} represents the random disturbance term.

3.5.2 Mediation Effect Model

To further explore the mediating mechanisms, the following models are constructed based on the baseline regression framework, drawing on the research of (Wen, Z. 2014).

$$TAC = \gamma_0 + \gamma_1 \mathrm{ADIG}_{it} + \gamma_2 M_{it} + \gamma_3 X_{it} + \delta_{it} + \tau_{it} + \mu_{it} \quad (10)$$

$$M_{it} = \beta_0 + \beta_1 \mathrm{ADIG}_{it} + \beta_2 X_{it} + \delta_{it} + \tau_{it} + \mu_{it} \quad (11)$$

In equations (10) and (11), M_{it} denotes the mediating variables, which include the scale effect, financial effect, and technological innovation effect, represented by the land transfer rate, agricultural loans, and agricultural science and technology patents, respectively. β, γ indicates the parameter estimates of the variables.

3.5.3 Variable Selection

(1) Explanatory Variable

This study, based on the theoretical framework established by Dan Wang (2024), has developed a comprehensive evaluation system for rural digital economic development (Table 1), utilizing the entropy method for weighting and scoring.

(2) Explained variable

Carbon emissions from six carbon source categories are computed (Table 2), with their total representing overall agricultural carbon emissions.

(3) Mediating Variables

The mediating variables include scale effects, financial effects , and technological innovation effects , following the studies of Kelly et al. (2021). These are proxied by land transfer rate (ltr), agricultural loans(flb), and per capita agricultural technology patents(flb), respectively.

(4) Control Variables

The model incorporates several key control variables as moderating factors, including: urbanisation level (URB), represented by the ratio of urban population to total population; agricultural structure ratio (AIS), denoting the share of agricultural output in the primary sector; agricultural labor productivity (ALP), reflecting the total output per unit of labor in the primary sector; rural electricity consumption (ELEC), measured through agricultural electricity usage; and agricultural disaster frequency (ADR), indicated by the proportion of disaster-affected farmland area relative to total farmland area. All variables are expressed as natural logarithm.

3.5.4 Data Sources

Explanatory Variable	Indicator	Data Sources	Explained Variable	Indicator	Data Sources
The level of rural digital economy development	Rural Internet Penetration Rate	China Statistical Yearbook	Agricultural carbon emissions	Fertilizer, Pesticides, Agricultural film, Diesel use, Land tillage, Irrigation	China Rural Statistical Yearbook
	Computer Penetration Rate	China Statistical Yearbook	Mediating Variables	Land transfer rate	China Agricultural Yearbook
	Communication Service Level	China Statistical Yearbook		Agricultural loans	China Agricultural Yearbook
	Mobile Phone Penetration Rate	China Statistical Yearbook		Per capita agricultural technology patents	China Agricultural Yearbook
	Rural Digital Transformation Model	China Statistical Yearbook	Control Variables	urbanization rate	China Statistical Yearbook
	Digital Talent Investment	China Statistical Yearbook		agricultural industrial structure	China Agricultural Machinery Industry Yearbook
	Information Transmission Level	China Rural E-Commerce Market Data Report		agricultural labor productivity	China Agricultural Machinery Industry Yearbook
	E-commerce Sales Volume	China Rural E-Commerce Market Data Report		rural electricity consumption	China Agricultural Machinery Industry Yearbook
	Digital Finance Index	Digital Finance Research Center at Peking University		agricultural disaster rate	China Statistical Yearbook

Figure 11 Data Source

3.5.5 Descriptive Statistics

As shown in Chapter 3.4, this study established a balanced panel dataset comprising 330 observations based on the collected basic data, covering data from 30 provinces in mainland China from 2012 to 2022. Due to the limited sample size, the data has certain limitations.

Table 6 Variable Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
lntac	330	5.273	1.055	2.457	6.769
lnadig	330	0.120	0.083	0.028	0.539
lnurb	330	0.472	0.072	0.307	0.642
lnelec	330	4.917	1.27	1.495	7.606
lnais	330	0.422	0.055	0.31	0.542
lnalp	330	10.904	0.512	9.400	12.127
lnadr	330	0.119	0.089	0.004	0.528

As shown in Table 6, from 2012 to 2022, the average agricultural carbon emissions were 5.273 (SD = 1.055), varying between 2.457 and 6.769. This indicates significant regional differences, potentially influenced by economic development and technology adoption. The average digital economy index was 0.12 (SD = 0.083), ranging from 0.028 to 0.539, reflecting generally low levels of rural digitalization but showing notable advancements in certain areas and substantial room for further growth.

The primary findings are displayed in Table 6, the correlation matrix. The data suggest a notable negative correlation between the rural digital economy and agricultural carbon emissions, yet this correlation falls short of statistical significance, indicating a relatively weak direct connection between the two.

It is crucial to recognize that correlation coefficients solely capture linear relationships between variables and do not consider other aspects like control variables, industry traits, time series impacts, or model optimization components. Depending exclusively on direct correlation tests as a theoretical foundation clearly diverges from the study's core. Subsequent empirical analyses will employ statistical methods to test and comprehensively assess the aforementioned theoretical hypotheses.

Table 7 Pairwise correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) lntac	1.000						
(2) lnadig	-0.073	1.000					
	(0.185)						
(3) lnurb	-0.503*	0.588*	1.000				
	(0.000)	(0.000)					
(4) lnelec	0.527*	0.471*	0.213*	1.000			
	(0.000)	(0.000)	(0.000)				
(5) lnais	0.258*	-0.277*	-0.386*	-0.078	1.000		
	(0.000)	(0.000)	(0.000)	(0.155)			
(6) lnalp	-0.132*	0.581*	0.691*	0.278*	-0.261*	1.000	
	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)		
(7) lnadr	0.031	-0.327*	-0.234*	-0.277*	0.056	-0.369*	1.000
	(0.581)	(0.000)	(0.000)	(0.000)	(0.310)	(0.000)	

*** p<0.01, ** p<0.05, * p<0.1

To examine whether model variables show multicollinearity problems, the variance inflation factor (VIF) is employed for a systematic analysis. Statistical data indicate that the average VIF value for each variable is merely 1.72, significantly lower than the conventional warning threshold of 5. This suggests that in the regression model developed in this study, these independent variables lack significant multicollinearity traits, thus offering a relatively robust econometric basis for subsequent empirical analysis.

CHAPTER 4
RESULTS

4.1 Analysis of the Benchmark Regression Results

Following variable selection through stepwise regression, the detailed data are presented in Table 8. Empirical evidence indicates that the development level of the 'digital economy' significantly reduces agricultural carbon emissions ($P < 0.01$), underscoring its vital role in mitigating agricultural emissions. This conclusion highlights the core mechanism by which the digital economy promotes agricultural low-carbon transformation through technological innovation, offering empirical evidence for Hypothesis H1 and affirming that the digital economy directly reduces agricultural carbon emissions.

The regression results of Model (6) show that the correlation coefficient between the digital economy and agricultural carbon emissions is -0.527, indicating that the impact of the digital economy on agricultural carbon emissions might be mediated by other potential intermediaries. Further testing showed that rural electricity consumption (lnelec) has a significant positive correlation in all models, with the highest regression coefficient of 0.975 in Model (6), indicating strong explanatory power. This study examines the fundamental mechanisms connecting the increase in rural electricity consumption to the growth of agricultural carbon emissions. The study reveals that although rural regions have advanced somewhat in adopting clean energy, fossil fuels still dominate, serving as the main factor behind rising agricultural carbon emissions. With the continuous increase in electricity demand, the efficiency of resource utilization is encountering significant challenges. Improving agricultural production efficiency and promoting rural transition to green and low-carbon development requires reliance on technological innovation and policy guidance to expedite the establishment of a rural green development system consistent with sustainable development needs.

Empirical studies indicate that the rural digital economy significantly reduces agricultural carbon emissions, with this impact remaining stable even after variable adjustments. This offers a theoretical foundation for further investigation into the underlying mechanisms. Additionally, various important factors, including rural electricity consumption patterns, urbanisation development levels, and agricultural labor productivity, directly affect agricultural carbon emissions. This highlights the necessity of creating a cross-sectoral collaborative governance framework, taking into account aspects like economic structural transformation and upgrading, energy structure renovation, scientific and technological innovation support, and ecological and environmental protection. In this situation, it is crucial to develop practical and targeted policies to drive progress.

Table 8 Stepwise regression results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lntac	lntac	lntac	lntac	lntac	lntac
lnadig	-1.299***	-1.056***	-0.819***	-0.811***	-0.567***	-0.527***
	(0.105)	(0.132)	(0.137)	(0.137)	(0.137)	(0.137)
lnurb		-0.748***	-1.358***	-1.362***	0.975**	1.070**
		(0.252)	(0.275)	(0.275)	(0.479)	(0.478)
lnelec			0.062***	0.061***	0.057***	0.059***
			(0.013)	(0.013)	(0.012)	(0.012)
lnais				-0.328	-0.434	-0.443
				(0.382)	(0.362)	(0.360)
lnalp					-0.208***	-0.205***
					(0.036)	(0.036)
lnadr						0.166**
						(0.075)
Constant	5.430***	5.754***	5.710***	5.853***	7.047***	6.947***
	(0.0137)	(0.110)	(0.107)	(0.197)	(0.278)	(0.280)
N	330	330	330	330	330	330
R^2	0.338	0.357	0.403	0.405	0.466	0.475
Number of id	30	30	30	30	30	30

*** p<0.01, ** p<0.05, * p<0.1

4.2 Robustness test

(1) Replacement of Dependent Variable

To enhance the reliability of the empirical findings, this study performed a robustness test by incorporating agricultural carbon emission intensity (log-transformed) as an additional independent variable into the model. The data in Table 3 (Model 1) show that, even with the dependent variable replaced, it continues to have a significant negative effect on agricultural carbon emissions, thus effectively confirming the scientific and rational basis of the benchmark regression conclusions.

Table 9 Robustness test results

VARIABLES	Replaced the Explained Variable Model(1) lnace	Replaced the Explanatory Variable Mode(2) lntac	Excluding municipalities Model(3) lntac
lnadig	-0.294**	-0.030**	-0.297***
	(-2.365)	(-2.471)	(-3.160)
lnurb	-0.854	1.048**	-0.113
	(-1.633)	(2.158)	(-0.30)
lnelec	0.012	0.071***	0.026
	(0.963)	(5.961)	(1.570)
lnais	-3.698***	-0.542	-0.103
	(-9.532)	(-1.489)	(-0.350)
lnalp	-0.617***	-0.252***	-0.124***
	(-16.999)	(-7.316)	(-4.620)
lnadr	0.187**	0.230***	0.066
	(2.332)	(3.009)	(1.360)
_cons	13.582***	7.405***	6.881***
	(48.285)	(28.285)	(30.990)
N	330	330	286
R^2	0.898	0.460	0.995
F	433.452	41.669	

*** p<0.01, ** p<0.05, * p<0.1

(2) Replacement of Explanatory Variable

To assess the level of digital economic development, we employ principal component analysis, as recommended by Nie et al. (2024) and other scholars, to derive an index reflecting digital economy development across regions. The results in Table 9 (Model 2). After replacing the core explanatory variable, it continues to show a significant negative effect, further supporting the benchmark regression results.

(3) Exclude municipalities directly under central government

Recognizing Beijing, Shanghai, Tianjin, and Chongqing, we exclude these municipalities to mitigate potential administrative biases in the benchmark regression outcomes. We rerun the regression after removing these municipalities from the sample. The results, presented in Table 9 (Model 3), are consistent with those of the benchmark regression, strengthening the study's overall conclusions.

4.3 Endogeneity Test

To avoid potential biases caused by endogeneity issues, this study employs the instrumental variables method for empirical analysis. The fixed-line telephone penetration rate per 10,000 people in each provincial-level administrative region in 1984 is selected as the core instrumental variable to measure the level of regional digital economic development. This selection is based on the following theoretical rationale: the digitalisation process in rural areas is closely linked to the promotion of fixed-line telephones, and the telephone coverage rate in 1984 reflects the cumulative status of local historical information infrastructure, which in turn influences the current scale of internet access, meeting the basic requirements for instrumental variable relevance. Additionally, the per capita telephone ownership rate in 1984 has a negligible impact on agricultural carbon emissions during the sample period, aligning with the primary criteria for instrumental variable exogeneity. Given that this study employs multi-period, cross-regional balanced panel data, directly incorporating this static indicator into a fixed-effects model could potentially induce measurement error issues in econometrics. To address this, we follow the methodology of Nunn and Qian (2014) and the number of telephones per 10,000 people in 1984 as an instrumental variable for the level of digital economic development.

Table 10 Endogeneity test results

VARIABLES	The first stage lnadig	The second stage lntac
iv	0.000***	
	(6.020)	
lnadig		-4.117**
		(-2.370)
lnurb	0.096	-10.127***
	(1.230)	(-10.970)
lnelec	-0.026***	-0.628***
	(-9.550)	(14.030)
lnais	0.141**	1.040
	(-2.290)	(1.560)
lnalp	0.036***	0.776***
	(4.18)	(6.910)
lnadr	-0.017	1.285***
	(-0.430)	(3.080)
Constant	-0.420***	-1.593
	(-4.170)	(-1.250)
N	330	330
R2	0.842	0.996
Anderson canon. corr. LM statistic	33.33***	
Cragg-Donald Wald F statistic	36.29***	
Sargan statistic(P)		0.000

*** p<0.01, ** p<0.05, * p<0.1

Empirical analysis reveals that the Anderson-Cannon correlation LM test statistic is 33.33, highly significant. The Cramer-Donald-Wald F test statistic is 36.29, far surpassing the critical value of 10, clearly indicating the model's strong identification ability and stability. The Sargan test produces a p-value of 0.000, confirming the reliability of the instrumental variables and effectively eliminating biases from weak instruments. Even after accounting for endogeneity, It still have a significant and robust inhibitory impact on agricultural carbon emission intensity.

4.4 Heterogeneity Analysis

(1) Regional Heterogeneity Analysis

Table 11 Heterogeneity analysis results (1)

VARIABLES	East lntac	Central lntac	West lntac
lnadig	-0.264***	-1.193**	-1.227**
	(-2.670)	(-2.430)	(-2.090)
lnurb	5.168***	0.067	2.006**
	(5.080)	(0.170)	(2.080)
lnelec	0.038***	-0.000	0.054
	(3.710)	(-0.010)	(1.270)
lnais	0.845	-0.018	-0.186
	(1.470)	(-0.050)	(-0.390)
lnalp	-0.053	-0.092**	-0.216***
	(-0.790)	(-2.490)	(-3.200)
lnadr	0.074	-0.080	0.105
	(0.850)	(-1.230)	(1.070)
Constant	2.458***	6.938***	6.521***
	(3.090)	(21.730)	(15.130)
N	132	88	121
R2	0.997	0.994	0.995

*** p<0.01, ** p<0.05, * p<0.1

China is a vast nation characterized by substantial spatial heterogeneity in both its natural geography and economic development. This structural disparity leads to distinct regional variations in the impact of the digital economy on agricultural carbon emissions across different areas. This enables a thorough examination of the mechanisms and underlying logic by which the digital economy drives changes in agricultural carbon emissions across these regions.

As illustrated in Table 11, the influence of the digital economy on agricultural carbon emissions across China's eastern, central, and western regions demonstrates notable spatial variations. In the eastern region, the development index reaches -0.264, suggesting a negative correlation, yet its influence remains limited. This could be due to the advanced level of agricultural modernisation and limited structural changes in the eastern region, which impede the unrestricted allocation of agricultural resources in the short term, thus diminishing the practical impact of digital economic growth. In contrast, the coefficient in the central region attains the highest value of -1.193, suggesting a stronger negative correlation. During the agricultural transformation phase, the digital economy cuts carbon emissions by enhancing resource allocation and innovating production methods. Related studies indicate that the correlation coefficient in the western region is -1.227, suggesting a substantial promotional impact on reducing agricultural carbon emissions. This phenomenon is mainly attributed to the ongoing enhancement of the regional agricultural structure. The integration of digital technology with traditional agriculture updates production methods and creates new business models, offering rural labor diverse employment opportunities while significantly cutting down on the use of chemical inputs like fertilizers.

The influence of the digital economy on agricultural carbon emissions shows clear spatial differences, with central and western areas displaying greater sensitivity and adaptability to the digital economy.

(2) Distinction of Major Grain Production Areas

The demarcation of grain production functional zones significantly affects agricultural carbon emissions, showing marked regional variations in crop planting structures, production methods, and pesticide use. These differences directly affect the spatial distribution patterns and evolutionary trajectories. This study uses provincial grain production function classifications to divide the nation's 30 provinces into two distinct sub-sample groups. The first group mainly comprises major grain-producing regions, such as Anhui, Hunan, Hubei, Henan, Heilongjiang, Hebei, Jiangxi, Jiangsu, Jilin, Liaoning, Inner Mongolia, Sichuan, and Shandong. The second category consists of the remaining provinces that are not key grain-producing areas. This study aims to uncover the fundamental logical relationship between the digital economy and the advancement of low-carbon agricultural development by comparing the distinct characteristics of these regions, while also analyzing the specific implementation mechanisms involved.

Table 12 Heterogeneity analysis results(2)

	Major grain_areas	Non major grain_areas
VARIABLES	lntac	lntac
lnadig	-0.681***	-0.371
	(-3.860)	(-1.500)
lnurb	-0.470	2.595***
	(-1.210)	(3.070)
lnelec	0.085***	0.051***
	(3.950)	(2.820)
lnais	0.213	-0.653
	(0.610)	(-1.160)
lnalp	-0.101***	-0.300***
	(-3.280)	(-4.490)
lnadr	-0.071	0.326***
	(-1.210)	(2.990)
Constant	6.835***	6.877***
	(21.370)	(14.460)
N	132	198
R^2	0.986	0.992

*** p<0.01, ** p<0.05, * p<0.1

The results reveal a significant negative correlation between digital economic and agricultural carbon emissions in major grain production areas at the 1% level, suggesting that digital economy growth effectively mitigates emissions and supports environmental sustainability. In contrast, in non-grain production areas, while a negative relationship persists, it lacks statistical significance. This is likely due to the limited scale of agricultural production, lower digitalization levels, and traditional industry structures, which impede the effective integration of digital technologies and constrain their potential to reduce agricultural carbon emissions.

4.5 Analysis of intermediation effects

The digital economy affects agricultural carbon emissions via multiple channels, such as scale effects, financial impacts, and technological innovation. The empirical research results (Table 13) show that these effects are all statistically significant, highlighting their key role as primary mediating variables in explaining the mechanism.

Studies indicate that it significantly reduces carbon emissions, with a regression coefficient of -0.356, statistically significant at the 5% level. This suggests that the digital economy impacts agricultural carbon emissions on a scale, with information networks and transaction platforms acting as the main mediating factors. These factors substantially lower transaction costs, encouraging small-scale farmers to optimize resource allocation and boost production efficiency. Digital technology fosters the advancement of efficient models like precision agriculture and supply chain collaboration, overcoming the traditional constraints of geography that have long hindered large-scale agricultural development.

Empirical research findings reveal that the regression results for variables (4) and (5) yield an estimated value of -0.372, statistically significant at the 5% level. This implies that digital finance curbs carbon emissions by enhancing financial intermediation mechanisms. Digital finance greatly improves the accessibility of financial services in rural areas due to its inclusive nature. Innovative mobile payment tools, like WeChat Pay, have significantly enhanced the convenience and reach of financial services for farmers.

Empirical analysis (6 and 7) reveals that the regression coefficient for technological innovation is -0.427, significant at the 1% level, demonstrating the crucial role of technological innovation in the emissions reduction process. Digital technology promotes innovation and accelerates information dissemination, facilitating the efficient promotion of modern agricultural technologies. The substantial enhancement in the efficiency of utilizing seeds, pesticides, fertilizers, and irrigation equipment has boosted agricultural productivity, offering vital support for attaining sustainable development objectives.

Table 13 Results of the Mediation Effect Regression Analysis

	Benchmark model	Scale Effects		Financial Effects		Technological Innovation Effects	
	Lntac	Ltr	lntac	lnflb	Lntac	Ptech	lntac
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnadig	-0.527***	58.355***	-0.356**	3.053***	-0.372**	1.344***	-0.427***
	(-3.853)	(6.771)	(-2.460)	(6.971)	(-2.549)	(3.471)	(-3.121)
M			-0.003***		-0.051***		-0.075***
			(-3.212)		(-2.819)		(-3.709)
lnurb	1.070**	179.304***	1.596***	3.522**	1.249***	5.169***	1.457***
	(2.241)	(5.965)	(3.205)	(2.306)	(2.623)	(3.828)	(3.042)
lnelec	0.059***	-1.418*	0.055***	0.042	0.061***	-0.012	0.058***
	(4.843)	(-1.842)	(4.548)	(1.079)	(5.067)	(-0.340)	(4.872)
lnais	-0.443	-25.213	-0.516	1.233	-0.380	-1.432	-0.550
	(-1.229)	(-1.112)	(-1.453)	(1.071)	(-1.065)	(-1.407)	(-1.554)
lnalp	-0.205***	-7.524***	-0.227***	0.504***	-0.180***	0.127	-0.196***
	(-5.792)	(-3.371)	(-6.392)	(4.447)	(-4.965)	(1.266)	(-5.627)
lnadr	0.166**	1.092	0.169**	-0.396	0.146*	-0.658***	0.117
	(2.206)	(0.230)	(2.283)	(-1.644)	(1.952)	(-3.092)	(1.559)
_cons	6.947***	41.712**	7.069***	-0.860	6.903***	-2.544***	6.756***
	(24.827)	(2.368)	(25.420)	(-0.961)	(24.922)	(-3.216)	(24.242)
N	330	330	330	330	330	330	330
R^2	0.475	0.437	0.493	0.708	0.489	0.543	0.498
F	44.308	38.104	40.656	119.076	40.012	58.128	41.590

***p<0.01, **p<0.05, *p<0.10

CHAPTER 5
CONCLISION, POLICY RECOMMENDATIONS AND OUTLOOK

5.1 Conclusion

This study seeks to advance the low-carbon transformation of Chinese agriculture. Using empirical data, it systematically examines the mechanisms by which the development status and spatial distribution of the digital economy affect agricultural carbon emissions. Grounded in the EKC theory, low-carbon economics, green development principles, and technological innovation theory, an integrated framework is developed to examine the inherent links between the digital economy's evolution and agricultural carbon emissions. Comprehensively analyzing the mechanisms of their interactive effects from three perspectives: scale effects, financial support effects, and technological advancement effects. Grounded in the aforementioned theoretical frameworks, empirical analysis the influence, leading to the following key findings:

(1) The study shows that China's digital economy displays a pronounced 'strong east, weak west' spatial distribution pattern, with the eastern region consistently leading and significantly outpacing the central and western regions in development levels. Although the central and western regions have shown strong development potential in recent years, their growth rates are still relatively low compared to those of the eastern region.

(2) The nationwide total agricultural carbon emissions have exhibited a steady downward trend. Regionally, the central area has the highest carbon emissions, followed by the eastern region, while the western region records comparatively lower emissions. At the provincial level, regions with high carbon emissions are mainly found in the core production zones of major grain crops, showing clear spatial distribution patterns.

(3) Empirical research shows that the swift expansion of the digital economy significantly suppresses agricultural carbon emission intensity. This conclusion stays strong even after addressing endogeneity with instrumental variables, incorporating additional control variables, excluding municipal samples, and performing multi-level

robustness tests. Further analysis shows that the emission reduction effects of the digital economy display clear spatial heterogeneity. In economically underdeveloped regions, moderately developed areas, and major grain-producing zones, the emission reduction impacts of the digital economy are especially notable. However, economically developed regions or non-grain-producing areas show no significant impact.

(4) For transmission mechanisms, it has notably reduced agricultural carbon intensity through various channels. These include the optimal allocation of land resources under economies of scale, technological innovations boosting agricultural service efficiency, and financial innovation tools enhancing the inclusive financial service system. In this process, new agricultural operators have played a key role in guiding small-scale farmers to adopt green production methods, effectively reducing the intensity of regional agricultural carbon emissions.

5.2 Policy Recommendations

The swift advancement of the digital economy has infused innovative energy and a bright future into the low-carbon transformation of agriculture. This study performs an in-depth analysis of the development status, underlying mechanisms, and regional differences of the agricultural digital economy based on empirical research. From the perspectives of infrastructure development, technological innovation, regional cooperation, and institutional framework enhancement, policy recommendations are suggested:

(1) Enhance the construction of rural digital infrastructure.

Although the digital economy has improved carbon emission management in agriculture, the sluggish development of rural digital infrastructure still poses a significant limitation. Overcoming this obstacle requires boosting targeted investment, prioritizing infrastructure upgrades in remote regions, and broadening financing options for rural projects to tackle key issues like aging equipment, funding gaps, and operational difficulties. Moreover, it is essential to strive for complete coverage of 5G communication, IoT technology, and gigabit broadband networks in rural regions. Enhance data transmission speeds and service stability ensuring efficient flow and proper allocation of production factors between urban and rural regions. Additionally, we must actively advance the digital and intelligent transformation of agricultural infrastructure, focusing on the research, development, and application of smart irrigation systems, smart grids, satellite remote sensing, Beidou navigation, and smart agricultural machinery to offer strong technological support for the sustainable growth of green agriculture.

(2) Execution of Regional Digital Economy Strategies

Heterogeneity analysis shows that the influence of the digital economy on agricultural carbon emissions is more significant in moderately developed regions, underdeveloped areas, and major grain-producing zones. Owing to substantial variations in agricultural ecological environments across regions, differentiated policy adjustments are crucial. In underdeveloped areas, it is essential to actively arrange focused science outreach and educational initiatives to improve farmers' comprehension of digital technologies and encourage their use in large-scale farming, thus fostering the establishment and growth of low-carbon agricultural practices. Non-major grain-producing areas can harness local resource advantages to develop and promote innovative low-carbon agricultural technologies, utilize the spillover effects of digital economy advancements to further improve emission reduction results, and enhance talent recruitment and retention strategies in underdeveloped regions. This involves enhancing incentive mechanisms and career advancement routes to offer continuous human resource support for green development driven by digital means.

(3) Encourage the Innovation and Application of Digital Technologies in Agricultural Production

Improving the use of digital technologies is vital for reducing carbon emissions in agriculture. During the pre-production phase, technologies like IoT, AI, and blockchain can aid in setting up strong monitoring systems for data collection, transmission, and application, reducing risks and enhancing efficiency and quality. During the production phase, digital upgrades of agricultural machinery and equipment, including precision farming, drone-based pesticide spraying, and intelligent fertilization, can greatly improve production accuracy and sustainability while lowering labor intensity. After production, strong traceability systems need to be established to ensure transparency in food sourcing, enhancing consumer confidence. Moreover, constructing intelligent logistics networks can cut down on post-harvest loss and waste, facilitating the digitalization and environmental sustainability of agricultural product distribution.

(4) Strengthen Institutional Support for Digital Inclusive Finance in Green Agriculture

Building an effective digital inclusive finance system is vital for reducing the financial barriers to agricultural digitization. On the one hand, commercial banks and rural credit cooperatives should be encouraged to create customized digital lending products that provide focused financial assistance. On the other hand, a thorough digital agricultural credit assessment framework and varied credit guarantee mechanisms need to be set up to facilitate financial access. At the same time, regulatory frameworks for digital finance need to be strengthened to reduce potential risks. By building a multi-layered, integrated financial service network, access to financial resources for agricultural producers can be significantly enhanced.

(5) Develop a Coordinated Governance Framework Merging Digital and Carbon Reduction Policies

At the national level, top-level design is essential to align green agricultural development with digital economy strategies and address fragmented policy implementation. It is advisable to integrate responsibilities across agriculture, environment, industry, and finance departments to collaboratively advance the issuance of an "Agricultural Digital Carbon Reduction Action Plan." This plan should encompass systematic policy guidance, standard-setting, and performance assessment. Simultaneously, a governance framework needs to be established, covering carbon labeling for agricultural products, a detailed carbon footprint database, and standardized carbon accounting methods, thereby providing the institutional basis for reaching dual carbon objectives in agriculture.

5.3 OUTLOOK

This study still has several limitations, which merit further exploration:

(1) Data Limitations and Opportunities for Refinement

This research relies primarily on macro-level provincial panel data, without incorporating micro-level household data, which constrains the ability to capture individual heterogeneity. Furthermore, the analysis focuses solely on carbon emissions from crop farming, excluding emissions from other agricultural sub-sectors such as livestock production. Future studies should consider integrating micro-level data, including household surveys, supply chain tracking, or satellite remote sensing, to better understand how farms of different sizes differ in their adoption of digital technologies and low-carbon practices.

(2) Geographical Scope for Further Expansion

This study investigates in the context of provinces. However, it does not account for dynamics at the urban or city-cluster level, which may constrain the depth and precision of the analysis. As urban agglomerations continue to play an increasingly significant role in regional development, future research could focus on city-level investigations to yield more nuanced insights.

(3) Limited Exploration of Alternative Mechanisms

This study does not examine alternative or indirect mechanisms. Future work should delve deeper into these indirect pathways to better understand the multifaceted nature of digital transitions. Such analyses could provide valuable guidance for formulating localized and differentiated policy interventions.

In sum, future research should adopt interdisciplinary perspectives that integrate technological, institutional, spatial, and behavioral factors using diverse methodologies. Doing so will help to advance theoretical understanding and generate empirical evidence that enhances the greening and decarbonization of agriculture.

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