THE IMPACT OF CHINA'S DIGITAL VILLAGE ON AGRICULTURAL GREEN TOTAL FACTOR PRODUCTIVITY

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The research uses panel data from 30 Chinese provinces from 2011 to 2022 and relying on endogenous growth theory, innovation theory, and resource and environmental economics, the study looks at how digital village development affects AGTFP. The EBM-GML model is used to estimate AGTFP, and mediation and heterogeneity analyses are performed to study the reasons behind the transmission. In summary, AGTFP continued to increase over the years, and many provinces achieved their best results in 2018. In particular, Tianjin and Beijing in the eastern coastal regions had the highest AGTFP index values, which were 0.994 and 1.129 respectively. On the other hand, the western region showed more change, as Qinghai Province's AGTFP changed from 0.915 to 1.047. (2) Building digital villages greatly supports AGTFP by encouraging green technological progress (coefficient = 0.105, statistically significant at the 5% level), but it does not influence green technology efficiency. (3) Digital village initiatives are seen to work through agricultural informatization ($p < 0.05$) and rural human capital ($p < 0.05$) to increase AGTFP. It is shown through the regional heterogeneity analysis that eastern provinces (coefficient = 0.151, $p < 0.05$) and southern regions (coefficient = 0.170, $p < 0.01$) experienced a stronger impact from digital village development. In the same way, major agricultural areas benefit from digital village construction, which has a positive effect on AGTFP (coefficient = 0.113, $p < 0.01$). Thus, the study suggests increasing the use of digital technologies in rural areas, updating the way land is transferred, creating combined agricultural information systems, investing in rural education, and adopting local strategies to support sustainable and inclusive growth in agriculture.

Keyword : digital village construction; agricultural green total factor productivity; agricultural informatization; rural human capital; regional heterogeneity

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INTRODUCTION

1.1.Background

There is a clear contrast between how various regions in China have adopted modern farming techniques, given that it is the world's biggest producer of agricultural goods. Regions with the highest incomes have achieved remarkable results in making farming more efficient and using up-to-date methods. In addition, regions that have not developed yet are handling old techniques and have low productivity. Since things are not progressing evenly, it is hard to accomplish both stable food and environmental protection.

Since 2000, China's farming industry has advanced at a very impressive pace. Back then, in 2000, the total value of what farmers produced was 2.49 trillion yuan. The figure rose to 19.85 trillion yuan by the end of 2023, which was an annual growth rate of more than 30%. The average annual increase in grain production was 2.2% as it rose from 462 million to 695 million tons. In the same period, the income that rural households could spend grew a lot—from 2,253 yuan in 2000 to over 21,000 yuan in 2023, which is an increase of almost 40% each year (National Bureau of Statistics of China, 2024).

Still, this growth has led to some serious issues. While the economy has improved greatly, the environmental problems have also become serious, which is making it difficult to maintain sustainable farming practices in China (Xu et al., 2025).

Yet, while the model with large inputs, high consumption, and high yields has helped the agriculture industry to grow fast, it has also resulted in major damage to the environment. The limits of the environment and the strength of farming resources are quickly being reached. The agricultural sector in China now faces the greatest environmental challenge, which is the increased problem of agricultural non-point source pollution (Guo, 2019). This pollution and the decline in farmland quality happen mainly because of using too much plastic mulch, applying too many fertilizers and pesticides, and not properly managing solid waste from farms. These methods seriously reduce the amount and safety of food crops. China's use of fertilizer is much higher than the global average, as it applies 338 kg per hectare compared to 125 kg/ha, and non-point source pollution affects an estimated 130 million hectares of arable land. Since these matters are so urgent, it is vital to farm sustainably, and digitalization in agriculture is an effective answer.

While addressing the 19th National Congress of the CPC in October 2017, General Secretary Xi Jinping introduced the Rural Revitalization Strategy, placing special attention on five main things: improving rural industries, education, culture, the environment, and public governance.

The concept of digital villages came about to help agriculture and rural regions upgrade by using digital tools like information systems and network hands networks in their plans.

At the Fifth Plenary Session in 2020, the central committee encouraged changes in agriculture so sustainability could be improved.

At the 2022 National Congress, it was made clear that handling the environment and improving the growth system will support progress and growth in agriculture.

In the year 2023, "Opinions on Comprehensively Advancing Key Tasks for Rural Revitalization" were issued by the CPC Central Committee and the State Council. Once more, this document topped the list as the chief policy guide for issues surrounding agriculture, rural areas, and farmers.

Although many papers have considered how new technology affects agriculture, such as Huang and Wang (2024); Lu et al. (2025), there is still not much available on the potential boost that digital village initiatives give to Agricultural Green Total Factor Productivity (AGTFP).

It brings forward many important contributions. First, it combines the principles of endogenous growth theory with the idea of digital villages to form a complete analysis. The research uses entropy weighting to assess digital village development because it is an effective and fair method for handling many aspects of the subject. The research also tracks AGTFP over time by using the EBM-GML model, which is one of the most up-to-date efficiency tools and accounts for matters that are not desirable and environmental obstacles. Analyzing data in two ways allows for a better and deeper look at the patterns of sustainable agricultural productivity.

It has also been found that better digital infrastructure in villages is very important for the digital reform of agriculture. It happens by making agricultural information more available and lifting the knowledge of people who live in rural areas. Through the adoption of precise farming, big data collections, and modern monitoring, digital villages make farming more sustainable and help maintain a balanced environment in the long term.

It is thirdly noted that the effectiveness of these digital village strategies varies a lot depending on the area and situation. These findings matter a lot to countries that are implementing digital farming. The study suggests that using local ideas in creating rural development strategies and digital plans could make digital transformation in agriculture very beneficial.

1.2. Research Questions

1. How much does the development of digital villages help to increase AGTFP?
2. How do the effects of digital village construction on AGTFP take place?
3. Is the effect of digital village construction on AGTFP different in different regions because of China's big territory and large differences in economic development, resources, and digital infrastructure?

1.3. Objectives of the Study

1.3.1. Theoretical Innovation and Literature Review

A theoretical model is made to study the link between digital village development and changes in agriculture. By using technological innovation theory, endogenous growth theory, and resource and environmental economics, the framework describes the main ideas explaining how digitalization affects sustainable agriculture. It shows how digital technology supports better farming and explains the reasons behind how digital villages are helping move to green agriculture.

Besides, the study looks at both domestic and international research on digital village projects and AGTFP, describing the existing literature and spotting any gaps. Researchers give special attention to the shortcomings of previous studies regarding the theories, research methods, and evidence they used. From this review, the study points out its unique ideas and stresses how important it is for scholars and practitioners.

1.3.2. Entropy Method Measurement and Analysis of Digital Village Construction

The researcher suggests using a systematic method and developing an aggregate index to assess how well Chinese villages are building in digital village infrastructure. This index uses the method of entropy weighting to give each indicator an objective value depending on how much it varies, for a balanced report based on data. The research analyzes 30 provinces, giving a wide and fair look at digital development all over the country.

In order to see spatially separate realities, the study looks at regions, focusing on the eastern, central, and western areas of China. With this approach, differences in development and the strengths or weaknesses of every region in embracing the digital village plan can be seen.

Besides, it follows the progress of digital village development by comparing various temporal trends at the provincial and regional scales. Analysis over a long time period has shown that digital transformation moves at different paces and levels of success in all areas, revealing how policy and infrastructure choices evolve regularly.

The study puts more emphasis on the changes happening in the digital village index across the different provinces using heat maps. Such tools make it clear that the divide among regions is getting larger, as the central and western parts are much less advanced than the eastern regions.

Combining statistics with an analysis of time and space helps this research give an in-depth explanation of the development of digital villages. This also builds the evidence required to analyze how digital infrastructure helps to make agriculture more sustainable when resources are limited in different settings.

1.3.3. Measurement and Comparison of Agricultural Green Total Factor Productivity

This study builds a way to evaluate green agricultural production efficiency by choosing indicators that represent agricultural inputs, outputs, and the challenges related to the environment, especially undesirable outputs. The model computes the AGTFP index and identifies the recent trends in green production efficiency from 2011 to 2022. Besides, the AGTFP is broken down to find out how much technological progress and changes in efficiency influence the overall output. By exploring these two factors, the study finds out how increased efficiency in agricultural green production happens.

1.3.4. The Impact Mechanism of Digital Village Construction on Agricultural Green Total Factor Productivity

The study looks into the link between digital development in villages and AGTFP by using panel data econometric methods. In the first step, fixed effects models are applied to deal with differences across provinces and find out the immediate influence of digital village construction on AGTFP. This makes it certain that lasting regional influences do not change the outcomes.

To discover the main reasons for this connection, AGTFP is divided into two important parts: technological progress and technical efficiency. After that, the analysis checks how digital village projects influence farm animal health, farm business access, and farmer training independently to give a clearer picture of how the digital transformation of agriculture works.

They also establish a mediation model to find out how digital village construction leads to better AGTFP. Especially, it studies two intermediary factors: the advancement of agriculture with technology and rural workers’ knowledge and skills. Such variables make it easier to distribute knowledge, help farmers decide on the best actions, and equip them with improved skills in agriculture.

The mediation analysis makes it possible for researchers to see the impact of each pathway and judge the importance of every effect. This way, it becomes clear to what extent digital village projects have affected progress in AGTFP through giving people access to more information and better skills. All in all, the study confirms that digital infrastructure boosts the sustainable development of farming.

1.3.5. Regional Heterogeneity Analysis

The study looks into the different ways in which digital village construction affects AGTFP in China's various regions. The study compares the effects of digital village development in different regions using various ways of grouping regions. It is hoped that this study will find out the differences in the mechanisms behind digital villages and increased green farming productivity across different regions. The research aims to guide regional strategies by providing a scientific reason for creating digital village policies that fit the area. In general, the study proposes various ways to improve green farming in different regions, support collective development across regions, and push for ecological changes and upgrades in agriculture.

1.4. Significance of the Study

1.4.1. Theoretical Significance

(1) Strengthening the basis of Digital Villages and Green Agricultural Development

It is important to study further how digital technology helps improve how efficiently agriculture is produced. This research explores how digital technology affects agriculture. By clearly showing the reasoning behind digital village development and its role in green agricultural change, the research enriches the conceptual basis of the digital economy's influence on sustainable agriculture, giving a solid base for upcoming advances in agricultural technology.

(2) Developing a better method to study the effect of digital villages.

A solid framework is proposed in this study that links digital village construction, agricultural informatization, human capital, and green production efficiency. It proves that digital tools play a role in improving how farms produce their crops and food. Using multiple approaches and analysis, this field of study explores agricultural economics theories and better explains how digital technologies improve how farming is done.

(3) Increasing the Range of Ideas in Research about Digital Villages and Green Farms

Researchers usually discuss digital village development and AGTFP separately, offering little connection between the two topics. On top of that, digital villages are still a new idea and challenging to measure. Our analysis counts among the initial efforts to study the link between digital villages and AGTFP. Combining different methods, it gives both explanatory and numerical insights into the effect of digital villages on the environmentally friendly production of crops, adding greatly to the available research on digital agriculture and sustainability.

1.4.2. Practical Significance

(1) The creation of a Multi-purpose Evaluation Framework for Developing Digital Villages

An organized and multi-faceted way to review the digital village progress is presented in this study. The system suggested in this solution includes digital infrastructure, modernizing agriculture, and digital progress in rural communities. This framework fixes the issue of disagreement among researchers on how to accurately monitor the progress of digital villages by using standard rates and various data. The design of the paper supports the methodology used for research and also acts as a useful reference point for scholars and policymakers in this area in the future.

(2) improving knowledge about digital tools' contribution to sustainable farming

This research looks into how digital village initiatives influence AGTFP by means of scientifically proven methods. Learning from the studies, it is obvious that smart farming, data analytics, and rural information networks are helping agriculture become more eco-friendly and larger amounts of food are being produced. In this way, the study shares new ideas and steps that can help make agriculture more sustainable and successful. Such results are especially important for guiding changes in the agricultural sector using technology.

(3) It is also important to support theories explaining how different regions are affected by digital development.

Going deeper into the topic, the information found explains why how digital village construction affects AGTFP can vary from one region to another. It explains that factors from the region, for example, the availability of resources, advanced technology, and policy implementation abilities, affect digitalization's impact on agriculture productivity. The study demonstrates the need for different strategies in different regions by pointing out the problems and patterns. According to this approach, it is important to support communities' leadership and design digital village models that fit their community and growth stage.

1.4.3. Method Innovation

(1) New approaches to conducting research

A new approach is used in this study by building a digital village development index with the entropy method and estimating Agricultural Green Total Factor Productivity (AGTFP) with the EBM-GML model. In addition, it develops a method that uses mediation analysis and studies differences among regions. The use of these new approaches makes the research more scientific and gives future researchers important references for similar studies.

(2) Examining Innovation with Several Different Dimensions

The study looks at how digital village construction influences the efficiency of agricultural green production in many different ways. It investigates the ways technology and human resources in agriculture help, and also decomposes AGTFP into two measures: green technical efficiency and green technological progress. The approach used helps us know more about how digital villages impact the shift toward sustainable agriculture.

By discussing problems in modern green agriculture from a digital village standpoint, this study fills important holes in what is already known. It explains step-by-step and from different angles the impact of the digital economy on sustainable changes in agriculture. By using digital technology, production efficiency, and regional differences, the research creates an interdisciplinary and multi-level framework that gives theoretical and practical help for advancing innovation in agricultural economics.

1.5. Scope of the study

This research focuses on various aspects like time, space, and subjects to analyze the relationship between the two. Defining the research boundaries makes the study more scientifically sound and guarantees that the findings reflect the whole population.

Table 1 The samples of 30 provinces selected

Eastern	Centra	Western
Beijing	Shanxi	Inner Mongolia
Tianjin	Jilin	Chongqing
Hebei	Heilongjiang	Qinghai
Liaoning	Anhui	Gaisu
Shanghai	Jiangxi	Shaanxi
Jiangsu	Henan	Ningxia
Zhejiang	Hubei	Yunan
Fujian	Hunan	Guizhou
Shandong		Sichuan
Guangdong		Xinjiang
Guangxi		
Hainan		

1.5.1. Time Range

Since not all data is available and digital transformation is happening at different rates, this research uses timeframes of different sizes. The period from 2011 to 2022 is included in the measurement of AGTFP, with 2011 as the base year, so the changes in green agricultural efficiency can be observed. The index for digital village construction uses data from 2012 to 2022, since this was a time when digital technologies were rapidly becoming part of rural development.

1.5.2. Spatial Scope

The study covers 30 administrative regions at the provincial level in China. Because there is not enough or complete data for the Tibet Autonomous Region, it is omitted from the analysis. There are study areas in each of the three main regions, which helps ensure the study represents China well geographically. Because of this, we can examine the diverse effects of digital village construction on AGTFP in different regions of the country. The provinces part of the study are shown in Table 1.

1.5.3. Research Objects

The key objects of this study are explained below.

(1) The analysis of Digital Village Construction is done through digital infrastructure, agricultural digitalization, and rural digitalization.

(2) AGTFP is assessed using the EBM-GML model and then split into green technical efficiency and green technological progress.

(3) The role of agricultural informatization and rural human capital in the process through which GDP affects rural areas.

1.5.4. Research limitations

The study reveals that there were some issues in the research process, mainly in these two areas:

(1) Problems with access to data

Because it is difficult to get detailed information on agriculture at the micro level, some errors may appear in measuring green production efficiency. Since these limitations exist, empirical results may not always be accurate, which may influence the clarity of the study's conclusions.

(2) There are wide differences between regions.

Because data quality and development can differ between regions, the study's results may be hard to generalize. The results may not be useful everywhere because the approach was not the same in every region.

However, the use of a thorough research approach and solid framework helps this study to deliver helpful ideas and results about digital village development and the advancement of sustainable farming.

1.6. Definition of Terms

(1) Rural Revitalization: Giving emphasis to Rural Revitalization as a key concern for the nation.

Rural revitalization is now a main focus in China's future plans for growth. During the 19th meeting of the Communist Party of China (CPC) Central Committee (2017), held on October 18, General Secretary Xi Jinping set out this strategic plan. In the speech, he pointed out that stable and healthy farm production, good living conditions for people in communities, and a secure life for farmers are essential for the country's economy and development. It was noted that dealing with rural development should consistently be a main priority for the leadership at every level.

Thus, boosting rural areas is now a major part of China's national strategy. Its intention is to bring change to rural regions through major changes, better facilities, improved public services, and productive farming, so there is no gap in development between urban and rural areas.

Interest from the public in Amir Foundation's work has not declined. Based on the 2022 National Two Sessions Survey, people in China still pay close attention and support for "rural revitalization."

In order to realize this ambitious goal, China has put together an extensive set of policies. It covers investments, handling paperwork, and structures that work to confirm the strategy is both carried out successfully and fits all the various needs of rural communities in different neighborhoods. All these initiatives are intended to turn rural China into a more modern, comfortable, and solid area of the country.

(2) digital village

The Central Committee of the Cyberspace Administration of China and the State Council released the Digital Village Development Strategy Outline in Central Committee of the Communist Party of China and State Council (2019), briefly discerning and outlining the fundamental framework for digital villages. In the document, it is noted that a digital village means bringing networking, informatization, and different digital platforms into all parts of rural life. It helps the agricultural sector and rural authorities modernize as it boosts the digital skills of farmers.

Table 2 Major digital village policies issued by the central government since 2018

Year	Policy	Key Content
2018	The 2018 Central Committee's No. 1 document	Made overall arrangements for prioritizing the development of agriculture and rural areas and comprehensively promoting rural revitalization in the new development stage, and pointed out the direction for the work of "agriculture, rural areas, and farmers."
2018	Opinions of the Central Committee of the Communist Party of China and the State Council on Implementing the Rural Revitalization Strategy	Clearly proposed to implement the digital village strategy
2019	Digital Village Development Strategy Outline."	Clearly states the development of digital villages
2020	Opinions on Adjusting and Improving the Scope of Use of Land Transfer Revenue to Prioritize Support for Rural Revitalization	Clarify the requirements for reforming the rural land transfer system and specifically plan to use the scope of rural land transfer income.
2021	Opinions of the Central Committee of the Communist Party of China and the State Council on Comprehensively Promoting Rural Revitalization and Accelerating Agricultural and Rural Modernization"	Consolidate and improve the basic rural management system, deepen the supply-side structural reform of agriculture, and place rural construction in an essential position in the socialist modernization drive.
2021	Establish a department directly under the State Council for rural revitalization.	The National Rural Revitalization Administration, an agency directly under the State Council, was established.
2021	Opinions on Accelerating the Revitalization of Rural Talents	Plan the implementation path of talent revitalization in the rural revitalization strategy.
2021	Rural Revitalization Promotion Law of the People's Republic of China	China's first law named after "rural revitalization"
2022	Rural Construction Action Implementation Plan"	The road map for rural construction actions has been clarified to ensure substantial progress in rural construction by 2025.
2023	Opinions of the Central Committee of the Communist Party of China and the State Council on Comprehensively Promoting Key Works of Rural Revitalization in 2023	Planning the development of rural revitalization in 2023

The approach sets digital villages as an important factor in rural renewal and a vital part of the aim to make China digital. Relying on digital tools and innovations in village development is meant to shrink the difference in technology between urban and rural regions, support fairer economies, and increase rural resistance to challenges.

The outline breaks down the approach into four stages for carrying out the project transformation. With these stages, China expects to accomplish important achievements like reaching major breakthroughs by 2035 and building full digital villages in the middle of the 21st century.

The initiative mainly relies on 5G networks, cloud computing, big data, and artificial intelligence to change how rural development takes place. With the start of the rural revitalization strategy, the central government has introduced special policies to increase and improve digital activities in rural communities. It can be found a detailed list of major national activities in Table 2 that have helped the steady progress of Digital Village across the country.

(3) Productivity in Agriculture

When the Cobb–Douglas (C-D) production function was introduced, it led to linking productivity studies with research on economic growth, and this eventually resulted in the idea of Total Factor Productivity (TFP). TFP is used to compare total output with combined inputs to judge overall productivity when there are multiple things being produced and used in the process. It measures efficiency of all inputs and allows both horizontal and vertical comparisons of production efficiency.

Tinbergen (1952) introduced TFP to the field by using the C-D production function to determine productivity levels in the United Kingdom and the United States. Afterward, Solow (1957) of the United States created the “Solow residual” method that calculates the difference between economic growth and growth of inputs, attributing the remaining growth to technological progress. Yet, according to Jorgenson and Griliches (1967), Solow’s method was too simplistic and restricted because it attributed everything that was unexplained to productivity.

To overcome some of these problems, Charnes, Cooper, and Rhodes (1978) presented Data Envelopment Analysis (DEA), which does not need a certain production function or distribution of inefficiency. Today, DEA is recognized and used as a standard for reviewing how efficient a company is. Eventually, Caves et al. (1982) created the Malmquist Productivity Index, which works with panel data to assess TFP without using prices, adding another useful tool to productivity measurement.

CHAPTER 2
THEORETICAL BASIS AND RESEARCH HYPOTHESIS

2.1. Theoretical Basis

2.1.1. Endogenous Growth Theory

According to Schumpeter (1976), innovation in technology is the main factor that stimulates economic growth, as it involves new ideas from entrepreneurs and the demolition of outdated practices. Romer (1990) went on to state that technological progress and the growth of knowledge help sustain economic growth in the long run.

According to endogenous growth theory, better technology and human education come from within a society and boost productivity. This theory gives a strong base for explaining how innovation and the development of skills can help boost farming output. In this way, building digital villages supports an increase in agricultural productivity by developing digital infrastructure, speeding up digital agriculture, and promoting a wider digital change in rural regions.

2.1.2. Technological Innovation Theory

Schumpeter (1976) believed that the main reason for economic growth is creative destruction, and this is clearly seen in the development of digital villages. Digital technology has disrupted the usual ways of farming and running businesses, resulting in a major shift in how agriculture is done.

Following this approach, Romer's endogenous growth theory points out that new technologies keep boosting economic growth and that building knowledge is essential for innovation. This approach points out that digital technology, sharing knowledge, and improving people's skills help improve AGTFP in digital villages.

Here, technology innovation also means reorganizing existing systems, as well as changing institutions, organizations, and how resources are used. Digital villages have greatly helped in improving agriculture by introducing digital platforms, spreading new technologies, and developing the digital abilities of rural areas.

2.1.3. Resource and Environmental Economics Theory

Resource and environmental economics theory is important for this research since it explains the key factors influencing AGTFP. The main ideas of this theory were presented by Dasgupta and Heal (1979), making the connection between resource shortages, economic expansion, and the earth's ability to support them. Dubey and Lal (2009) extended research by focusing on the carbon emissions and sustainability related to farming, pointing out how economic activities, natural resources, and the environment affect one another.

Traditional economic models usually assume that water and air are limitless and free, while failing to consider the environmental effects of using them. As a result, the environment becomes damaged, resources are less useful, and ecosystems cannot restore themselves as well.

Looking at digital village development, resource and environmental economics introduces a new way to evaluate the sustainability of agriculture. Since agriculture is closely linked to the environment, digital technologies can provide creative answers to the problems caused by this connection. The use of precision agriculture, real-time monitoring of the environment, and smart ways to use resources helps balance the input used and reduces damage to the environment, which leads to a more sustainable way of developing agriculture.

2.1.4. Human Capital Theory

Human capital theory is an important basis for understanding the innovation processes in digital village construction. Schultz (1961) Investment in Human Capital was the first to clearly explain how education, skills, and knowledge play a key role in economic development. Schultz considered human capital to be a main resource in production that can be strengthened by providing continued education and training. Nowadays, digital transformation means that attention is given to what people know and can do, rather than simply counting their hours at work.

Lucas Jr (1988) also made clear that human capital theory helps individuals work better and, at the same time, brings about benefits that add to the overall growth of productivity. This view is especially important in digital transformation, since people are seen as playing a key role in using and gaining from new technology.

AGTFP research reveals that human capital is an essential factor inside the process that leads to the growth of digital villages. Programs that teach rural people about technology, train farmers in new agriculture methods, and encourage innovation have greatly increased how efficiently agriculture is done. As a result, digital villages create an important base to boost rural people's skills, encourage new technology, spread knowledge, and enhance farm productivity.

2.1.5. Institutional Innovation Theory

This theory gives useful explanations for the changes occurring in the structure of digital villages. Starting from the key work Institutions of North (1990), Institutional Change and Economic Performance, this theory focuses on the main role of institutional change in guiding the economy. North explains that institutions include both set rules and unwritten customs that direct people's actions, which affects the way people in the economy are motivated and behave. Besides adapting equipment and methods, institutional innovation in agriculture covers major changes in how organizations are structured, how they are managed, and how resources are handled.

Institutional innovation in digital village development includes creating systems for keeping digital infrastructure available, promoting changes in organizations to help with digital farming, and forming an environment that supports the uptake of digital technology. The use of digital technologies in agriculture is made better by these changes, which in turn help transform methods of production and increase the efficiency of the whole system.

2.2. Research Hypotheses

The theory of economics is concerned with the relationship between economic development and the environment as it is affected by natural resource availability. It gives a framework for analyzing AGTFP with regard to how much resources and the environment are considered. When it comes to digital village construction, this framework clarifies that digital technologies help in making agriculture more sustainable by better using resources and reducing any negative effects on the environment.

2.2.1. Direct Effects of Digital Village Construction on Agricultural Green Total Factor Productivity

2.2.1.1. Technology Efficiency Effect

Liu et al. (2020) found that with IoT and other digital technologies, Agriculture 4.0 makes it possible to practice precision agriculture, which helps to save resources. In addition, using both IoT and artificial intelligence can support the environment and keep agriculture productive. All these effects together help digital village construction boost innovation and drive changes in farming.

2.2.1.2. Technology Progress Effect

Building digital villages is helping to improve farming technology by setting up related digital infrastructure and platforms. The way technology progresses is mainly through several important mechanisms. To begin with, better digital infrastructure is needed to power green improvements in farming. The use of digital platforms helps to reduce costs for introducing new green technologies, which makes them spread more quickly to different areas. In addition, thanks to digital tools, farmers can use practices that are good for the environment. Besides, building digital platforms is useful for enhancing the system for distributing agricultural technology. Ensuring the whole value chain is connected, these platforms increase the quality and efficiency of technology sharing. They also help people in agriculture share knowledge and work together, which improves the industry’s ability to innovate.

So we propose the following:

H1: Digital villages have a positive effect (positive correlation) on Agricultural Green Total Factor Productivity (AGTFP).

H1a: Digital village construction helps increase the efficiency of agricultural green technology.

H1b: Constructing the digital village encourages growth in agricultural green technology.

Figure 1 shows a proposed framework that explains the link between digital village building and AGTFP. The framework shows the main effects as well as the indirect ones that happen through important mechanisms.

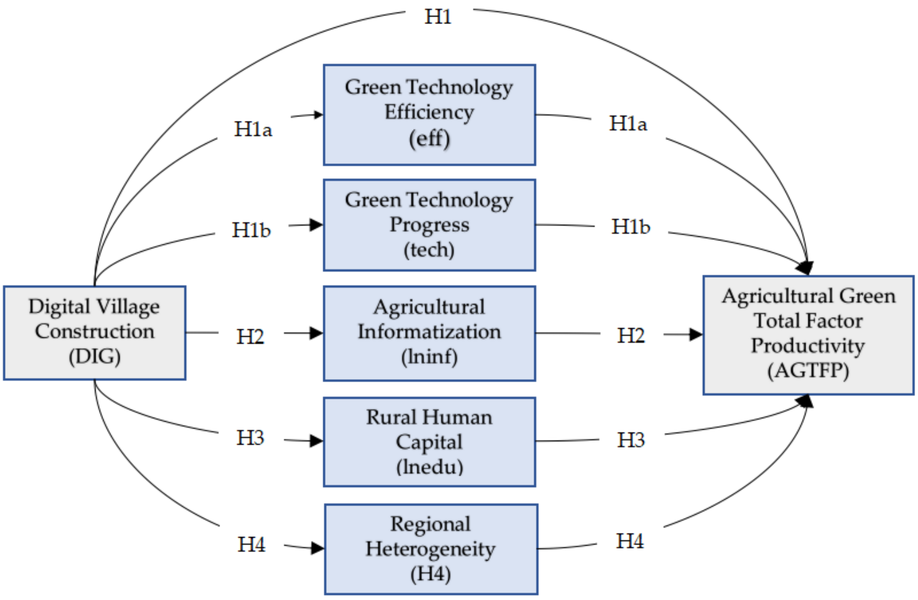

Figure 1 Theoretical Framework.

2.2.2. Mediating Effect Analysis

2.2.2.1. Mediating Role of Agricultural Informatization

Endogenous growth theory and technological innovation theory show that economic growth is mainly driven by the steady buildup of technology and knowledge (Nelson & Winter, 1985; Romer, 1990). This theory explains that digital village construction helps increase AGTFP mainly due to agricultural informatization, which acts as a link between the two.

In the agricultural field, informatization helps add digital tools to farming, which improves both how efficiently and sustainably things are produced. For farmers, agricultural informatization means they get accurate support and constant updates from digital agricultural platforms. This results in using less of the earth's resources and having better environmental effects from farming. Because of informatization, online platforms for agricultural products are being developed, giving green products more ways to reach buyers. Consequently, farmers are motivated to use eco-friendly ways of farming, which helps to enhance AGTFP.

H2: Agricultural informatization greatly helps explain the impact of digital village construction on Agricultural Green Total Factor Productivity (AGTFP).

2.2.2.2. Mediating Role of Rural Human Capital

Digital villages are important in increasing the digital skills of people living in rural areas. Based on Lucas Jr (1988) ‘s theory, here the advancement of technology and the growth of human capital go hand in hand. In digital villages, spillover effects matter a lot since people share knowledge through both planned programs and casual interactions with others.

Studies have proven that digital knowledge and skills affect farmers' readiness to adopt environmentally safe practices. In 2025, Gong et al. (2025) reported that having stronger digital human capital encourages farmers to participate in green agriculture, and informal learning platforms play a bigger role than formal ones. It has been shown that informal learning platforms help people adopt practices that are good for the environment. This information agrees with Lucas's (1988) idea that human capital helps people become more productive and also supports the growth of technology in the community.

H3: The development of digital villages has a strong effect on AGTFP because of rural human capital.

2.2.2.3. Regional Heterogeneity in Digital Transformation Effects

Different digital conditions, economies, and support in different regions create unequal results of digital village construction on Agricultural Green Total Factor Productivity (AGTFP) in China's eastern, central, and western areas. The positive influence of AGTFP is more noticeable in the eastern region because it is well-equipped with modern digital technology and has a strong economy. Despite being slightly behind the east in overall development, the central region has progressed a lot by investing in the latest technology for farming and in rural people's education. Wang et al. (2024) point out, in spite of infrastructure and resource issues, the western region can improve by using new technology and adopting it in a step-by-step manner. Evidence from research proves that strategies should be adjusted for each region to maximize the success of digital village projects.

H4: The digital village construction has a greater effect on AGTFP in places with better infrastructure and a developed economy.

CHAPTER 3
METHODOLOGY

3.1. Variable Description

3.1.1. Core Explanatory Variable

Based on the concepts in the works by Li et al. (2022) and Wolfert et al. (2017), this research designs a multi-dimensional assessment model for digital village development (Indig). Three main aspects make up the model: the digital infrastructure for business, how digitalized agriculture is, and the steps forward in rural digital transformation. All of these aspects together describe how much digital technology is used in remote areas.

You can find here dependable information on how access to internet, finances, and e-commerce varies around the world.

Vehicle assignment values are weighted using the entropy method because this helps to reduce bias by human choice. This way, it shows how much measurements differ amongst various regions, which allows for effective calculation of regional digital development scores. As a result of the index, provinces can be fairly compared and this forms the base for additional research on digitalization and its impact on agriculture.

3.1.2. Explained Variables

In conducting this study, the main dependent measure is AGTFP, which reflects how sustainable and efficient agriculture is in its production. Guo (2019) developed the AGTFP method by applying an improved version of the EBM-GML (Epsilon-Based Measure–Global Malmquist–Luenberger) approach. Because of this advanced style, the assessment considers useful products from farming such as food and harmful ones such as detrimental conditions for the environment, offering a better and greener idea of productivity.

According to what Huang et al. (2022) propose, AGTFP measures technical efficiency change (Effch) and technological progress (Tech) independently. It shows the increase in using resources productively within farming, whether land, labor, or capital.

But the Tech part chiefly deals with anything that uses technology to help farms, using eco-friendly inputs, practicing precision farming, and producing less carbon in the process. Thanks to this decomposition, the reasons behind changes in AGTFP are easier to understand and it becomes simpler to recommend policies to promote a sustainable transformation in agriculture.

3.1.3. Control Variables

To mitigate the potential impact of omitted variable bias in the econometric analysis, this study incorporates four theoretically grounded control variables, each selected based on existing literature and empirical relevance.

First, agricultural structure (denoted as Instr) is measured by the ratio of the grain crop cultivation area to the total area of cultivated land. This variable captures regional variations in cropping patterns and specialization, which can influence agricultural productivity outcomes. Its inclusion follows the rationale outlined by Ma et al. (2018), who emphasized the importance of crop composition in agricultural performance.

Second, agricultural fiscal support (Infisc) is represented by the share of government expenditure allocated to agriculture, relative to total fiscal spending. This indicator serves as a proxy for the level of institutional and financial commitment to the agricultural sector, reflecting how public investment shapes production capacity and green development. The measure is consistent with the work of Wang et al. (2024), who linked fiscal inputs to agricultural modernization outcomes.

Third, the agricultural production price index (Inapi) is calculated as the natural logarithm of a weighted index comparing current agricultural prices to those in a base reference year. This control accounts for the influence of price fluctuations on production incentives and resource allocation, particularly in relation to input use and output decisions.

Finally, effective irrigation rate (Ineir) is defined as the proportion of farmland equipped with functional and efficient irrigation systems. This variable reflects the level of agricultural infrastructure and water resource management, both of which are critical for maintaining productivity and environmental sustainability. The inclusion of this measure draws upon the findings of Zhang et al. (2023), who highlighted regional disparities in irrigation as a determinant of agricultural efficiency.

Together, these control variables help ensure that the regression model accurately isolates the effect of digital village construction on AGTFP by accounting for key structural, institutional, market, and infrastructure-related influences.

3.1.4. Mediating Variables

This study incorporates two mediating variables to investigate the mechanisms through which digital village construction influences Agricultural Green Total Factor Productivity (AGTFP). The first, Agricultural Informatization (Ininf), is measured by the ratio of postal and telecommunications business volume to regional GDP. This indicator reflects the role of digital information infrastructure in optimizing resource allocation and enhancing production efficiency, as emphasized in the theoretical framework of evolutionary economics (Nelson & Winter, 1985) and supported by empirical studies (Zhang et al., 2023).

Rural Human Capital (Inedu) is quantified through weighted average years of schooling in rural areas, calculated as:

The formula adds the weighted total for each education level and divides the sum by the total number of rural residents aged 6 and above.

(Number of People with No Formal Education × 1 + Number with Primary School Education × 6 + Number with Junior Middle School Education × 9 + Number with Senior Middle School or Technical Secondary Education × 12 + Number with College or Higher Education × 16)/Total Rural Population Aged 6 and Above.

Human capital theory is the basis for this approach, which shows the variations in rural schooling levels (Lucas Jr, 1988). Studies on the subject indicate that spending on education greatly helps people use new technologies and boosts their ability to innovate (Li et al., 2022) . All the descriptive statistics for the variables are shown in Table 3.

Table 3 Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
AGTFP	330	1.015	0.025	0.915	1.237
eff	330	0.996	0.029	0.809	1.191
tech	330	1.021	0.036	0.859	1.282
lnedu	330	2.176	0.070	1.924	2.390
lninf	330	0.063	0.082	0.015	1.256
lndig	330	0.123	0.073	0.023	0.493
lnstr	330	0.497	0.087	0.304	0.678
lnfisc	330	0.108	0.030	0.040	0.186
lnapi	330	4.642	0.045	4.483	4.782
lneir	330	0.360	0.117	0.159	0.804

3.2. Model Construction

3.2.1. Fixed Effect Model Construction

To examine the connection between digital village development and AGTFP, a panel regression model was set up that covered both individual and time fixed effects. First, an analysis was done using an individual fixed effects model, and then time fixed effects were introduced to form a two-way fixed effects model. The model uses AGTFP for agricultural green total factor productivity and digital village to show how digital village development is in province i for year$t$.X_{it} means the vector of control variables, α is the intercept, δ_{it}, θ_{it} explain the effects of each province and each year, and ε_{it} stands for the random error term. When the coefficient β is statistically significant and positive, it implies that development in digital villages is helpful for AGTFP.

$$\begin{aligned} AGTFP_{it} &= \alpha_1 + \beta_1 DIG_{it} + \lambda_1 X_{it} + \delta_{it} + \varepsilon_{it} \\ AGTFP_{it} &= \alpha_2 + \beta_2 D_{it} + \lambda_2 X_{it} + \delta_{it} + \theta_{it} + \varepsilon_{it} \end{aligned} \quad (1)$$

Fixed-effects models are considered appropriate thanks to the results of several statistical tests. The Hausman test delivers a value of $\chi^2 = 20.796$ ($p < 0.01$), which means that random effects are not appropriate and the null hypothesis must be rejected. Moreover, the F-test ($F = 20.796$, $p < 0.001$) shows that there are significant differences among individuals, and the Lagrange Multiplier (LM) test ($LM = 20.796$, $p < 0.001$) proves that there are also panel effects. All in all, the test findings support the use of a fixed-effects model for the analysis in this study.

3.2.2. Mediating Effect Model

This study includes two middle variables—agricultural informatization and rural human capital level—to investigate the ways in which digital village construction helps AGTFP. For this reason, the following regression models are made to study the mediating effects in this framework.

$$AGTFP_{it} = \alpha_0 + \alpha_1 DIG_{it} + \alpha_2 X_{it} + \varepsilon_{it} \quad (2)$$

$$M_{it} = b_0 + b_1 DIG_{it} + b_2 X_{it} + \varepsilon_{it} \quad (3)$$

$$AGTFP_{it} = c_0 + c_1 DIG_{it} + c_2 M_{it} + c_3 X_{it} + \varepsilon_{it} \quad (4)$$

Here, M includes two mediators, which are agricultural informatization and rural human capital level. Both of them function as intermediary ways that digital village construction affects AGTFP.

3.3. Measurement of Digital Village

3.3.1. Index System Construction and Data Sources

Since there is not a common way to assess digital village construction in existing research, this study uses the models of Li et al. (2022) and Wolfert et al. (2017) to create a complete index system. Three major elements are part of the index: digital infrastructure, digital farming, and rural areas. The system joins ideas from theories with what can be used in practice, making data easy to collect and ensuring it is representative.

The entropy method is used to gauge digital village development, in line with the traditional ways of measuring digitalization in rural areas (Tang & Chen, 2022). The weights assigned to indicators are chosen based on how much they differ, making the comparisons between regions more accurate and less open to subjective opinions.

Because Tibet's data was incomplete and unclear, it was decided not to include that region in this study using data from 30 other provinces, autonomous regions, and municipalities. Data collected for the analysis comes from many well-known and detailed sources. Important data for this study is taken from the China Statistical Yearbook, Provincial Statistical Yearbooks of China (covering 2013 to 2023), the China Taobao Village Research Report by the Alibaba Research Institute (2013 to 2023) and the Peking University Digital Inclusive Finance Index (2013 to 2023).

This study deals with missing data by imputing it using techniques called linear interpolation and moving average smoothing. These processes support the stability and availability of the data, guaranteeing better and dependable economic analysis.

A multidimensional evaluation system was established to look at the degree of digital village development, based on three main aspects, as shown in Table 4.

The Digital Infrastructure Environment ($X_1 - X_4$) is about assessing the basics for digital growth in rural areas, which include agricultural input (X_1), the state of digital infrastructure (X_2), the level of rural logistics (X_3), and digital financial services (X_4).

Table 4 Digital Village construction indicator system and reference source.

Indicator Category	Variable Name	Variable Description	Reference Sources
Digital Infrastructure Environment	Agricultural financial investment ($X1$)	Balance of agricultural loans	(Wang, Wu et al. 2024)
	Digital base level (X2)	Proportion of Taobao villages in administrative villages	(Li, Singh Chandel et al. 2022)
	Rural circulation facilities (X3)	Length of rural delivery routes	(Wolfert et al., 2017)
	Digital Financial Services (X4)	Digital Financial Services	(Zhang et al. 2025)
Agricultural Digitalization	Digital transaction level (X5)	E-commerce retail sales and purchases	(Zhu & Chen, 2023)
	Online payment level (X6)	Rural Digital Financial Inclusion Index	(Wang, Wu et al. 2024)
	Rural residents' communication expenditure (X7)	Proportion of transportation and communication expenditure	(Li, Singh Chandel et al. 2022)
	Agricultural Fiscal Expenditure (X8)	Fiscal Expenditure on Agriculture, Forestry, and Water	(Ma, Renwick et al. 2018)
Rural Digitalization	Rural Internet penetration (X9)	Number of Internet users per regional population	(Liu, Ma et al. 2020)
	Environmental Monitoring Stations (X10)	Number of agricultural meteorological stations	(Zhu & Chen, 2023)
	Smartphone penetration (X11)	Number of mobile phones per rural household	(Wang, Wu et al. 2024)
	Rural Electricity Consumption (X12)	Rural Electricity Consumption per Capita	(Ma, Renwick et al. 2018)

Agricultural Digitalization ($X_5 - X_8$) means how much agriculture relies on digital technologies in its activities. The factors are the amount of online transactions (X_5), the level of internet payments (X_6), how much rural residents spend on communication (X_7), and government spending on agricultural finances (X_8).

This area ($X_9 - X_{12}$) focuses on how many people and businesses in rural communities use digital technologies. Some of the indicators are the Internet penetration rate (X_9), how many agrometeorological monitoring stations there are (X_{10}), the rate of smartphone use (X_{11}), and electricity used per person in rural areas (X_{12}).

This indicator system is built according to three main principles: it is scientific, it represents diverse data, and the data is easily accessible. The National Bureau of Statistics and the China Statistical Yearbook are the most reliable sources used for data collection, which guarantees the accuracy and consistency of the results in various regions.

3.3.2. Research Methods

There is no common or standard way for researchers to measure digital village development at present. Therefore, this research uses entropy analysis as its key tool to discover the mechanisms behind digital village construction with a more scientific approach.

The entropy method applies information theory to assign weights to indicators depending on how much their information entropy varies. The method's main strength is that it shows how every indicator's effect is measured in comparison to the entire system, using its inherent spread in data. Unlike other ways of weighting, the entropy method is known for its objectivity and clear structure. When an indicator has a higher entropy, it means it carries more information and can be used to better show its importance.

The method was chosen for three important reasons. First, the entropy method ensures that weighting is not influenced much by people's opinions. Second, using this approach, one can easily manage complex and multidimensional indicator systems, just as in the case of digital village construction. Also, because the boundaries of digital village concepts are not clear and keep changing, the entropy method allows for a clear and measurable approach to analysis. Unlike the AHP and Delphi techniques, the entropy method is better at analyzing numbers and clearly explains how every indicator helps in building the digital village development framework.

1.Standardize each indicator. Because the selected indicators have a positive impact on the system, the treatment of negative indicators is not considered:

$$X'_{dij} = \frac{X_{dij} - min(X_{dj})}{max(X_{dj}) - min(X_{dj})} \tag{5}$$

2.Calculate the proportion of indicator j in province i

$$P_{dij} = \frac{X'_{dij}}{\sum_{d=1}^{a} \sum_{i=1}^{b} X'_{dij}} \tag{6}$$

3.Determine the entropy of indicator j

$$E_J = -k \sum_{d=1}^{a} \sum_{i=1}^{b} \left[P_{dij} \ln\left(P_{dij}\right)\right], \text{ in } k = \frac{1}{\ln(ab)} \tag{7}$$

4.Calculate the coefficient of difference of indicator j

$$G_J == 1 - \mathrm{E}_j \tag{8}$$

5.Calculate the weight of indicator j

$$W_j = \frac{G_j}{\sum_{j=1}^{c} G_j} \tag{9}$$

6.Calculate the development index of province i in different years

$$Z_{di} = \sum_{j=1}^{n} \left(W_j X'_{dij}\right) \tag{10}$$

3.3.3. Digital Village Measurement Results

3.3.3.1. Time Series Analysis of Measurement Results

It is necessary to evaluate the progress of digital village development when considering its effect on AGTFP. The research examines the development of 30 provinces by using a framework that has three key dimensions: digital infrastructure environment, agriculture going digital, and rural digitalization. Using the entropy method for assigning weights helps the evaluation system highlight how different provinces are in their digital village development. The regional difference in digital progress is clear from Table 5, which shows the average scores and rankings of digital village development for every province from 2012 to 2022.

Differences in digital advancement among Chinese regions are very clear from the provincial rankings created using average digital village scores from 2012 to 2022. The highest average score goes to Zhejiang (0.3310), then Shanghai (0.3154), and Guangdong (0.2830). The main reason for the quick development of digital villages in these provinces is their common features such as a solid economy, a lot of cities, and a large investment in digital technology.

Jiangsu and Shandong are also among the top performers because of their active economic settings and ongoing technological developments. As the capital, Beijing has an average score of 0.1815 due to its many policies backing development and easy access to resources.

However, Hainan (0.0602), Ningxia (0.0635), and Qinghai (0.0653) are at the bottom of the ranking. Because of limited economic progress, a lack of urbanization, and geographical obstacles, it is difficult for these regions to set up digital infrastructure. Since their scores are not very high, it is clear that more investment and government support are required to improve digital connections and technology use.

The middle tier provinces, for example Henan (0.1378), Sichuan (0.1354), and Hubei (0.1276), are making progress with digital village development. While there are small improvements, more has to be done to catch up with the best provinces.

Table 5 2012-2022 Digital Village Construction Ranking

province	Average score	rank
Zhejiang	0.3310	1
Shanghai	0.3154	2
Guangdong	0.2830	3
Jiangsu	0.2595	4
Shandong	0.1997	5
Beijing	0.1815	6
Fujian	0.1504	7
Hebei	0.1460	8
Henan	0.1378	9
Sichuan	0.1354	10
Hubei	0.1276	11
Liaoning	0.1215	12
Inner Mongolia	0.1134	13
Hunan	0.1097	14
Anhui	0.1080	15
Yunnan	0.1052	16
Tianjin	0.1022	17
Heilongjiang	0.0994	18
Xinjiang	0.0958	19
Shanxi	0.0957	20
Shaanxi	0.0955	21
Jiangxi	0.0910	22
Guangxi	0.0903	23
Guizhou	0.0896	24
Chongqing	0.0869	25
Jilin	0.0861	26
Gansu	0.0843	27
Qinghai	0.0653	28
Ningxia	0.0635	29
Hainan	0.0602	30

All in all, the ranking points out that certain regions are not keeping up in digital development and that suitable policies are required to fill this gap. The most economically and urbanized areas of China are leading in digital transformation, so it is important to pay more attention to less developed provinces to boost their digital infrastructure, make technology more accessible, and teach digital skills. It is important to deal with these differences to encourage balanced regional growth and to make sure digitalization benefits everyone in the country.

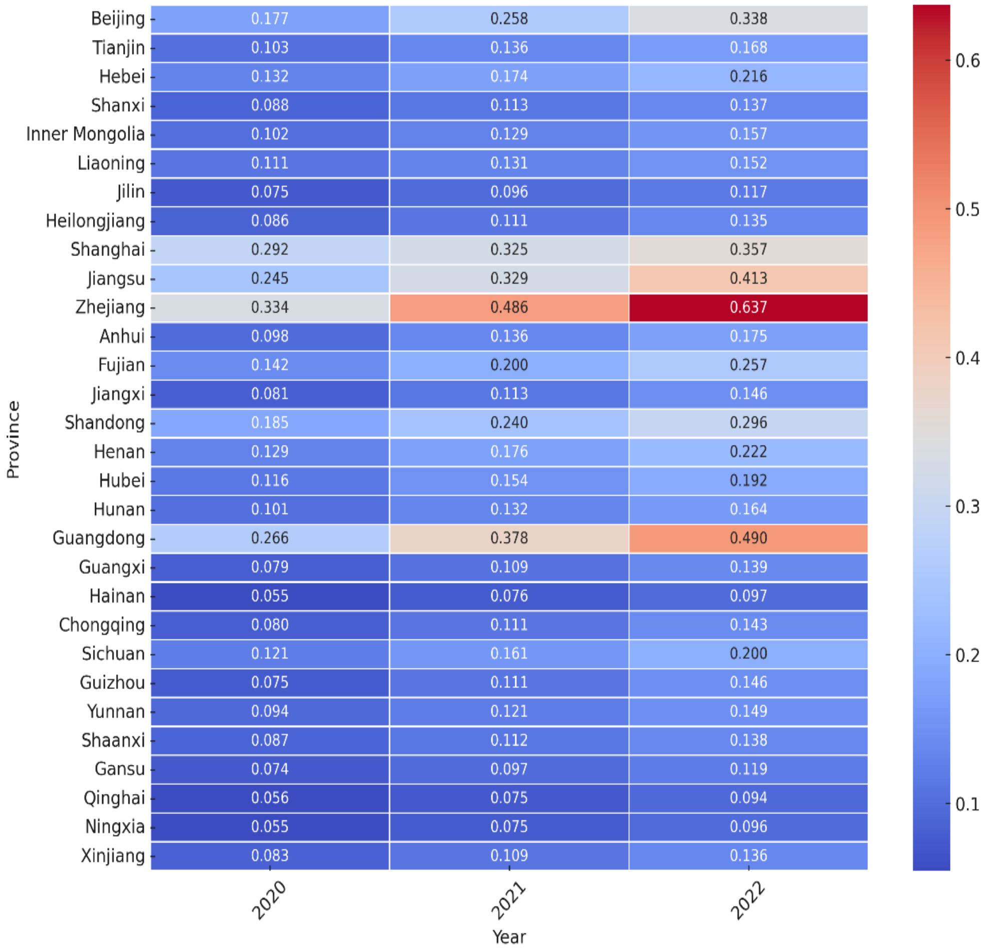

Figure 2 Heat map of digital village construction measurement results.

It is evident from analyzing digital village development in 30 Chinese provinces from 2012 to 2022 that there are significant differences between regions and that growth over time is obvious. To sum up, the digital village rankings are moving upwards, and the biggest developments are seen in the eastern regions. In particular, Zhejiang and Guangdong experienced their indices rise strongly from 0.162 and 0.138 in 2012 to 0.637 and 0.490 in 2022, thanks to their strengths and continued investments in infrastructure for digital technologies.

At the same time, central and western regions had some improvements, but they were still less developed. The provinces of Henan and Hubei advanced in growth, but not as fast as the eastern parts of China. Qinghai and

Ningxia, found in the west, had the lowest indexes in 2022 with values of 0.094 and 0.096 respectively, which shows that digitalization is developing gradually in these areas.

Even though there is steady growth in digital villages, the existence of big gaps between regions means that targeted actions are needed right away. It is important to bridge the digital divide so that all regions can participate in digital transformation and there is equal growth among them.

3.3.3.2. Analysis of Regional Differences in Measurement Results

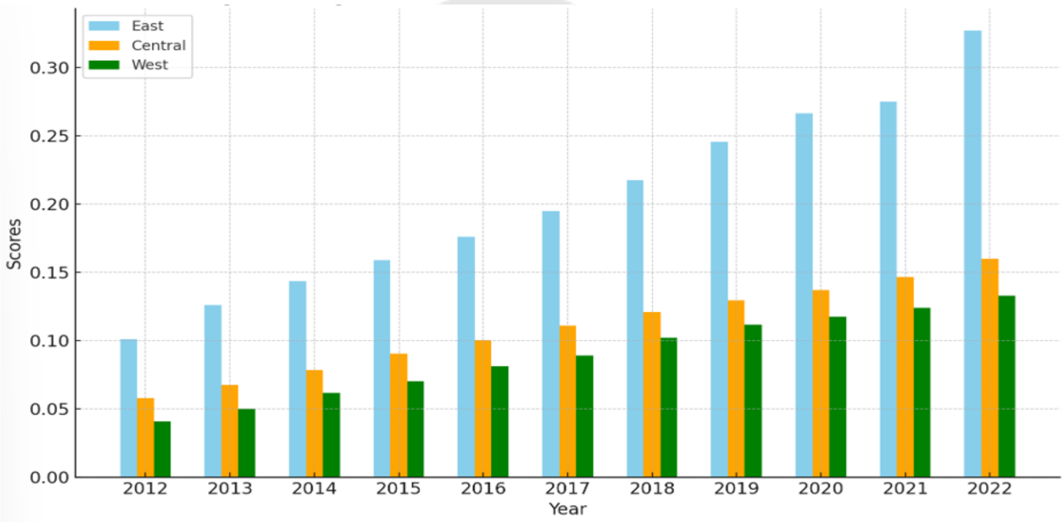

Figure 3 2012-2022 Digital Village Scores for Eastern, Central, and Western

The graph in Figure 3 shows the changes in digital village development scores in eastern, central, and western China from the year 2012 to 2022. By looking at different eras and places, we can notice a number of important trends and characteristics.

The Eastern Region has maintained higher digital village scores than both the central and western regions for the whole period. The reason for this is that eastern countries moved first, keeping up their investments in digital infrastructure, digital economy, and digital governance.

The central region has consistently improved, and the improvement has picked up pace after 2018. Increased efforts in both regional technology and policy may explain why this improvement happened.

The western region is the lowest in results, but scores keep going up slowly each year. It seems that there is a decreasing difference in digital development, thanks in part to national efforts to boost infrastructure and digital skills in less-developed areas.

Although the eastern region is still in the lead, the difference between central and western regions has been decreasing over the past decade. Even though the gap between regions has decreased, the eastern region still has much greater structural advantages.

Changes in regional digital development have been guided by major policy decisions, for example, the introduction of the rural revitalization strategy in 2017 and the digital village strategy in 2018. They seem to have helped improve the digital development path, mainly in the regions that were falling behind.

In short, the chart in Figure 3 outlines the changes in digital village development among regions in China, exposing areas of difference and similarity. The results reveal useful lessons about coordination in digital policy and show that it is important to keep differentiating policies to help close the digital divide and ensure the same level of digital transformation throughout the nation.

3.3.3.3. Summary

Using the data from digital village construction over the years 2012 to 2022, this part of the report analyzes the many aspects and regional changes in China's digital village development.

It can be seen from the analysis of inter-provincial scores that there is a clear regional pattern. Zhejiang (0.3310), Shanghai (0.3154), and Guangdong (0.2830) from the East lead in digital village development because they have good digital infrastructure, a strong economy, and effective government. But western provinces Hainan (0.0602), Ningxia (0.0635), and Qinghai (0.0653) are far behind, showing that there are major differences in their development.

Heat map visualization presents a clear overview of the way digital villages are built. The line, changing from dark blue to dark red, displays the progress of the digital index in each province and also highlights the disparity between regions as well as the general increase from east to west.

The analysis of time series data uncovers the way digitalization is progressing in each region. Between 2012 and 2022, most provinces kept making progress. The digital village index for Zhejiang went up from 0.162 to 0.637, and for Guangdong it rose from 0.138 to 0.490. While primary provinces kept growing steadily, those in the west, starting with lower numbers, accelerated their growth and are catching up.

All in all, the research proves that digital villages have brought good results at the national level, but unequal development between regions is still a main issue. We should now put in place specific and individualized digitalization policies that take into account how regional areas develop differently. When support is given according to the level of development in each region, it leads to more inclusive and united digital village development in China.

3.4. Measurement of AGTFP

3.4.1. Indicator Selection and Measurement Methodology of AGTFP

3.4.1. 1. Input Variables

In this study, labor, land, capital, water, and energy are used as five main input indicators to examine how well and in what ways inputs are used in agricultural production. Using the methods of Guo (2019), Liu et al. (2021), and Lu et al. (2024), an input index system is formed to analyze the complexity of farming.

Labor in agriculture is the main factor, and it is given in terms of the number of people employed in the sector (unit: 10,000 persons). The indicator covers the number of workers in agriculture as well as their quality, which goes straight to productivity and the outcomes of the sector.

Land is still a main resource needed in farming. This research relies on the total crop planting area (in 1,000 mu) as the land indicator. It demonstrates the efficiency of using land in farming and how much land is being used.

The presence of capital in agriculture represents how advanced it is and is made up of several parts:

Representing the increased work done by machines in agriculture, the country's agricultural machinery power is 10,000 kilowatts.

The use of fertilizers (10,000 tons) is key for proper crop growth, but it has to be controlled to protect the environment.

Although using pesticides (10,000 tons) is important for pest control, they need to be handled carefully not to damage the environment.

However, if not handled correctly, the use of agricultural mulch can create pollution and other environmental problems.

Water is a key part of making agriculture sustainable. In agriculture, the input of water is measured by the amount of water used for irrigation (in 100 million cubic meters) and how efficiently it is used, which are important factors for evaluating the environment.

This dimension, energy input, indicates the level of energy used in farming activities.

Diesel use in the form of 10,000 tons is mainly applied to machinery and transport.

More electricity (in kilowatt-hours) is being used to help with agricultural work that involves machinery. All these factors show the level of energy use and progress in modern farming..

3.4.1. 2. Output Variables

According to estimates by Dubey and Lal (2009), agricultural irrigation activities contribute approximately 25 kilograms of carbon dioxide emissions per hectare. However, this figure does not account for the fact that most irrigation systems rely heavily on electricity, which in turn is largely generated from fossil fuels such as coal, oil, and natural gas. To better reflect this dependency and improve the accuracy of carbon emission estimates, a correction factor was introduced. This adjustment was derived using the average thermal power generation coefficient calculated over a long-term period—from 1993 to 2016—thus enabling a more realistic assessment of emissions associated with irrigation-related electricity consumption. As a result of this correction, the revised carbon emission coefficient was recalibrated to 20.476 kg per hectare (hm^2).

Table 6 Carbon emissions sources, emission factors, and reference sources in agriculture.

Source	Coefficient	Reference
fertilizer	0.8956 $kg \cdot kg^{-1}$	T.o.west, Oak Ridge National Laboratory, USA
pesticide	4.9341 $kg \cdot kg^{-1}$	Oak Ridge National Laboratory, USA
agricultural film	5.18 $kg \cdot kg^{-1}$	Institute of Agricultural Resources and Ecological Environment, Nanjing Agricultural University
diesel fuel	0.5927 $kg \cdot kg^{-1}$	IPCC (2022). United Nations Intergovernmental Panel on Climate Change
plow	312.6 $kg \cdot km^{-2}$	College of Biology and Technology, China Agricultural University
agricultural irrigation	20.476 kg/hm^2	Adjusted according to Dubey

Building upon the framework developed by Huang et al. (2022), the present study adopts a dual-output evaluation model that considers both beneficial (desirable) and harmful (undesirable) outcomes in agricultural production. For desirable output, the study employs the total output value from agriculture, forestry, animal husbandry, and fishery sectors, all measured at constant 2011 prices to account for inflation and maintain consistency over time. In contrast, the undesirable output is represented by the volume of agricultural carbon emissions, which reflects the environmental cost associated with production activities.

To quantify these emissions, the study follows the methodological guidelines provided by the Intergovernmental Panel on Climate Change from IPCC (2022), as well as the emission coefficients outlined by Dubey and Lal (2009). These references provide standardized formulas for calculating emissions from various carbon-intensive agricultural inputs—such as fertilizers, diesel, electricity, and plastic films—ensuring that the estimation process is grounded in internationally recognized scientific principles.

Table 6 provides a detailed overview of both the input indicators and their corresponding carbon emission coefficients. The data used in this study are sourced from multiple authoritative and nationally recognized publications, including the China Statistical Yearbook, China Agricultural Yearbook, China Rural Statistical Yearbook, and various provincial statistical yearbooks. These sources ensure a high level of credibility and consistency in the data collection process. To maintain methodological uniformity across the entire research framework, identical measurement standards and calculation techniques are applied to all variables throughout the study period.

Table 7 AGTFP measurement indicator system

Indicator category	variable name	Indicator name	Evaluation index	unit
Input indicator	Labor input	Labor force input	Agricultural employment Number of people	Ten Thousands of people
	Land input	Land Investment	Land investment Crop sowing area and aquaculture area	thousand hectares
	Capital input	Mechanical power	Total power of agricultural machinery	Ten thousand kilowatts
		Amount of chemical fertilizer used	Pure use of agricultural fertilizers	Ten thousand tons
		Pesticide usage	Pesticide usage	Ten thousand tons
		Amount of agricultural film used	Amount of agricultural film used	Tons
	Water input	Agricultural water	Agricultural water	100 million cubic meters
	Energy input	Diesel usage	Agricultural diesel usage	10,000 tons
		Agricultural electricity use	Agricultural electricity use	100 million kilowatt hours
Output indicator	Desirable output	The total output value of agriculture, forestry, animal husbandry, and fishery	The total output value of agriculture, forestry, animal husbandry, and fishery	100 million yuan
	Undesirable output	Agricultural carbon emissions	Agricultural carbon emissions	Ten thousand tons

Table 6 consolidates all relevant variables and emission coefficients used in the calculations, serving as a comprehensive reference for understanding the measurement process. By consistently applying the same estimation framework across all provinces and years under investigation, the study ensures the reliability and comparability of its findings, thereby enhancing the robustness of the empirical results.

In Figure 2, you can see the framework for agricultural total factor productivity, and Table 7 gives the full list of input and output indicators.

3.4.2. Measurement Methodology of AGTFP

3.4.2.1.Extended EBM model

EBM (Epsilon-Based Measure Model) has made great progress compared to the standard Data Envelopment Analysis (DEA). The EBM model stands out from conventional DEA models by evaluating both radial and non-radial efficiency, allowing it to represent the complicated ways that agricultural production systems work. It also helps to assess the environment's efficiency, especially when there are both positive and negative results, like pollution.

Its strong point is that it looks at negative effects, which makes it suitable for calculating AGTFP. These methods are useful because they remain the same as inputs change, are the same in different languages, and help find unused resources, which can be applied to improve how things are managed and run.

Guo (2019) proved in his study that the EBM-GML method improves agricultural efficiency analysis and can be trusted to evaluate green productivity in agriculture.

The input-oriented EBM model is shown in Equation (11):

$$\gamma^* = \min_{\theta,\lambda,\bar{s}} \theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{iq}}$$

$$\begin{cases} \theta x_{iq} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_i^- = 0, i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{ij} \geq y_{nq}, r = 1, \dots, s \\ \lambda_j \geq 0 \\ s_i^- \geq 0 \end{cases} \tag{11}$$

Among them, $\gamma*$ represents the optimal efficiency value under VBS conditions; θ refers to the efficiency value under radial conditions; s_{i-} represents the slack amount of input i under non-radial conditions; λ is the linear combination between DMUs Coefficient; (x_{iq}, y_{rq}) represents the input and output vector of the q-th DMU; w_{i-} is the weight reflecting the relative importance of i input factor, and$\sum_{i=1}^{m} w_i^- = 1$; $w_i^- \geq 0$, ε_x is the core parameter that reflects both the change ratio of the radial relaxation variable and the non-radial relaxation vector, and $0 \leq \varepsilon_x \leq 1$. The parameters

w_i^- and ε_x need to be determined in advance. If $\gamma^*=1$, the technology is valid. As the measurement of AGTFP involves both good and bad outputs, and includes both types of input–output relationships, the study uses an extended non-oriented EBM model to handle undesirable outputs. The modified EBM model is used to determine how efficiently agricultural production is carried out. The details of the model are shown in Equation (12).

$$\gamma^* = min \frac{\theta - \varepsilon_x \sum_{i=1}^{m} \frac{w_i^- s_i^-}{x_{iq}}}{\varphi + \varepsilon_y \sum_{r=1}^{s} \frac{w_r^+ s_r^+}{y_{rq} + \varepsilon_b \sum_{p=1}^{q} \frac{w_p^{b-} s_p^{b-}}{b_{pq}}}} \tag{12}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- - \theta x_{iq} = 0, i = 1, \cdots, m, \\ \sum_{j=1}^{n} y_{ij}\lambda_j - s_r^+ - \varphi y_{rq} = 0, r = 1, \cdots, s, \\ \sum_{j=1}^{n} b_{pj}\lambda_j + s_p^{b-} - \varphi b_{pq} = 0, p = 1, \cdots, q, \\ \lambda_j \geq 0, s_i^- \geq 0, s_r^+ \geq 0, s_p^{b-} \geq 0 \end{cases}$$

In Equation (8), the importance of everything is set manually, which makes the process subjective and can miss the real significance of each factor. So, this study adds the entropy weight method to the EBM model to address this problem. Thanks to this integration, the representation of the differences in AGTFP between Decision-Making Units (DMUs) is made more accurate and reliable.

3.4.2.2.GML Index

The agricultural production process is continuous and long-term. As time goes by, the level of agricultural technology continues to develop. For example, constant technological advancement will lead to improvements in production levels. When the data of the decision-making unit (DMU) is panel data, in order to more accurately reflect the changes in production efficiency, using the Malmquist index becomes a reasonable choice. When considering undesired output, the Malmquist-Luenberger index is constructed by combining the Malmquist index with the directional distance function containing the undesired output, as shown in Equation (13).

$$M_{t,t+1}=\left[\frac{1+D_0^t(x_i^t,y_i^t,b_i^t,y_i^t,-b_i^t)}{1+D_0^t(x_i^{t+1},y_i^{t+1},b_i^{t+1};y_i^{t+1},-b_i^{t+1})}\times\frac{1+D_0^{t+1}(x_i^t,y_i^t,b_i^t;y_i^t,-b_i^t)}{1+D_0^{t+1}(x_i^{t+1},y_i^{t+1},b_i^{t+1};y_i^{t+1},-b_i^{t+1})}\right]^{1/2} \quad (13)$$

Among them, $D_0\ (x,\ x,\ b,-\ b)$ is the distance function value in four directions.

The ML index can be decomposed into green technology efficiency change index (TEC) and green technology progress change index (TC), see Equations (14), (15), (16).

$$ML_{t,t+1}=TEC\times TC \quad (14)$$

$$TEC_{t,t+1}=\left[\frac{1+D_0^t(x_i^t,y_i^t,b_i^t;y_i^t,-b_i^t)}{1+D_0^{t+1}(x_i^{t+1},y_i^{t+1},b_i^{t+1};y_i^{t+1},-b_i^{t+1})}\right] \quad (15)$$

$$TC_{t,t+1}=\left[\frac{1+D_0^{t+1}(x_i^{t+1},y_i^{t+1},b_i^{t+1};y_i^{t+1},-b_i^{t+1})}{1+D_0^t(x_i^{t+1},y_i^{t+1},b_i^{t+1};y_i^{t+1},-b_i^{t+1})}\times\frac{1+D_0^{t+1}(x_i^t,y_i^t,b_i^t,y_i^t,-b_i^t)}{1+D_0^t(x_i^t,y_i^t,b_i^t,y_i^t,-b_i^t)}\right]^{1/2} \quad (16)$$

The ML index does not meet the conditions of circularity, and there is a possibility of no solution using linear programming. Scholars have proposed many improvement methods to address this shortcoming. Pastor and Lovell (2005) used all inspection periods of all DMUs as a benchmark to construct the production frontier. They constructed a global index, which not only effectively avoids situations where there may be no solution but also meets the requirements of circularity and allows technological regression. For comparison, the production possibility sets constructed by the current benchmark and the global benchmark are listed respectively. For details, see Equation (17) and Equation (18).

Current period base: $P_C^T(x^t)=\{(y^t,b^t)\mid x^t\ are\ able\ to\ produce\ (y^t,b^t)\}$ (17)

Global benchmark: $P_G=P_C^1\cup P_C^2\cup..UP_C^n$ (18)

C and G refer to today's standards and worldwide standards, respectively. All of the period's frontiers are combined into one global production possibility set that serves as a common benchmark for all times. Using the same production frontier from the global benchmark for each period is the main difference between the M index and other indexes under adjacent periods. Therefore, M index reflects a consistent and unified measure of productivity change, so it allows us to compare different years.

The global GML exponential expression is shown in Equation (19):

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = 1 + D_G^T(x^t, y^t, b^t)/1 + D_G^T(x^{t+1}, y^{t+1}, b^{t+1})$$
$$D_G^T(x, y, t) = max\{\beta \mid (y + \beta y, b - \beta b) \in P_G(x)\} \quad (19)$$

Obtained from the global benchmark production possibility set PG.

If $GML^{t,t+1} > 1$ it means that AGTFP increases; if $GML^{t,t+1}$, which is a value less than 1 indicates a decline in AGTFP. The Global Malmquist–Luenberger (GML) index can be further decomposed into two components: the Green Technology Efficiency Change Index (GTEC) and the Green Technology Progress Index (GTC). These components allow for a more detailed analysis of whether changes in AGTFP are driven by improvements in efficiency or advancements in green technology. The decomposition is formally presented in Equation (20):

$$GML^{t,t+1}(x^t, y^t, b^t, x^{t+1}, y^{t+1}, b^{t+1}) = \frac{1 + D_G^T(x^t, y^t, b^t)}{1 + D_G^T(x^{t+1}, y^{t+1}, b^{t+1})^t}$$
$$= \frac{1 + D_C^t(x^t, y^t, b^t)}{1 + D_C^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \times \left[\frac{\left(1 + D_G^T(x^t, y^t, b^t)\right)/1 + D_C^t(x^t, y^t, b^t)}{\left(1 + D_G^T(x^{t+1}, y^{t+1}, b^{t+1})\right)/\left(1 + D_C^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})\right)}\right]$$
$$= \frac{GTE^{t+1}}{GTE^t} \times \left\{\frac{PG_{t+1}^{t,t+1}}{PG_t^{t,t+1}}\right\} = GTEC^{t,t+1} \quad (20)$$

In Equation (20), GTE measures green technology efficiency, and GTEC shows the rate at which it is changing over the years. PG compares how much better the best DMUs are at making decisions than those that are below the global benchmark. GTC reflects the state of green technology, and when GTC is greater than 1, it means progress, while a value of GTC lower than 1 indicates technology is going backwards.

3.4.3. Measurement Results of AGTFP

This study used the EBM-GML model to calculate the AGTFP of 30 Chinese provinces from 2012 to 2022 (Table 8). The average AGTFP index was 1.015, indicating gradual progress toward sustainable agricultural development, consistent with findings by Wolfert et al. (2017)

Regionally, AGTFP showed significant spatial differences. Eastern coastal provinces like Tianjin and Beijing led with AGTFP values between 0.982 and 1.129, while the western region, such as Qinghai, had more fluctuation (0.915–1.047), highlighting the need for improvement in green production efficiency.

Table 8 Measurement Results of AGTFP.

Province	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012
Beijing	1.011	1.002	0.998	1.003	1.059	0.994	1.031	0.982	1.052	1.043	1.033
Tianjin	1.032	1.014	1.048	1.026	1.129	1.036	1.015	1.022	1.011	1.018	1.013
Hebei	1.011	1.014	1.029	1.022	1.031	1.011	1.009	0.998	1.001	1.008	1.010
Shanxi	1.010	1.022	1.029	1.018	1.017	1.000	1.009	0.998	1.008	1.011	1.006
Inner Mongolia	0.997	1.006	1.015	1.010	1.010	1.001	1.003	0.99	0.993	1.003	1.004
Liaoning	1.009	1.019	1.010	1.025	1.021	1.014	1.008	1.006	1.000	1.008	1.010
Jilin	1.016	1.005	1.047	1.025	1.015	0.991	0.990	0.996	1.000	1.003	1.007
Heilong jiang	1.082	1.017	1.066	1.070	1.009	1.030	1.006	1.009	1.012	1.03	1.027
Shanghai	1.051	0.974	1.000	1.000	1.237	0.993	0.939	0.946	0.981	1.007	0.927
Jiangsu	1.022	1.033	1.020	1.013	1.002	1.000	1.008	1.022	1.005	1.008	1.016
Zhejiang	1.013	1.014	1.020	1.027	1.010	1.005	1.024	1.007	1.003	1.015	1.013
Anhui	1.007	1.010	1.024	1.016	1.004	1.007	1.013	1.004	1.009	1.007	1.008
Fujian	1.019	1.034	1.029	1.034	1.03	1.016	1.038	1.012	1.011	1.014	1.018
Jiangxi	1.007	1.007	1.025	1.029	1.006	1.004	1.024	1.007	1.008	1.022	1.011
Shandong	1.015	1.033	1.014	1.011	1.012	1.007	1.000	1.008	1.013	1.015	1.009
Henan	1.007	1.018	1.028	1.02	1.009	1.009	1.004	1.001	1.011	1.005	1.008
Hubei	1.000	1.090	1.072	1.044	1.009	1.012	1.025	1.007	1.005	1.011	1.018
Hunan	1.030	0.966	1.084	1.041	1.006	1.006	1.015	1.003	1.004	0.996	1.004
Guangdong	1.013	1.030	1.036	1.048	1.026	1.007	1.032	1.009	1.008	1.017	1.01
Guangxi	1.058	0.992	1.022	1.052	1.032	1.013	1.010	1.001	0.984	1.015	0.979
Hainan	1.020	0.980	1.002	1.028	0.973	1.000	1.085	0.966	0.992	0.983	0.974
Chongqing	1.043	1.048	1.085	1.056	1.018	1.008	1.033	1.010	1.006	1.007	1.012
Sichuan	1.010	1.002	1.045	1.023	1.010	1.007	1.019	1.012	1.005	1.002	1.012
Guizhou	1.024	0.978	1.090	1.049	1.000	1.033	1.047	1.056	1.035	1.020	1.026
Yunan	1.015	1.021	1.044	1.046	1.055	1.005	1.008	1.002	1.004	1.013	1.011
Shaanxi	1.012	1.016	1.041	1.029	1.009	1.006	1.015	1.000	1.016	1.021	1.015
Gansu	1.005	1.013	1.017	1.023	1.010	1.022	1.025	1.003	1.003	1.008	1.010
Qinghai	1.024	0.975	1.047	1.027	1.034	0.988	1.026	0.915	0.977	1.002	1.000
Ningxia	1.006	0.998	1.037	1.000	1.022	1.010	1.031	1.014	1.013	1.017	1.012
Xinjiang	1.005	1.022	1.018	1.009	1.007	1.009	1.007	0.997	0.993	1.004	1.015

AGTFP values around 1 indicate benchmark green efficiency levels. Values above 1, like Tianjin's 1.129 and Beijing's 1.059, show technological or resource advantages. Values below 1, such as Qinghai's 0.915, signal inefficiencies needing optimization.

Overall, most provinces' AGTFP indices fluctuated slightly between 0.99 and 1.01, reflecting the gradual shift toward sustainable agricultural development in China.

CHAPTER 4
EMPIRICAL RESULTS

This study aims to comprehensively examine the impact of digital village construction on AGTFP in China. The analysis is based on panel data covering 30 provinces, autonomous regions, and municipalities across the country over the period from 2011 to 2022. Due to persistent gaps and incomplete data availability, the Tibet Autonomous Region is excluded from the scope of the study to maintain the integrity and consistency of the dataset.

The data sources employed in this research are carefully selected to ensure reliability, accuracy, and comprehensive coverage. Agricultural input and output indicators are obtained from nationally recognized publications, namely the China Statistical Yearbook, China Rural Statistical Yearbook, and various provincial-level statistical yearbooks, which collectively provide detailed annual data on key variables such as land use, labor, capital inputs, and output value across different sectors of agriculture, including farming, forestry, animal husbandry, and fisheries.

In addition, information pertaining to digital village development, along with relevant control and mediating variables, is collected for the years 2012 to 2022. These data are drawn primarily from two major sources: the China Taobao Village Research Report (compiled by the Alibaba Research Institute), which tracks the development of e-commerce and digital infrastructure in rural areas, and the Digital Inclusive Finance Index produced by the Digital Finance Research Center at Peking University, which measures the accessibility and usage of digital financial services across regions.

The methodological framework of the study consists of several distinct stages:

Construction of the Digital Village Development Index

To quantitatively assess the level of digital transformation in rural areas, the entropy weighting method is applied. This method is particularly suitable for composite index construction, as it objectively assigns weights to multiple indicators based on their informational entropy—that is, the degree of dispersion or variability in the data. This process enables the generation of a single, comprehensive score that captures the extent of digital village development across provinces and over time.

Measurement of AGTFP Using the EBM-GML Model

To evaluate the level of green productivity in agriculture, the study adopts the extended EBM-GML (Epsilon-Based Measure – Global Malmquist-Luenberger) model, as proposed by Guo (2019). This model is capable of accounting for both desirable outputs (e.g., agricultural production value) and undesirable outputs (e.g., carbon emissions), making it well-suited for assessing sustainability. Furthermore, AGTFP is decomposed into two components: technical efficiency change and technological progress, allowing the study to capture the dynamics of both resource use efficiency and innovation in green agricultural practices.

Panel Regression Using a Fixed Effects Model

To investigate the overall impact of digital village development on AGTFP, a fixed effects panel regression model is employed. This econometric approach controls for unobserved, time-invariant heterogeneity across provinces, thereby enhancing the robustness and internal validity of the estimated results.

Mediation Mechanism Analysis

To explore the pathways through which digital village construction influences AGTFP, the study introduces a mediation analysis framework. Specifically, two key mediating variables are considered: agricultural informatization and rural human capital. Agricultural informatization reflects the extent to which modern information and communication technologies are applied in farming activities, while rural human capital captures the educational and skill levels of the rural workforce. By incorporating these mediators, the study identifies indirect effects and evaluates the strength and significance of each transmission channel.

Regional and Functional Heterogeneity Analysis

Recognizing the diversity of economic development and digital infrastructure across China's regions, the study further conducts subgroup analyses based on geographic location (eastern, central, and western provinces) and functional roles (e.g., grain-producing vs. non-grain-producing regions). This stratified analysis reveals spatial differences in how digital village initiatives affect green agricultural productivity.

Robustness Tests and Sensitivity Checks

To verify the reliability of the empirical findings, multiple robustness checks are conducted. These include alternative model specifications, changes in variable definitions, and the use of different subsamples. The consistency of results across these tests lends credibility to the study's conclusions and confirms that the observed effects are not driven by model artifacts or outliers.

By integrating advanced modeling techniques with high-quality data sources and a rigorous empirical design, this study provides a detailed and evidence-based evaluation of how digital village construction contributes to the green transformation of agriculture in China. It offers valuable insights for policymakers, particularly in designing region-specific digital strategies to enhance sustainable rural development.

4.1. Benchmark Regression Results

The researchers choose to use a fixed-effects panel regression model after confirming it through the LM test, F test, and Hausman test. The results of stepwise regression are shown in Table 9. In the first column, there is a baseline regression, and control variables are added one at a time, starting with Column (2) and ending with Column (5). Because the digital village variable shows the same positive and significant effect in all models, this proves that its positive impact on AGTFP is strong.

The specification in column (5) shows all the control variables along with the other variables. Indig has a positive and significant relationship with AGTFP, which means digital village development is important for improving AGTFP. It is probably thanks to better use of resources, faster agricultural progress, and new environmentally friendly technologies.

Table 9 Stepwise Regression.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	AGTFP	AGTFP	AGTFP	AGTFP	AGTFP
Lndig	0.126 ***	0.133 ***	0.147 ***	0.140 ***	0.132 ***
	(0.032)	(0.032)	(0.032)	(0.031)	(0.032)
Lnstr		0.122 *	0.149 **	0.117 *	0.123 *
		(0.065)	(0.065)	(0.065)	(0.065)
Lnfisc			0.388 ***	0.449 ***	0.439 ***
			(0.134)	(0.134)	(0.134)
Lnapi				0.096 ***	0.096 ***
				(0.030)	(0.030)
Lneir					0.069
					(0.050)
Constant	1.000 ***	0.938 ***	0.881 ***	0.446 ***	0.420 ***
	(0.004)	(0.033)	(0.038)	(0.140)	(0.141)
Observations	330	330	330	330	330
R-squared	0.051	0.062	0.087	0.118	0.124
Number of id	30	30	30	30	30

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Besides, all the coefficients for the control variables such as fiscal spending (Infisc), agricultural structure (Instr), agricultural production price (Inapi), and effective irrigation (Ineir) are positive and significant, meaning that they help increase AGTFP.

The fact that the R^2 value is only 0.124 may be explained by several things. One reason fixed-effects models have lower R^2 values is that they take away both individual and time-specific differences from the data. Second, AGTFP covers many factors, and some of them, such as the climate, disasters, and policy changes, are hard to measure. Also, the fact that the model includes 30 provinces with different levels of resources and agriculture could lead to the lower model fit. In addition, the fact that the key explanatory variable has a very high significance supports the model and proves that it captures the link between digital village construction and AGTFP.

According to the regression results, digital village development helps to increase AGTFP, proving the first hypothesis right. In other words, the baseline model reveals that as the digital village development index increases by one shard, there is a 0.132-unit rise in the country's AGTFP. The fact shows that digitalization improves the sustainability of farming by allowing for better resource management and using ecologically friendly technology.

4.2. Robustness Tests

In the basic regression analysis, steady values and significances for the digital village development variable proved the findings to be solid. The findings were checked further by conducting various tests of robustness. These assessments were run using model subscription, switching some variables, and studying different samples, and the results are shown in Table 10.

First, the authors used a random-effects model (column 2) instead of the fixed-effects model (column 1), and the results were still significant, proving once again that digital village development has an impact on AGTFP and confirms the baseline findings. Secondly, we replaced the dependent variable with AGTFP-GML that was calculated using output-oriented EBM-GML. Digital village effects continued to prove statistically significant as shown in the results (column 2). Thirdly, instead of the main independent variable, DIGT was used, which was computed by applying the Principal Component TOPSIS method. All the results remained the same, which showed that the digital village metric was reliable. In conclusion, the fact that the urban-rural divide is not an issue and that farming is not major in Beijing, Shanghai, Tianjin, and Chongqing, these areas were not included in the sample. The findings in column (4) prove that, even without the outliers, digital village construction is still closely linked to AGTFP.

Table 10 Robustness Tests.

	(1)	(2)	(3)	(4)
	AGTFP	AGTFP-GML	AGTFP	AGTFP
	RE	FE	FE	FE
lndig	0.073 ***	0.072 ***		0.109 ***
	(2.954)	(3.491)		(4.411)
DIGT			0.146 ***	
			(4.016)	
lnstr	0.027	0.072 *	0.134 **	0.067
	(1.379)	(1.709)	(2.053)	(1.259)
lnfisc	0.071	0.065	0.476 ***	0.387 ***
	(1.149)	(0.746)	(3.506)	(3.931)
lnapi	0.096 ***	0.025	0.100 ***	0.094 ***
	(3.248)	(1.284)	(3.374)	(4.141)
lneir	—0.005	—0.026	0.089 *	0.103 **
	(—0.315)	(—0.789)	(1.812)	(2.004)
_cons	0.542 ***	0.85.1.49 ***	0.386 ***	0.451 ***
	(3.919)	(9.207)	(2.729)	(4.177)
N	330	330	330	286
R2	0.086	0.050	0.120	0.175

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

All in all, the checks on robustness keep proving that the findings are stable and dependable. In all model specifications, using various key variable measurements, and alterations to the sample, digital village building keeps enhancing AGTFP in a significant manner. Because of these results, there is strong evidence that backing Hypothesis 1, by showing that rural use of digital tools greatly contributes to improving sustainability in farming through bigger resource availability, new technology, and efficiency.

4.3. Heterogeneity Analysis

The primary regression analysis is centered on evaluating the general impact of rural digitalization. Nevertheless, considering China's extensive landmass and considerable disparities in terms of geographic positioning, resource availability, levels of agricultural economic development, and agricultural infrastructure, it is crucial to investigate the varied impacts across these diverse aspects.

Table 11 Heterogeneity Test.

Variable	(1) Eastern AGTFP	(2) Central AGTFP	(3) Western AGTFP	(4) South AGTFP	(5) North AGTFP	(6) Producing AGTFP	(7) Marketing AGTFP	(8) Balance AGTFP
Indig	0.151 **	0.133	0.137	0.170 ***	−0.006	0.113 ***	0.162 *	0.197 *
	(2.424)	(1.535)	(1.629)	(3.624)	(−0.128)	(2.785)	(1.905)	(1.980)
control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	(1.683)	(0.407)	(0.256)	(0.061)	(3.943)	(0.669)	(1.477)	(0.777)
constant	0.194	0.454 **	0.657 ***	0.263	0.357 ***	0.520 ***	0.153	0.514 **
	(0.582)	(2.201)	(3.171)	(0.855)	(2.745)	(3.785)	(0.302)	(2.180)
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	121	88	121	176	154	143	77	110
R2	0.112	0.186	0.161	0.159	0.222	0.180	0.108	0.190
F	2.646	3.432	4.018	5.882	7.696	5.483	1.570	4.463

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

1.Heterogeneity Across Eastern, Central, and Western Regions

The study looks at how rural digitalization affects agricultural green total factor productivity (AGTFP) in China’s eastern, central, and western regions using the usual regional divisions by the National Bureau of Statistics as a guide. The region is divided into the following parts:

Eastern China: Includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan.

Central China: Comprises Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan.

Western China: Consists of Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang.

Table 11 shows that there is significant difference across regions in how digital village development affects AGTFP. For the eastern region, the coefficient of Indig is 0.151 and important at the 5% level, which means that digitalization brings about a significant rise in AGTFP. This finding matches well with the region’s solid economy, well-established digital infrastructure, digital abilities of its agricultural workers, and innovation centers that speed up the adoption of new technologies.

On the other hand, the central region's coefficient (0.133) and the western region's coefficient (0.137) rise, but neither is significant in statistical terms. Because of both adequate digital infrastructure and reasonable economic numbers, the central region has a positive effect. Even though the impact is not significant for the western region, the rising trend suggests that more growth is possible in the future. By receiving expanded policy help and technology ideas from the east and center, the western region can progress and decrease the digital gap in at least two years.

2. Important Differences Regional is Between Southern and Northern China

Using geography, the study divides the provinces into the regions of the north and the south. In the northern part are Beijing, Tianjin, Hebei, Liaoning, Shandong, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Henan, Gansu, Qinghai, Ningxia, and Xinjiang. Places found in the southern region include Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Anhui, Jiangxi, Hubei, Hunan, Guangxi, Chongqing, Sichuan, Guizhou, and Yunnan.

It is clear from the regression analysis that rural digitalization affects AGTFP differently in Asia and Latin America. In this region, the Indig coefficient is 0.170, and it turns out to be statistically significant at a 1% level, showing that more digital villages have greatly boosted agricultural green production. It is the result of the south moving quickly to make use of digital village approaches, backed by higher economic income, more use of technology in farming, and a well-established e-commerce community.

The Indig coefficient in the north is -0.006, but since it is not significant, we should not conclude anything from it. It means that digital village initiatives have not led to real improvements in AGTFP in the northern region. Some possible reasons are that farmers move slowly to digital technology, they have limited digital skills, and they continue to rely on old ways of farming. From what these findings suggest, it is vital to work on digital infrastructure, teach people how to use technology, and support institutions to help the success of digital village initiatives in northern China.

3. Diversity Among the Grain's Different Areas

Considering their agricultural capabilities, China's regions are split into three grain zones. Lots of grain is grown in the main areas of Hebei, Liaoning, Jiangsu, Shandong, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Sichuan that are known for large-scale farming. Beijing, Tianjin, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan together make up the grain-marketing regions that handle most of China's agricultural consumption and transport. In addition, Shanxi, Guangxi, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang have a stable balance between how much they produce and consume.

It is noticeable from the regression analysis that the effects of rural digitalization on AGTFP vary considerably between each of these functional zones. In places that produce grains, the estimated coefficient for rural digitalization (Indig) is 0.113, and it is statistically significant. For this reason, it is clear that digital technologies play a central role in boosting productivity thanks to precision farming, real-time use of data, and proper resource management.

The Indig coefficient in the grain-marketing regions is 0.162 and significant to a 10% level. According to the outcome, these village initiatives aid agriculture by making supply chains smoother, cutting costs per transaction, and increasing the efficiency of distribution.

The Indig coefficient for the balanced regions rises to 0.197 and is still important at a 10% significance level. Even though it brings positive results, the size and significance are lower than seen in other zones. It could be due to how economic activity is spread across these regions, since less attention is paid to farming and business is done mostly using support from outside companies and authorities.

All in all, a lack of uniformity among grain regions demonstrates that digitalization has variable consequences for AGTFP, based on where a region's agriculture stands. These kinds of technologies boost overall productivity the most where farming is well-developed or where markets play a big role. Therefore, for digitalization to work well, new policies must target different aspects of farming in every region to achieve maximum efficiency and sustainable changes.

According to the research, it is the particular features of different communities and the framework of policies that plays a major role in making digital village initiatives successful. The results from eastern with a coefficient of 0.151 ($p < 0.05$) and southern provinces with a coefficient of 0.170 ($p < 0.01$) substantiate that agglomeration and institutional relations aid in spreading technology and are consistent with the main ideas in endogenous growth theory (Acemoglu, 2008).

It is evident from the study that unequal distribution of resources in various grain zones produced different benefits, including a strong and significant positive result in main grain-producing areas (coefficient = 0.113, $p < 0.01$). According to Li et al. (2022), countries that have robust institutions usually rely on path dependency, so as they grow and improve, they further build themselves up with innovation. This observation agrees with the basic principles of technological innovation theory that stress the need for continual learning and changes in institutions (Nelson & Winter, 1985).

All in all, the investigation points out that rural digitalization does not influence AGTFP the same across regions, depending on their economic and agricultural roles, among other differences. This points out that strategies should fit each region perfectly to ensure fair and inclusive development in digital agriculture. The results strengthen the idea presented in Hypothesis 4.

4.4. Impact Mechanism Test

This study adopts a dual analytical strategy to assess the influence of digital village initiatives on Agricultural Green Total Factor Productivity (AGTFP). First, AGTFP is decomposed into two distinct components: green technology efficiency (denoted as eff) and green technology progress (denoted as tech). This decomposition allows for a more granular understanding of how digital village development affects each aspect of green productivity separately. The results from this initial stage are presented in Columns 1 and 2 of Table 12.

In the second part of the analysis, a three-step mediation framework is employed to explore the indirect pathways through which digital village construction influences AGTFP. Specifically, two mediating variables are introduced: rural human capital (measured by lnedu) and agricultural informatization (captured by lninf). This framework aims to uncover whether the impact of digital village initiatives is transmitted through improvements in education and digital infrastructure in rural areas. The mediation analysis proceeds as follows:

Step A: Assess the effect of digital village development on each mediating variable (i.e., whether digitalization improves human capital or informatization);

Step B: Evaluate the influence of each mediator on AGTFP while controlling for digital village development;

Step C: Examine whether the direct impact of digital village development on AGTFP diminishes after including the mediators, which would indicate the presence of an indirect (mediated) effect.

The regression results, presented in Columns 3 through 6 of Table 12, provide estimates of the coefficients for each pathway, along with their statistical significance. These findings offer empirical evidence on the mechanisms through which digital transformation at the village level contributes to sustainable agricultural productivity, highlighting the critical role of both digital literacy and technology adoption in rural settings.

Researchers frequently evaluate Green Technology Efficiency (eff) and Green Technology Progress (tech) as two distinct components of Agricultural Green Total Factor Productivity (AGTFP). These metrics offer insights into the extent to which agricultural practices are both resource-efficient and technologically innovative in achieving environmental sustainability.

Based on the regression results presented in Column 1, the study finds that digital village development does not have a statistically significant impact on green technology efficiency. This observation suggests that the diffusion of digital initiatives may not directly enhance the efficiency with which agricultural resources are utilized in environmentally friendly ways. Several interrelated factors may help explain this outcome.

One of the key challenges lies in limited digital adoption among smallholder farmers. These farmers often lack the resources, training, or technical support needed to effectively integrate digital tools into their farming operations. Additionally, the application of digital agricultural technologies is unevenly distributed and strongly influenced by regional disparities in economic development and digital infrastructure. In less developed regions, farmers may face greater obstacles in accessing and implementing advanced technologies due to weaker institutional support and infrastructure gaps. These barriers collectively hinder the widespread uptake of green-efficient technologies at the grassroots level.

This interpretation is further supported by the regional heterogeneity analysis presented in Table 7. The findings indicate that the effect of digital village initiatives on AGTFP is significantly stronger in the eastern region of China, where the coefficient is 0.151 and statistically significant at the 5% level ($p < 0.05$). This region tends to have more advanced digital infrastructure, larger-scale farms, and better access to training and financial services, all of which facilitate the effective adoption of green technologies.

Table 12 Mechanism of Impact Test.

Variable	(1) eff	(2) tech	(3) lnedu	(4) AGTFP	(5) lninf	(6) AGTFP
lndig	0.025	0.105 **	0.291 ***	0.099 ***	0.313 ***	0.120 ***
	(0.639)	(2.181)	(10.909)	(2.646)	(2.923)	(3.756)
lnedu				0.115 **		
				(1.665)		
lninf						0.040 **
						(2.363)
control	Yes	Yes	Yes	Yes	Yes	Yes
constant	1.134 ***	330	1.835 ***	0.209	−0.705	0.448 ***
	(6.437)	0.077	(15.440)	(1.107)	(−1.475)	(3.190)
Year	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes
N	330	330	330	330	330	330
R^2	0.030	0.077	0.368	0.132	0.100	0.140
F	1.813	4.916	34.326	7.466	6.539	8.000

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Another critical factor involves institutional constraints within the rural land tenure system. In many parts of rural China, the ability to consolidate and manage large-scale farmland remains restricted by longstanding land contract arrangements and high transaction costs associated with land transfers. As a result, it becomes difficult for farmers to achieve economies of scale that would justify investment in digital agricultural technologies. These institutional barriers reduce incentives for smallholders to adopt advanced, green-focused technologies that are often more feasible and cost-effective on larger plots.

The data also provide supporting evidence for this explanation. Table 7 shows that the impact of digital village development is more pronounced in major grain-producing areas, where farms are typically larger and more mechanized. Specifically, the coefficient for these regions is 0.113, which is significantly higher than that of other areas. This suggests that farm size and scale are crucial enabling factors that determine the extent to which digital tools can be effectively applied to improve green agricultural productivity.

Market Factors: Since there is not sufficient development of an agricultural market system, and especially no effective way to organise resources, farmers are not as motivated to use digital technologies. When information is not shared rightly or the price of goods is set wrongly, digital transformation does less good for the agriculture industry. Additionally, the baseline regression results in Section 4.1 confirm that prices play a key role, since lnapi is positively associated and proven to be statistically significant.

Because of these barriers, digital village initiatives do not have the ability to make green technology use more efficient. According to the theory discussed in this work, the findings are proven true by the collected data.

Column (2) that digital villages encourage progress in green technology. From these results, it is clear that digital villages play a big part in helping people use environmentally sensitive technological solutions. These initiatives push for more research and development, fast adoption of green inventions, and encourage using advanced environmentally friendly practices in agriculture, contributing positively to its development. So, Hypothesis 1a turns out to be wrong, but Hypothesis 1b is backed up by evidence.

Mediation Effects.

Columns (3) to (6) study how human capital from rural areas and the use of information technology in farming affect the connection between digital village construction and modern agriculture. The significant 99% level shown in Column (3) shows that digital village construction contributes positively to rural human capital. The fourth column further indicates that human capital in rural areas encourages AGTFP growth by a significant 0.115. All in all, these discoveries show that digital village development makes a positive impact on AGTFP by raising the level of rural education and skills.

Likewise, evidence of the medium role of agricultural informatization is found in columns (5) and (6). According to the results, the coefficient for digital village construction is 0.313, and for informatization it is 0.040, all statistically significant at respectively the 1% level and the 5% level. As a result, digital village building greatly helps with the informatization of farming, which has a good influence on AGTFP. By informatizing, we accurately distribute resources, make better decisions, and adopt advanced technology faster in farming, which makes agriculture more sustainable.

All in all, digital village construction leads to higher AGTFP indirectly by improving human resources in rural areas and making farming more technology-based. Such programs make it possible for rural groups to learn new information and gain useful skills, helping them practice eco-friendly agriculture. They confirm that Hypotheses 2 and 3 are valid empirically.

It is also necessary to improve people's digital literacy, reduce problems in handing down land, and develop clearer and market-based systems in agriculture, to get the most from these new green technologies.

CHAPTER 5
FINDINGS AND POLICY RECOMMENDATIONS

5.1. Findings

The study examines the impact of digital village construction on China's AGTFP and draws the following main conclusions:

5.1.1. Promoting AGTFP

It is revealed through this study that digital villages have a strong positive influence on agricultural green total factor productivity (AGTFP). It can be seen from the fixed effects model that a 1% increase in the digital village index increases the AGTFP by 0.132%, which is significant at the 1% significance level. It is mainly the progress in green technology, rather than the improvements in its efficiency, that forms the crux of this outcome. As for specifics, the elasticity coefficient for digital village development's influence on green tech progress is 0.105, which is important at the 5% level, yet its effect on efficiency is light (coefficient = 0.025) and couldn't be picked up through statistics. This shows that digital village development is mostly about getting new ideas spread, rather than improving how resources are used. All in all, digital technology has speeded up advances and dissemination of information in the field of agriculture.

5.1.2. Role of Mechanisms

The analysis finds that constructing a digital village mainly improves AGTFP by boosting agriculture innovative thought and enhancing rural people's skills. Results based on evidence suggest that if digital village construction increases by 1%, agricultural informatization and the rural population's education both improve by 0.313% and 0.291% respectively, and these improvements are significant at the 1% level. Besides, improved informatization in agriculture and an increase in rural human capital add significantly to Aleksander farm's performance, with coefficients of 0.040 and 0.115, respectively, showing statistical significance at the 5% level. Thus, we can see that these programs raise AGTFP without direct approaches and instead by increasing the knowledge and skills of people in rural areas.

The introduction of digital technologies has helped to change the way resources are used, therefore leading to greater efficiency, less consumption of resources, and less environmental damage. Thanks to this approach, agriculture is being made greener. With agriculture and human capital in the countryside playing the main roles, digital projects are able to increase market efficiency, teach people new skills and knowledge, and encourage the use of eco-friendly farming practices.

5.1.3. Regional Heterogeneity Analysis

According to the study, there is a strong location difference in how digital village construction affects the AGTFP of agriculture.

Among the different regions, the eastern region shows the highest impact, and its coefficient is 0.151, proving to be significant at 5% probability. The reason for this outcome is the region's modern digital infrastructure and the fact that more people are using digital agricultural technologies. While both the central and western regions experience growth, it is statistically unimportant, probably because it is challenging for these areas to introduce new technology due to issues with infrastructure.

In terms of north-south differences, digital village construction plays a bigger role in the coastal provinces of Shanghai, Jiangsu, Zhejiang, Fujian, Guangdong, and Hainan, and this can be confirmed since the coefficient of 0.170 is significant at 1%. On the contrary, the northern region, including the cities of Beijing, Tianjin, Hebei, Liaoning, and Shandong, does not influence the growth of GDP. The reason for this difference is that the south enjoys better digital connections and excellent soil conditions that allow digital farming technology.

Among agricultural zones, the effect can be clearly seen in the main grain-growing areas with a coefficient of 0.113 that is important at the 1% level. It proves digital technologies can make the distribution of resources and the running of large farms more efficient. Meanwhile, the effects noted in grain-marketing and balanced areas are noticeable although they are milder since production habits and layouts differ.

Basically, the best effects of building a digital village can be seen in the eastern and southern regions and grain-producing zones because their infrastructures, economies, and population sizes help support the use of digital technology. Alternatively, the effects are not as noticeable in the central, western, and northern regions due to the problems related to inadequate infrastructure, fairly low digital literacy, and the customs of farming on a small scale. These results point out that every region needs its own digital strategy to achieve sustainable and just growth in agricultural green productivity.

5.1.4. Temporal Change Characteristics

It is likewise seen in this study that AGTFP and digital village construction both developed dynamically from 2012 to 2022.

To begin with, digital village construction kept improving throughout the whole decade. Eastern coastal provinces appeared in the upper ranks every time in the categories related to digital infrastructure, digital farming, and rural communities.

In addition, AGTFP also went up over time during this period, and most provinces hit their highest marks in 2018. That said, provinces in the east such as Tianjin and Beijing held lasting AGTFP values between 0.994 and 1.129, in contrast to western areas such as Qinghai, where the AGTFP index fluctuated a lot more between 0.915 and 1.047.

The trend shows that digital village efforts have greatly improved AGTFP mainly by supporting the growth of green technologies and helping resources to be managed in a more efficient way. Still, the issue of inequality between regions has not been overcome. As a result, it is obvious that national digital policies should reflect the special needs of every region found in its infrastructure, human resources, and institutions. Proper policies are required to make the best use of digital tools in supporting green changes in farming across many regions.

5.2. Policy Recommendations

5.2.1. Promote the Integrated Development of Digital Green

Although digital villages have played a big role in advancing green technology, developing technical efficiency is still challenging. For farmers to tackle these problems, speedy adoption of precision agriculture and smart farming must happen. The digital systems used in farming should be fit to the natural and productive conditions in every area. The creation of agricultural environmental monitoring can make farming use resources efficiently and decrease the negative effects on nature. The agricultural sector should be encouraged through incentives to choose green approaches and use digital technology along the entire chain of agricultural production.

5.2.2. Improve Institutional Support for Land Transfer and Large-Scale Management

It is shown by facts that a lack of institution around land in rural areas stops many farmers from using digital technologies in agriculture. It is necessary to speed up reforms in the rural land transfer process, lower transaction costs, and work on land consolidation to make large-scale farming possible, which will create a good climate for promoting digital technologies. Also, the function of agricultural cooperatives should be recognized as important in helping people adopt new technologies. Setting up an agricultural service platform that covers production, distribution, and additional functions enables resources in farming to be allocated by the market, increases the movement of labor and capital, and boosts the productivity and efficiency of agriculture.

5.2.3. Strengthen the Construction of Agricultural Informatization

Agricultural informatization helps raise AGTFP mainly by making use of agricultural digital village initiatives. To fully gain from this, it is very important to create an informative platform that covers production management, market data, and technical support. This kind of platform will greatly enhance the science and accuracy of decisions made in farming. Also, digital applications should be made to face problems specific to production in different areas. It is essential that agricultural e-commerce developments allow more farmers to secure their places in the market and offer a greater incentive for them to use environmentally friendly ways.

5.2.4. Build a Multi-Level Human Capital Cultivation System

Advancing green agriculture using the methods of digital village construction depends greatly on rural human capital. It is necessary to design a training system that divides digital skills into different levels and that best fits the various needs of people living in rural areas. Finally, establishing digital agriculture demonstration bases in important grain-producing areas helps people learn and get access to new technologies. When universities, research institutions, and top agricultural businesses join forces and utilize their resources, it becomes possible to design an effective plan for talent development that ensures cooperation between schools and the industry. Applying this approach will boost rural people's ability to use and absorb digital technologies, leading to stronger and fairer progress in agriculture.

5.2.5.Implement Differentiated Regional Development Strategies

This study revealed that the effects of digital villages on Agricultural Green Total Factor Productivity in China are quite different in its eastern, central, and western areas. In this region where technology is well established, main effort should be on developing digital technology further and boosting digital innovation in agriculture. Alternatively, the central and western parts, where the infrastructure is weak and digital services are not available widely, must concentrate on boosting digital investment and updating the system for providing farming details to help meet the requirements of sustainable agriculture.

It is important to put in place a system that helps transfer digital agricultural technology from the eastern region to other parts of the country. In addition, working together regionally on development platforms will make it easier to allocate resources and achieve balanced growth, which will help in closing the technology and work rate differences among regions.

5.3. International Implications of the Study

Base information for this study includes provincial panel data from China, as it looks at the effect of digital village construction on AGTFP, returning several important points to the international academic discussion.

This study moves beyond the usual studies by focusing on research in a country that is developing. Even though digital agriculture has been widely examined in Europe and North America, there are not many studies of the subject in developing countries at the scale required. This study supplies the missing information by examining China, a key emerging economy from a critical viewpoint.

Moreover, the article includes thorough findings from empirical research that point out that the impact of creating a digital village on AGTFP varies by region. It proves that the positive impact is seen mostly in eastern areas and areas that produce most of the nation's grain. Such findings show other nations with similar level of development how digital tools can enhance the sustainability of agriculture.

Also, this study creates a workable and repeatable model by including the entropy method, EBM-GML model, and mediation analysis. This way of studying sets a good basis for further international studies in digital agriculture and green development.

Additionally, it highlights the need to consider differences in agricultural development stages, resource endowments, and institutional environments across countries, pointing to new directions for cross-national comparative research.

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