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Academic and Practical Cases: From TFP Variables in DEA-Malmquist Model to the Conduction of County-Level Digital Agriculture

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Abstract: This paper investigates the construction and practical implementation of digital agriculture at the county level in China by integrating academic theories and real-world cases. Utilizing the DEA-Malmquist index model, key input variables such as labor, land, machinery, chemical fertilizers, and irrigation are analyzed to measure total factor productivity (TFP) growth in digital agriculture. The study highlights the critical role of smart sensors, big data, artificial intelligence, and Internet of Things technologies in enhancing agricultural productivity, resource optimization, and sustainable development. The paper further explores digital agriculture management systems, including production management, product traceability, and integrated management platforms, which collectively facilitate precision farming, traceability, and intelligent decision-making. The construction path emphasizes government-enterprise cooperation, data integration, and technological innovation, driving transformation from traditional experience-based agriculture to data-driven precision agriculture. The practical value lies in ensuring food security, promoting industrial upgrading, increasing farmers' income, and supporting the global green transformation. Finally, the paper provides policy recommendations focusing on technological advancement, infrastructure improvement, and talent cultivation to foster the sustainable development of digital agriculture in China.

Keywords: digital agriculture; total factor productivity; DEA-malmquist index; smart sensors; precision agriculture

1. Introduction

As we know, total Factor Productivity (TFP) and factor inputs drive economic growth. In agriculture, by measuring the input and output factors of TFP, we can explore the agricultural growth achieved through technological progress, organizational innovation, and other factors. Agricultural TFP is the part of agricultural growth that cannot be explained by input growth, which is known as the Solow Residual. The growth rate of agricultural TFP can also be regarded as the rate of technological progress. This article analyzes actual cases of digital agriculture in Chinese counties from an innovative perspective — the TFP input variables of digital agriculture. It further explores the construction path and suggestions for digital agriculture in China.

2. Literature Review

2.1. Selection of Production Factor Indicators for Digital Agriculture

In recent years, digital technologies represented by big data, artificial intelligence, and the Internet of Things have penetrated into agriculture, and the trends of digital industrialization and industrial digitization have become increasingly prominent. Measuring the evolution trend of TFP is an academic direction that many scholars are researching in agricultural development. However, when measuring TFP, it is necessary to consider the social and technological context. TFP in digital agriculture is an important indicator of agricultural modernization and also a significant indicator for the world to achieve a green transformation.

The variable selection for digital-agriculture TFP requires defining input variables and output variables. Most literature interprets agricultural output as the total output value of agriculture, forestry, animal husbandry, and fishery. Some studies adopted the added value of the primary industry as agricultural output [1], while others used the total agricultural output value per unit of cultivated land as the agricultural output variable [2].

For agricultural input variables, some literature, such as Some research adopted the growth kernel algorithm, setting input variables as eight categories including labor, land, machinery, etc. when measuring TFP [3]. The DEA-Malmquist index method has been used to set labor, chemical fertilizer, machinery, and irrigation area as input variables [4]. The Malmquist-Luenberger index method has been applied to set labor, land, machinery, chemical fertilizer, livestock, and irrigation as input variables [5]. Land, labor, machinery, and chemical fertilizer have been used as input variables [6]. The Färe-Primont index method has been used to set labor, land, machinery, fertilizer, livestock, and irrigation as agricultural input variables [7]. The DEA-Malmquist index method has also been adopted to set land, labor, machinery, and fertilizer as input variables [8]. To avoid the correlation between sown area and irrigation area, as well as the statistical errors that arise from using large livestock to represent livestock.

2.2. Explanation of Agricultural Production Factor Indicators in Digital Agriculture

Most historical documents use the DEA-Malmquist index method to analyze TFP, with agricultural output variables typically employing the total output of agriculture, forestry, animal husbandry, and fishery, while input variables generally involve labor, land, machinery, chemical fertilizers, and irrigation. Regarding the explanation of each variable, first, the land input indicator is divided into cultivated land area and sown area; second, labor input involves economic activity population, employed persons, and employed persons per unit. Among them, the economically active population refers to individuals aged over 16 who have the ability to participate in or are required to participate in social economic activities; employed persons refer to individuals aged over 16 who engage in certain social labor and earn labor remuneration or operate businesses; employed persons in units refer to all individuals working in national organs at all levels, party organs, social organizations, enterprises, and public institutions, who earn wages or other forms of labor remuneration. Third, mechanical input, agricultural machinery refers to the total machinery power used in agriculture, forestry, animal husbandry, and fishery. Fourth, fertilizer input refers to the quantity of nitrogenous fertilizer and compound fertilizer used in agricultural production, with most using the amount of fertilizer application (purity-weighted) as the variable for fertilizer input. From various literature, the data sources for the variables are primarily based on official data, with main sources including the "Statistical Yearbook of New China for 70 Years," the CEIC database, the National Bureau of Statistics, and local statistical data, among others.

From historical documents, regarding the factor analysis of TFP input variables, this paper will demonstrate and analyze the construction of digital rural villages in Chinese counties by combining academic theory.

3. Case Study on the Construction of Digital Agriculture in China

3.1. Digital Agriculture Data Element Foundation: Digital Agriculture Database System

From an academic perspective, under the DEA-Malmquist index model, the input variables of agricultural TFP in the DEA-Malmquist index model basically include labor, land, machinery, organic fertilizer, draft animals, and irrigation.

Labor is a very critical input variable. In the county-level digital agriculture data system, the main system is the digital agriculture database. The labor data is included in the digital agriculture database. In the county-level digital agriculture cases, the labor data is divided into rural human resources data and administrative human resources data. Rural human resources data mainly includes the local rural registered population, permanent resident population, and floating population with long-term residence. Human resources data is collected on different types of rural human resources according to gender, age, education level, family member status, and other information. Meanwhile, in the county-level digital agriculture cases, the database also includes civil petition records and displays policies related to rural credit. Based on the actual operation of county-level cases, the database updates every quarter or every six months. By explaining the input variables in the previous DEA-Malmquist index model, this reflects the effective combination of academic theory and practical cases.

In the DEA-Malmquist index model, the level of agricultural mechanization is the core role of technological upgrading in agricultural development. In historical research, the mechanical data source in the DEA-Malmquist index model is basically the total power of agricultural machinery. The total power of agricultural machinery refers to the total power of all agricultural machinery in a certain region. In the county-level digital agriculture database, the total power of agricultural machinery is included in the production statistics related to tools and resources. The database of local production resources includes natural resources and non-natural resources. Non-natural resources mainly refer to the database of agricultural machinery available to the local area. In the database, data on the total power of agricultural machinery is classified from the source, such as the use of drones for sowing or irrigation within the region, which the database clearly and intuitively reflects. Regarding data updates, the database is updated every quarter or every six months. Through the explanation of input variables in the previous DEA-Malmquist index model, it reflects the effective combination of academic theory and practical cases.

Based on the DEA-Malmquist index model, land is also a very key input variable. In historical literature, land input has two dimensions of indicators: cultivated land area and sown area. In the county-level digital agriculture database, it is also classified according to academic perspectives. Moreover, based on the development needs of digital agriculture, the newly added cultivated land area and newly added sown area after the implementation of digital agriculture technology are also recorded in the digital agriculture database.

Regarding the use of chemical fertilizers in the region, the DEA-Malmquist index model involves fertilizer. In the county-level digital agriculture database, the use of chemical fertilizers is recorded in the regional procurement system and traceability system. Generally, in the DEA-Malmquist index model, the input of chemical fertilizers is represented by the pure quantity of chemical fertilizers. In the county-level digital agriculture database, records are maintained for the use of chemical fertilizers, suppliers of chemical fertilizers, and procurement situations. The regional agricultural database primarily includes large-scale farmers' purchases of chemical fertilizers as the main data source, while the behavior of small-scale farmers or individuals is not considered. Based on the various situations when large-scale farmers purchase chemical fertilizers, such as agricultural input dealers, agricultural cooperatives, chemical fertilizer manufacturers, e-commerce platforms, group purchasing, and direct purchasing, the digital agriculture database will conduct statistics on these several models.

The county-level digital agriculture database, in addition to data elements related to land, labor, machinery, and chemical fertilizers, also conducts statistics on output value, sales, and investment within the region. It compiles statistics on the local agricultural output value for the current year and cumulative total, sales data of agricultural products and by-products, external investment received locally, and the status of village and town enterprises. It also collects information on local village and town enterprises, including company name, operating revenue, net profit, business scope, and other details.

In the construction of the county-level digital agriculture database, in addition to the main system, corresponding subsystems related to production are also built. These subsystems and the digital agriculture database form the basic digital agriculture management system. Examples include crop production management systems, agricultural product traceability management systems, and agricultural comprehensive management platforms.

Agricultural Production Management System: the system includes data analysis on breeding, seedling cultivation, field production, and sales distribution. It will effectively manage production based on the results, achieving intelligent perception, forecasting, early warning of crop planting environments, providing smart analytical decision-making, and offering online expert guidance. Smart sensors are very important in the construction of digital agriculture. Smart sensors are used to receive internal and external environmental data for crop growth. In the fields, smart sensors collect relevant information about the planting and growth of crops, and then use big data models in the system to simulate and predict crop production. During the subsequent growth process, decisions are made on the amount of fertilizer to apply, as well as humidity and water levels, to ensure that the crops grow in a relatively optimal environment. Smart sensors include millimeter-wave radar, video weather monitoring equipment, greenhouse monitoring cabinets, water and fertilizer valves, and other devices. The crop production management system interface will display personnel management, farm management, planting management, agricultural input management, sales management, and IoT management.

Agricultural Product Traceability Management System: this system, based on the integration of block-chain technology and the Internet. It can provide unified traceability for agricultural products in counties and achieve unified management of economic crops. In the agricultural product traceability management system, it organizes information on locally produced agricultural products, uniformly displaying product information, raw material information, production information, inspection reports, and enterprise information. It also provides a QR code for each product, allowing users to trace the entire process of the agricultural product from planting to sales through the QR code.

Agricultural Integrated Management System: The agricultural comprehensive management platform relies on LoRa/NB-IoT low-power IoT and data cloud security technology to establish standardized processes and workflows, creating a traceable management platform that provides decision support and scientific management assistance for medium and large-scale agricultural production enterprises. This system empowers the comprehensive integration of agricultural production, operations, management, and services, accelerates the transformation of agricultural production methods, innovates agricultural product distribution channels, and achieves efficient and transparent business management.

3.2. The Construction Path of China's Digital Agriculture

From academic research to real-world cases, this paper aims to explore the construction cases of digital agriculture in China's county-level areas by discussing the ways to integrate academic research with real-world cases.

By combining the model of government-enterprise cooperation to implement digital agriculture special projects like the case in this article mentioned nationwide, and connecting special agricultural data projects to the national digital agriculture data center, the final goal of agricultural digitalization can be achieved. From "pilot" to "full-scale popularization," the integration of "point, line, and plane", through a three-tiered advancement method from "point" to "line" and then to "plane," a paradigm shift from "experience-based cultivation" to "algorithmic cultivation" is ultimately achieved. In this article, the "point" is analyzed, but it is clear that the construction of regional digital agriculture alone is insufficient to complete China's comprehensive layout for digital agriculture.

The core of China's digital agriculture is data. The various types of smart sensors mentioned in the text collect agricultural data, human resource data within the county, and other important data for the development of China's digital agriculture. These data form a very important database for the conduction of digital agriculture. Data, as the "fifth major factor of production" following land, labor, capital, and technology, are profoundly reshaping the development paradigm of Chinese agriculture and serving as the core engine for the development of China's digital agriculture. Through refactoring productivity (precision agriculture), reshaping production relations (direct connection between production and sales), and innovating governance models (digital villages), data has become the core driving force of China's agricultural transformation.

First, reconstruct the agricultural production system, drive precision agriculture, and improve the efficiency of the entire industrial chain. By collecting real-time data on soil moisture, crop growth, pests and diseases through IoT sensors, satellite remote sensing, weather stations and others, combining AI models to generate optimal planting plans, precision agriculture is achieved. Second, release the "multiplier effect," activate model innovation, and reconstruct rural governance and services. Agricultural e-commerce data is used in "production based on demand," and agricultural finance data supports farmers' credit enhancement to resolve the issues of farmers' difficulty and high cost in obtaining financing. Agricultural labor data integration combines population, land, and economic data, driving decision-making from "experience-driven" to "data-driven." Thirdly, policies and ecology complement each other, top-level design continues to improve, and infrastructure and standard construction are constantly optimized.

3.3. The Practical Value of China's Digital Agriculture Construction

The practical value of China's digital agriculture construction lies in its ability to reconstruct productivity through technology, optimize resource allocation, reshape industrial forms, and provide systematic solutions for national food security, farmers' income increase, rural governance, and ecological sustainable development.

Ensure food security. The practical value of China's digital agriculture construction lies in improving land yield and risk resistance. By building digital agriculture, precision planting technology can be improved, and meteorological disasters can be warned and reduced. Relying on the big data platform of digital agriculture can enhance the efficient utilization of seed industry and resources. For example, the crop production management system mentioned in this article can effectively reduce water consumption and break the constraints of water and soil scarcity through the intelligent irrigation system set up.

Promote industrial upgrading. Through the data platform of digital agriculture, combined with the Internet of Things, the efficiency of the entire production chain can be improved, production intelligence can be enhanced, and traceability and efficient quality control of production products can be achieved. With the increasing activity of e-commerce "going to the countryside", e-commerce drives direct production and sales, achieving integrated innovation.

Promote farmers' income. Through the construction of digital agriculture, by leveraging platform data and smart devices, combined with new technologies such as the Internet of Things (IoT) and AI, farmers' income can be increased and production costs can be reduced. In the future, as China's digital agriculture big data center is completed, farmers will be able to access technical guidance and financial loans through apps.

Assist in the global green transformation. Through the construction of China's digital villages, by leveraging emerging technologies such as big data, smart devices, AI, and the Internet of Things to drive agricultural innovation, efficiently saving resources, and conducting environmental governance through emerging technologies, we contribute to the global green transformation. This is also the practical operation in the county-level cases discussed in this article.

4. Conclusion and Recommendations

Through case studies, this paper outlines that the implicit prerequisite for the development of digital agriculture is the integration of data elements, taking technology as the engine for China's digital agriculture development, and formulating policies in an orderly manner that align with China's digital agriculture development.

Policy promotion and infrastructure are being upgraded with intelligence. As the case discussed in this article shows, it is the result of intelligent infrastructure upgrading, policy promotion is very important. According to the analysis of China's digital agriculture county cases in the text, it is crucial to improve the national agricultural and rural big data platform. Refine agricultural technology policies, break through core technologies, establish special funds to support the R&D of agricultural sensors, AI models, chips, and achieve industry-academia-research collaboration. Refine agricultural subsidy policies by continuing machinery purchase subsidies with a focus on intelligent equipment. Additionally, include IoT sensors and AI diagnostic systems in the subsidy list. Refine fiscal policies by establishing a national digital agriculture special fund, achieving agricultural financial innovation through the integration of China's digital agriculture data.

Technology upgrade, achieve agricultural modernization and promote the global green transformation. Promote the research and development of smart agricultural equipment, such as agricultural sensors, AI models, chips, etc. Due to China's vast land area, rich resources, and complex hydrography and geography, new agricultural technologies are needed to achieve localized upgrading and transformation. For example, developing small smart agricultural machinery for hilly and mountainous areas to reduce terrain applicability costs. Enhance the intelligence level at the production end, promote the program for increasing output per unit, incentivize green production, and achieve energy saving and emission reduction in agriculture through technological upgrades. Through technological transformation, achieve digitalization in grassroots governance. Utilize satellite remote sensing technology to construct an ecological monitoring network.

Educational promotion aims to cultivate digital talents. Train digital leaders to learn courses such as AI operations and data analysis. Encourage enterprises to incubate new professions like "drone pilots" and "AI plant protection workers," providing subsidies to the main bodies creating new job opportunities.

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