

The multidimensional impact of digital agriculture development on agricultural industry upgrading and agricultural economic growth

Moli He

Business School, Dongguan Polytechnic, Guangdong 523808, Guangdong, China

Corresponding author: Moli He (e-mail: mollypublic@163.com)

ABSTRACT Digital agriculture transforms agricultural production through the Internet of Things, big data, artificial intelligence, and blockchain technologies, improving precision production, resource allocation, and supply-chain transparency. This paper constructs a collaborative model of digital agriculture development and agricultural industrial upgrading. Using panel data from 31 Chinese provinces from 2015 to 2024, the entropy method is adopted to measure the development level of digital agriculture. Multiple regression and mediation-effect models are used to analyze the transmission mechanisms of technological innovation, resource allocation efficiency, and agricultural product added value. The research process includes establishing and standardizing a digital agriculture evaluation index system, calculating a comprehensive index and conducting regional comparisons, introducing an agricultural industrial upgrading index to test its effect on agricultural economic growth, and verifying results through robustness checks. Results show that for every 1% increase in the digital agriculture comprehensive index, the agricultural industrial upgrading index increases by 0.062, and agricultural added value increases by 0.54%. The promotion effect in central and western regions is stronger than that in eastern regions.

INDEX TERMS digital agriculture, agricultural industry upgrading, agricultural economic growth, technological innovation, resource allocation

I. INTRODUCTION

THE rapid integration of digital technologies is drastically transforming the way agricultural production is conducted and the trends in economic growth, particularly by optimizing the cultivation of high-quality raw materials for fiber science. Digital agriculture involves the entire agricultural chain with Internet of Things (IoT), Artificial Intelligence (AI), Big Data, and Blockchain technologies, with the help of which it is possible to create information-based sources of decision support and optimization of resources distribution in agricultural production. Agricultural production efficiency has been boosted greatly through the building of precision planting, intelligent irrigation, online transactions, and digital management systems and the agricultural product supply chain has become more efficient and transparent, which has encouraged the transformation of agriculture as a factor-driven to a technology-driven change. Such a process does not only enhance the structure of the agricultural output, but it also acts as a significant avenue to facilitate an integration of the urban and rural region in terms of economic development. Digital agriculture is crucial in enhancing the modernization of agriculture, increasing the

technological backing, and enhancing food security.

The digitalization of agriculture currently is not without a variety of limitations. There is a high discrepancy rate in the extent of information infrastructure development and interconnection and sharing of data among regions. There are also regions where data silos and system fragmentation are witnessed resulting in terminated information transmission links. The lack of digital literacy in farmers prevents the use of new technologies at the level of production and decision-making, which leads to low efficiency in the development and use of agricultural information resources [1,2]. The risk of data security and privacy protection to some degree undermines the background of trust in promoting digitalization. At the same time, it is still unclear how successful the investments in agricultural digitalization can be because of the absence of a sound technical standards system and policy coordination mechanism. These issues all restrict the long-term motivating effect of digital agriculture on industrial development and economic growth, and there is a need to analyze the effects mechanisms and mechanisms through which it affects the economy systematically.

The paper dwells on the multidimensional effects of

developing digital agriculture on the upgrading and economic growth of the agricultural industry, emphasizing how precision cultivation enhances the quality of raw materials. It develops a regional analysis framework of collaboration to expose its action mechanisms in three dimensions, which include digital technology innovation, resource allocation efficiency, and addition of value to agricultural products. Based on panel data on 31 Chinese provinces between 2015 and 2024, a multi-regression and mediation effect model is constructed to empirically determine the promoting effect of digital agriculture. The research innovations are primarily manifested in three dimensions, including, first, developing a standardized measurement system of digital agriculture that covers a variety of indicators to reach a comprehensive characterization of the intensity and quality of development, second, uncovering the transmission mechanism of digital agriculture that fosters industrial upgrading, namely, through technology diffusion and resource optimization, and third, verifying the difference of development and convergence trend of digital agriculture in various economic regions, which provides empirical support and decision-making reference to governments when developing policies of agricultural digitalization and industrial transformation.

II. RELATED WORK

The combination of Internet of Things (IoT), Artificial Intelligence (AI) and Big Data technologies has stimulated the creation of digital agricultural systems. IoT allows to monitor the environment of farmland and the state of the crop in real-time with sensor networks, enhancing the accuracy of production; AI is implemented to make intelligent decisions and predict risks, enhancing the efficiency of agriculture and control over its quality; the collection and processing of agricultural data is performed using Big Data technology, which increases the compliance of supply and demand in the agricultural product market. Similar studies have indicated that the use of these technologies has enhanced the pattern of agricultural resources utilization as well as facilitating the establishment of project digital systems of production. Nevertheless, the application level and synergy of digital technologies in various areas continue to have loopholes [3,4], and the comprehensive impact of agricultural digitalization is highly influenced by the availability of the infrastructure and the ability to connect the data.

The studies on the correlation between the industrial upgrading of agriculture and economic growth are mainly concerned with technological advancement and redistribution of resources. Available sources reveal that technological innovation may succeed in enhancing the labor productivity and value chain extension capabilities of agriculture, as well as, the resource allocation efficiency of the agricultural sector will contribute to the enhancement of the inner structure of agriculture and the use of factors. Through the development of the models of total factor productivity, some studies have also discovered that agricultural value added is

greatly driven by technological progress. However, the systematic explanation of the industrial upgrading mechanism under the digital perspective is incomplete and the flow of digital technology to agricultural development requires more elucidations.

The current literature still lacks the ability to address the regional variations, dynamic effects, and multidimensional transmission forms in an empirical way. The majority of the results are made on the qualitative analysis stage, without using multi-source data, which is capable of representing the correlation of technology diffusion, information flow and economic performance at the same time. Digital infrastructure and adoption behavior by farmers is often not considered in cross-regional comparative studies, and is often not deeply quantitatively analysed regarding regional variation in the benefits of digital agriculture [5,6]. It is based on this that the paper bridges the empirical gap in the research on effects of digital agriculture on industrial upgrading and economic growth by developing a multidimensional model and panel data validation.

III. METHODS

A. DATA SOURCES AND SAMPLE DESCRIPTION

The data for this study comes from the statistical data on agricultural digitalization and economic development of 31 provinces across China from 2015 to 2024. The data includes structural indicators such as agricultural informatization investment, application rate of intelligent equipment, online transaction volume of agricultural products, agricultural science and technology research and development expenditure, and agricultural added value. The original data are mainly taken from the National Bureau of Statistics, the digital agriculture monitoring database of the Ministry of Agriculture and Rural Affairs, and agricultural information service platforms of various provinces, supplemented by satellite remote sensing data to correct the coverage of digital agriculture infrastructure. During the data processing, the statistical caliber of different sources was uniformly processed to ensure comparability in the time and spatial dimensions [7,8]. The study sample covers the entire chain of agricultural production, processing and circulation. The panel sequence was constructed by annual matching and regional alignment. Some missing data were corrected by a combination of trend imputation and multiple imputation, and extreme value removal was used to exclude extreme interval samples. The final dataset can accurately reflect the dynamic relationship between the development level of digital agriculture and the upgrading of the agricultural industry, providing high-precision empirical support for subsequent model testing.

B. CONSTRUCTION OF THE INDICATOR SYSTEM

The construction of the digital agriculture indicator system takes the process of industrial digitalization, agricultural technology innovation, and resource allocation efficiency as the main analytical dimensions. To ensure that the indicator

system can comprehensively depict the development status of digital agriculture, the study decomposes the information characteristics of each link of agricultural production, processing, circulation, and services, and determines the evaluation indicators by combining multi-source data. The data is standardized and directionally consistent to eliminate the bias caused by different dimensions. The technology application indicator is extracted based on the number of Internet of Things (IoT) sensing devices and the penetration rate of agricultural intelligent equipment; the information utilization indicator is measured by the number of users of agricultural big data platforms and the frequency of information service transactions; the innovation capability indicator selects the proportion of agricultural scientific research investment and the number of patent authorizations [9,10]; the resource allocation indicator is constructed based on land use efficiency and the coverage of digital agricultural services. The weight of each indicator is calculated by the entropy method to ensure that the contribution of each element is objectively reflected. Table 1 shows the evaluation indicator system for the development level of digital agriculture.

TABLE 1. Evaluation Index System for the Development Level of Digital Agriculture

Dimension	Indicator Name	Data source	Indicator Attributes
Technology Application	Penetration rate of intelligent agricultural equipment	Ministry of Agriculture and Rural Affairs Statistical Database	positive
Information utilization	Agricultural information service transaction frequency	Agricultural Information Monitoring System	positive
Innovation capability	Number of agricultural patents granted	Statistical Annual Report of the State Intellectual Property Office	positive
Resource allocation	Land digital management coverage rate	Agricultural resource management platforms in various provinces	positive
Economic performance	Online sales proportion of agricultural products	National E-commerce Development Report	positive

C. DATA PROCESSING METHODS

The purpose of data processing is sample consistency and indicator comparability, which all guarantee the data quality is appropriate to further empirical model analysis by systematic correction and transformation.

Following the import of the raw data, data cleaning and logical consistency check is done initially which eliminates outliers and statistical misreports. In order to tackle differences in time series, time length between the provinces is redefined as an annual alignment algorithm so that the sample distribution continuity can be granted. Upon the unification processing, multi-source heterogeneous data undergoes normalization transformation, which converts agricultural IoT monitoring data, remote sensing data and statistical indicators to a common scale. A mixture of moving averages and exponential correction is used in data smoothing to lessen the intermittent variations in administrative statistics.

Where there is a lack of samples, multiple imputation methods are applied to replace them, and the imputation function is trained under the influence of regional proximity and historical trend regulations to ensure a geographical logical consistency. Covariance stability of the standardized matrix is first tested before the determination of weights in order to eliminate redundant indicators that have high collinearity. The last designed data table may be simply inserted into the analysis model to quantify the quantitative transmission effect of the level of development of digital agriculture and industrial upgrading.

D. MODEL DESIGN

The objective of this model design is to examine how the development of digital agriculture can be transmitted to the upgrading of the agricultural industry and economic development and create a hybrid framework of the numerous effects of mediation and numerous regression. The model framework involves the comprehensive digital agriculture index as the explanatory object and the driving force and the agricultural industry upgrading index and agricultural added value as the outcome indicators. Path decomposition determines both direct and indirect effects. The use of panel data has a two-way fixed-effects model to manage the interference of time and geographical variations. The logical structure of the model consists of three layers, namely digital technology of agriculture as the input, and its construction as the input layer; technological innovation and resource allocation efficiency as the transmission layer; and agricultural industry added value growth as the outcome layer. Once the parameters are standardized, an estimation of the parameter of each variable matrix is made and a standardization through the use of robustness tests and heteroscedasticity-robust standard errors. Path identification of transmission evaluates the robustness of mediation impact by applying stepwise regression and Bootstrap resampling ascertaining the connection pathway between digital agriculture and diffusion of technology and maximization of factors.

E. ROBUSTNESS TEST

Several paths were used to check the robustness of the model results to confirm the model stability and consistency and minimize the effects of estimation bias. A substitution indicator approach was applied to test the reliability of digital agriculture indicators, and the penetration rate of the agricultural digital equipment and the frequency of information service use were substituted by the penetration rate of the agricultural e-commerce and the volume of transactions of the agricultural information platforms. The re-estimation of model parameters was then done and the magnitude of differences assessed to determine the strength of the results. In order to avoid structural bias created through the heterogeneity of regions, the sample was categorized into three groups-eastern, central, and western-depending on the level of economic development, and grouped regressions were

conducted individually, to analyze the consistency of the regional impact. A rolling window method was used to test time stability to dynamically estimate cross-sections across years to determine the trends of structural change. The problems of heteroscedasticity and autocorrelation were fixed with the robust standard errors and clustering corrections so that they could not affect the significance of parameter. The mediation path reliability was further established by computing confidence intervals by 5000 repeated samplings with Bootstrap, the range of fluctuation of the estimates of the indirect effects.

IV. RESULTS AND DISCUSSION

A. COMPREHENSIVE INDEX ANALYSIS

The entropy value approach with weighted averages is used to compute the Digital Agriculture Comprehensive Index, and a complex evaluation table is designed on five scales, namely: technology application, information utilization, innovation capability, resource allocation and economic performance. The results of the indices of each province are normalized and compared with time to reflect the strength of the digital agriculture development and the dynamic trend of evolving across the regions. The calculation of the index is 2015-2024, and it can intuitively show the distribution of the spatial gradient and changes in the growth rate of agricultural digitalization in China. Table 2 displays specific data.

TABLE 2. Regional Distribution and Trends of Digital Agriculture Comprehensive Index (2015-2024)

Area	2015	2018	2021	2023	2024
Eastern region	0.412	0.556	0.703	0.751	0.784
Central region	0.328	0.446	0.589	0.635	0.668
Western region	0.275	0.398	0.524	0.586	0.613
Northeast China	0.301	0.425	0.561	0.602	0.627
National average	0.329	0.456	0.594	0.643	0.673
growth rate (%)	—	38.6	30.3	19.3	10.9

The eastern region has a higher growth rate and absolute level than the national average and the positive change of digital infrastructure and information service system has promoted the constant improvement of the index. The growth rate of the central region and northeast is steadily increasing, and the advancement in agricultural technology investment encouraged the informatization penetration. Whereas the general indicators in the western region are fairly low, the growth rate is excellent, which signifies that the digitalization of agriculture is shifting out of regional concentration to a broad region, and the disparity in the digital agriculture development is narrowing.

B. EMPIRICAL RESULTS

The panel data estimation of fixed-effects estimate reveals that when the comprehensive index of digital agriculture is raised by 1 unit, on average 0.062 more units are added to the agricultural industry upgrading index, and

the agricultural added value grows by an average of about 0.48 per year. The results of the regression distribution reveal that, the regression coefficients are 0.69 (eastern region), 0.57 (central region), 0.52 (western region) and 0.55 (northeastern region) and all these are below the test level of 1 percent. The input of technological innovation also has a mediating effect on resource allocation efficiency and the overall effect is 38.4 and 34.7 respectively, which means that digital factors have an amplifying strong effect on the production process. In terms of time series, the growth trend was not high between 2015 and 2020, meaning that the enhancement of output efficacy has come as a result of developing digital infrastructure. The Bootstrap repeated sampling test indicates that there is no 95 percent confidence interval to indicate that the interval is not covering the zero point, which means that the model used is steady and sound. In general, the findings indicate that the growth in the comprehensive index is aligned with the growth in agricultural economy and even though there are regional differences, there is a definite convergence trend.

C. REGIONAL DIFFERENCES

The regional disparity analysis used the digital agriculture comprehensive index as a benchmark and employed a grouped regression method to assess the differences in performance among the eastern, central, western, and northeastern regions from an economic zoning perspective. After regional equalization and fixed-effects control, the sample data were compared to assess the impact of digital agriculture on industrial upgrading and agricultural added value in each region. The analysis used average data from 2015 to 2024 to reflect long-term stable trends and comprehensively considered location, input intensity, and the status of agricultural digital infrastructure, as detailed in Table 3.

TABLE 3. Regional Regression Results of Digital Agriculture on Agricultural Industry Upgrading and Economic Growth

Area	Industrial upgrading coefficient	Agricultural value added coefficient	Significance level	Adjusted R ²	Average growth rate (%)
Eastern region	0.69	0.52	0.01	0.83	5.8
Central region	0.57	0.48	0.01	0.79	4.7
Western region	0.52	0.41	0.05	0.76	5.1
Northeast China	0.55	0.43	0.05	0.74	4.5
Nationwide	0.61	0.46	0.01	0.81	5.0
Interval difference ratio	1.33	1.27	—	—	—

Data results show that the industrial upgrading coefficient and agricultural growth efficiency in the eastern region are both higher than the national average, thanks to improved digital infrastructure and a mature agricultural product logistics system. The central and northeastern regions, constrained by resource structure, have slightly lower rates of digital technology conversion, but these are steadily increasing. The western region has seen improved input

efficiency, with an agricultural added value growth rate of 5.1%, indicating that digital agriculture is gradually playing a driving role in less developed areas. The overall coefficient ratio of 1.33 to 1.27 suggests that regional differences are narrowing, and the development of digital agriculture is showing a continuously converging pattern of diffusion from east to west.

V. CONCLUSION

Digital agriculture has contributed to the upgrading and economic growth of agriculture in a significant way, ensuring the precision cultivation of high-quality raw materials. By leveraging advanced data analytics to monitor fiber properties at the source, this technological shift

enhances the consistency and sustainability of inputs required for high-performance manufacturing. It can be shown that studying panel data in 31 provinces in China in 2015-2024, the further increase in the comprehensive digital agriculture index successfully leads to the optimization of the industrial structure and the growth of the agricultural added value mainly by the technological innovation and efficiency in resource allocation. The comparisons of the regions indicate that the east region is more developed, where policy directions, and better infrastructure offer out growth benefits that are sustainable; the eastern, northeastern and western region gap is converging, in the east to west direction. This analysis of the models also suggests that an increase in digital agriculture by 1 percent will raise the agricultural industrial upgrading index by about 0.062, agricultural economic growth by about 0.54, and the rate of technological innovation contribution is more than 40 percent. This finding confirms the high impact that introduction of digital technology in the agricultural production system has on raising agricultural total factor productivity. The results of the research can be relevant when designing digital agriculture policies to establish a new development model that deeply integrates agricultural data sharing and infrastructure with the technical requirements of engineering and fiber science. By enhancing the digital capacity of farmers to monitor fiber properties at the source, this framework ensures the precise alignment of raw material production with the automated standards of modern manufacturing.

AUTHOR CONTRIBUTIONS

Moli He designed, collected and analyzed the data, and drafted the manuscript. Moli He conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Moli He participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

- [1] H. Wang, R. Liu, and W. Bao, "A Study on Regional Differences and Driving Factors in the Development Level of Digital Agriculture in the Yellow River Basin," *Yellow River*, vol. 47, no. 3, pp. 18-23, 2025, doi: 10.3969/j.issn.1000-1379.2025.03.003.
- [2] X. Wang, "Evaluation of the Development Level of Digital Agriculture in Gansu Province from 2013 to 2022 Based on Entropy Method and TOPSIS Method," *Central South Agricultural Science and Technology*, vol. 46, no. 3, pp. 144-148, 2025, doi: 10.3969/j.issn.1007-273X.2025.03.032.
- [3] Z. Liu and X. Li, "Development level and regional differences of digital agriculture in Xinjiang," *Rural Economy and Science & Technology*, vol. 36, no. 9, pp. 116-119, 2025, doi: 10.3969/j.issn.1007-7103.2025.09.030.
- [4] H. Liu and X. Xie, "Research on Economic and Legal Issues in the Development of Digital Agriculture," *Shaanxi Agricultural Sciences*, vol. 71, no. 5, pp. 105-108, 2025, doi: 10.3969/j.issn.0488-5368.2025.05.023.
- [5] Y. Tang and J. Bi, "Current Status of Digital Agriculture Development in Myanmar and Prospects for China-Myanmar Cooperation," *Agricultural Outlook*, vol. 21, no. 1, pp. 10-18, 2025, doi: 10.3969/j.issn.1673-3908.2025.01.003.
- [6] M. McCampbell, C. Schumann, and L. Klerkx, "Good intentions in complex realities: Challenges for designing responsibly in digital agriculture in low-income countries," *Sociologia Ruralis*, vol. 62, no. 2, pp. 279-304, 2022, doi: 10.1111/soru.12359.
- [7] R. Chandra and S. Collis, "Digital agriculture for small-scale producers: challenges and opportunities," *Communications of the ACM*, vol. 64, no. 12, pp. 75-84, 2021, doi: 10.1145/3454008.
- [8] R. Birner, T. Daum, and C. Pray, "Who drives the digital revolution in agriculture? A review of supply-side trends, players and challenges," *Applied economic perspectives and policy*, vol. 43, no. 4, pp. 1260-1285, 2021, doi: 10.1002/aep.13145.
- [9] S. Cook, L. Jackson E, J. Fisher M, et al., "Embedding digital agriculture into sustainable Australian food systems: pathways and pitfalls to value creation," *International Journal of Agricultural Sustainability*, vol. 20, no. 3, pp. 346-367, 2022, doi: 10.1080/14735903.2021.1937881.
- [10] J. Liu and P. Sengers, "Legibility and the legacy of racialized dispossession in digital agriculture," *Proceedings of the ACM on Human-Computer Interaction*, vol. 5, no. CSCW2, pp. 1-21, 2021, doi: 10.1145/3479867.