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The Impact of Digital Infrastructure Spatial Association Networks on the Spatial Convergence of Agricultural Carbon Productivity

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The Impact of Digital Infrastructure Spatial Association Networks on the Spatial Convergence of Agricultural Carbon Productivity

Abstract: Utilizing panel data from 31 Chinese provinces spanning 2011 to 2023, this study systematically examines the impact of digital infrastructure (DI) development on agricultural carbon productivity (ACP). By employing a modified gravity model (MGM) and social network analysis (SNA), we characterize the structural evolution of the Digital Infrastructure Spatial Association Network (DISAN) and evaluate its influence on the spatial convergence of ACP. The findings reveal that: (1) While China's ACP improved steadily during the sample period, significant regional disparities persist. The Northeast maintains a leading position, while the Southeast coast exhibits a rapid catch-up trend; notably, the central and western regions demonstrate "late-mover advantages", with several western provinces excelling through clean energy integration. Simultaneously, DI development follows a polarized "east-high, west-low" distribution. (2) The inter-provincial DISAN is becoming increasingly cohesive, characterized by rising network density, clustering coefficients, and "small-world" effects. This network structure has significantly accelerated the cross-regional diffusion of low-carbon technologies, the exchange of green management expertise, and the mobility of digital factors, thereby enhancing regional synergy. (3) A significant convergence trend exists in China's ACP, with the convergence rate under DISAN notably surpassing that under traditional geographical proximity. DI effectively mitigates geographical constraints and amplifies spatial spillover effects, fostering the coordinated growth of regional ACP. This study provides empirical evidence of the spatial nexus between digital integration and agricultural decarbonization, offering strategic insights for regional coordinated development and carbon reduction policies.

Keywords: Agricultural Carbon Productivity; Digital Infrastructure; Spatial Association Network; Spatial convergence; China

1.Introduction

The dual imperatives of global climate change and stringent carbon reduction targets have created significant challenges for the agricultural sector in its pursuit of low-carbon transformation and development. As a unique industrial sector characterized by the coexistence of carbon emissions and sequestration, agriculture serves as both a primary source of greenhouse gases and a critical medium for carbon sinks. Against the backdrop of China's "Dual Carbon" goals, ACP has emerged as a pivotal metric for evaluating low-carbon development and resource efficiency. Unlike traditional productivity indicators, ACP emphasizes the economic value generated per unit of carbon emitted, thereby providing a more nuanced reflection of agricultural performance within a sustainable development framework (Xu et al., 2024; Xinyao & Dan, 2025). Existing literature suggests that China's ACP exhibits distinct spatial and temporal convergence, implying that regional disparities may gradually diminish through policy intervention, technological diffusion, and regional synergy (Sun et al., 2022).

The rapid expansion of DI provides fresh momentum for enhancing ACP. DI serves not only as the backbone of the digital economy but also as a prerequisite for the optimal allocation of agricultural factors and green industrial upgrading. Through "new infrastructure"—such as

broadband networks, 5G, data centers, and the Internet of Things (IoT)—the speed of information transmission and technology diffusion has been significantly accelerated. This contributes to reducing carbon footprints, improving resource efficiency, and fostering the adoption of green technologies (Zhong et al., 2022; Xing et al., 2025). Crucially, DI development exhibits pronounced spatial spillover effects and network externalities. Its spatial associations transcend geographical boundaries to facilitate cross-regional knowledge transfer and production optimization, thereby profoundly influencing the spatial convergence of ACP.

DISAN influences ACP through three primary channels: information transmission, factor allocation, and regional synergy. First, cross-regional DI networks accelerate the diffusion of low-carbon agricultural technologies, enabling regions to share advanced clean production expertise and narrowing the ACP gap (Hong et al., 2023). Second, DI enhances market transparency and precision, optimizing input-output efficiency and aligning production with intensive, low-carbon goals (Feng et al., 2025). Third, DISAN promotes institutional alignment and industrial coordination. Supported by digital platforms, the greening of agricultural supply chains is being realized, accelerating the convergence of inter-provincial ACPs.

Given China's vast territory and heterogeneous regional development, the role of DISAN is particularly vital. While eastern coastal areas lead in DI and green transformation, digital foundations in central, western, and northeastern regions have historically lagged (Li & Liu, 2021). However, under the national "New Infrastructure" strategy, cross-regional DI networks are maturing, and barriers to information sharing are being dismantling, which is expected to strengthen ACP convergence further.

Accordingly, this study utilizes panel data from 31 Chinese provinces (2011–2023) to systematically explore the impact of DISAN on the spatial convergence of ACP. We incorporate control variables including economic development (ED), urbanization level (UL), industrial structure (IS), education level (EL), and financial support for agriculture (FSA). By constructing a DISAN and employing convergence models, we test the convergence characteristics and underlying mechanisms. Robustness is ensured through various spatial weight matrices and alternative estimation methods. The results indicate a significant spatial convergence trend in China's ACP, with DISAN playing a crucial role in bypassing geographical constraints and enhancing regional synergy.

This paper offers two primary contributions: (1) Theoretically, it integrates DISAN into the ACP convergence framework, revealing the mechanisms of agricultural decarbonization through digitalization. (2) Practically, by comparing convergence results across multiple spatial weights, it identifies the unique effects of DISAN, providing policy references for national low-carbon strategies and regional green development.

The remainder of this paper is organized as follows: Section 2 reviews the literature; Section 3 explicates theoretical mechanisms and hypotheses; Section 4 details the methodology and data; Section 5 presents stylized facts; Section 6 examines the role of DISAN; and Section 7 concludes with policy implications.

2.Literature Review

As a cornerstone of the contemporary technological revolution and industrial transformation, DI is profoundly reshaping agricultural production methods and development paradigms. Since the inclusion of "new infrastructure construction" in the 2018 Central Economic Work Conference,

scholars have increasingly integrated emerging technologies—such as broadband networks, 5G, data centers, artificial intelligence, and the IoT—into research frameworks. These technologies are regarded not only as essential components of the digital economy but also as catalysts for the green and low-carbon transformation of agriculture (Dai et al., 2023; Zhou et al., 2025). The OECD defines DI as a technical system supporting data acquisition, transmission, processing, and application, emphasizing its role in accelerating information flow, optimizing factor allocation, and facilitating technology diffusion. Recently, aligned with “Carbon Peaking and Carbon Neutrality” objectives, research has pivoted toward the mechanisms by which DI enhances agricultural efficiency and mitigates emissions—specifically its impact on ACP through resource optimization and low-carbon technology diffusion. As a core metric for sustainable agriculture, ACP measures the economic output generated per unit of carbon emission, reflecting green development levels by internalizing carbon constraints (Wu et al., 2024; Wang & Li, 2025). Thus, exploring the nexus between DI and ACP represents both a frontier in agricultural economics and a response to the "Dual Carbon" strategy.

Existing research on ACP primarily focuses on measurement methodologies and determinant factors. Methodologically, scholars typically utilize non-parametric and parametric approaches for efficiency evaluation. Non-parametric methods, predominantly DEA, have evolved to include the SBM-Undesirable model, Super-efficiency DEA, and the Malmquist-Luenberger index to capture the dynamic evolution of agricultural efficiency under carbon constraints (Tone, 2001). Parametric methods largely rely on Stochastic Frontier Analysis to estimate and decompose ACP by accounting for environmental variables and stochastic disturbances (Aigner et al., 1977). Furthermore, techniques such as kernel density estimation, the Theil index, and convergence models have been applied to examine the spatiotemporal evolution and regional disparities of ACP (Jin et al., 2019; Bai et al., 2019). Regarding determinants, low-carbon technological progress is widely considered the primary driver of ACP (Liu et al., 2025). Additionally, structural adjustments, environmental regulations, mechanization, financial support for agriculture, and human capital have significant effects. Notably, in China, disparities in economic development, resource endowments, and governance have led to a pronounced pattern of regional differentiation in ACP (Liu & Yang, 2021).

With the rapid expansion of DI, research has broadened to assess its impact on ACP. In the production phase, IoT and smart equipment enhance precision, reducing energy waste and emissions (Dong et al., 2025). In the distribution phase, DI fosters digital and green supply chains, lowering logistical carbon footprints while boosting value chain efficiency (Remondino & Zanin, 2022). At the governance level, DI improves emission monitoring and policy precision through big data, strengthening low-carbon policy effectiveness (Liu & Li, 2025). However, the uneven distribution of DI in China—characterized by advanced coastal regions and lagging inland areas—may exacerbate regional ACP disparities (Li et al., 2025).

From a spatial perspective, DI exhibits significant spillover effects and network associations. Scholars employ Moran’s I, spatial autocorrelation, and spatial econometric models to reveal regional agglomeration and diffusion patterns (Liu et al., 2025). Research suggests that high-DI regions act as hubs, driving the cross-regional flow of low-carbon technologies and green production modes, which helps narrow the ACP gap (Chang, 2025). Furthermore, σ-convergence and β-convergence models have been used to examine the dynamic convergence of ACP, highlighting the critical role of digital factors (Cui et al., 2022).

Despite these insights, several gaps remain: (1) most studies focus on the direct impact of DI on ACP, lacking a systematic explanation of the spatial association mechanisms; (2) research on the link between DISAN and ACP spatial convergence is limited, with no established theoretical framework; and (3) empirical studies mostly rely on geographical proximity matrices, often ignoring the cross-regional network connectivity inherent in DI. Accordingly, this paper adopts the perspective of the DISAN to systematically examine its mechanism and effect on ACP convergence, providing theoretical and practical references for agricultural decarbonization.

3.Theoretical Analysis and Research Hypotheses

Under the "Dual Carbon" strategy, enhancing ACP through technological and institutional innovation to achieve a synergy between low-carbon production and high efficiency has become a central priority for both researchers and policymakers. The accelerated deployment of DI has significantly increased the efficiency of information transmission and knowledge sharing. This expansion is reshaping regional interaction mechanisms and spillover effects, providing new impetus for ACP enhancement and regional convergence.

Historically, traditional agricultural models have been characterized by persistent inter-provincial ACP disparities. Lagging regions often struggle to narrow the gap with developed provinces due to infrastructure deficits, obstructed technology diffusion, and inefficient resource allocation (Zhang et al., 2025). DISAN—underpinned by broadband networks, the IoT, and big data—enhances the fluidity of information and technology while reducing the costs associated with cross-regional knowledge transfer (Huang & Liu, 2025). Regions with lower carbon productivity can leverage DI to rapidly adopt energy-saving technologies, clean energy models, and green management expertise, thereby strengthening their catch-up capacity. Accordingly, this study proposes:

H1: Under the conditions of DISAN, China's ACP exhibits significant convergence characteristics.

Under traditional geographical proximity, the diffusion of agricultural technology and innovation is often constrained by physical distance, resulting in a pronounced lag in the adoption of carbon-reduction solutions (Wei et al., 2023). In the agricultural sector, high adoption costs, inadequate monitoring, and low factor mobility further impede the spread of low-carbon practices. However, DI transcends geographical constraints, enabling remote regions to engage in cross-regional learning and experience sharing via digital platforms (Jia et al., 2025). For example, smart agricultural cloud platforms and cross-regional monitoring systems reduce the spatiotemporal costs of technology diffusion, allowing lower-ACP regions to converge with advanced areas more rapidly. Thus, compared to traditional geographical proximity, DISAN is expected to significantly accelerate the convergence rate. Consequently, we propose:

H2: Compared with traditional geographical conditions, DISAN significantly accelerates the convergence rate of ACP.

ACP improvement depends not only on local factor endowments but also on inter-regional spillover effects. In traditional frameworks, spillovers rely primarily on industrial transfers and limited physical technology diffusion, which are geographically bounded (Tong et al., 2013). Conversely, DI reinforces the "small-world" nature of spatial connectivity by establishing a nationwide network that fosters both dense local clusters and long-distance cross-regional linkages. This network structure allows low-carbon technologies and green management expertise from

core hubs to diffuse rapidly to the periphery, amplifying the overall spatial spillover effect (Liu et al., 2023). For instance, integrated carbon databases and intelligent supply chains provide channels for provinces to synchronize carbon-reduction efforts. Based on this, we propose:

H3: Compared with traditional geographical conditions, DISAN exerts a stronger spatial spillover effect on ACP.

4. Research Design

4.1 Research Methodology

4.1.1 Global Scatter-degree Analysis

To ensure the comparability of evaluation indicators across different years, this study employs the Global Scatter-degree Analysis (G-SARA) method—also known as the "horizontal and vertical scatter-degree method"—to assign weights to the various indicators of the DI index. The specific steps are as follows:

Assume there are n provinces, m basic evaluation indicators, and k years. The matrix for the basic indicators is defined as:

$$X = x_{ij}^{t},\ \ (i = 1,2,\cdots,n;\ \ j = 1,2,\cdots,m;\ \ t = 1,2,\cdots,k) \tag{1}$$

In Equation (1), x_{ij}^{t} denotes the value of the j-th indicator for the i-th province in the t-th year. After performing dimensionless standardization on the indicators, the expression for the DI index of the i-th province in the t-th year is given by:

$$z_i^t = \sum_{j=1}^{m} \delta_j y_{ij}^t \tag{2}$$

In Equation (2), z_i^t represents the composite evaluation result for the i-th province in the i-th year. The term δ_j denotes the weight assigned to each indicator, which is determined by maximizing the total sum of squared deviations. The objective function of this method is expressed as:

$$\sigma^2 = \sum_{t=1}^{k}\sum_{i=1}^{n}(z_i^t - \overline{z})^2 \tag{3}$$

In view of the fact that all aforementioned indicators have undergone dimensionless standardization, the mean value $\overline{z} = 0$. Accordingly, Equation (4) can be expressed as:

$$\sigma^2 = \sum_{t=1}^{k}\sum_{i=1}^{n}(z_i^t)^2 = \sum_{t=1}^{k}\delta^T H_t \delta = \delta^T \sum_{t=1}^{k} H_t \delta \tag{4}$$

In Equation (4), the indicator weight vector is defined as $\delta = (\delta_1, \delta_2, \cdots, \delta_n)^T$. The term $H = \sum_{t=1}^{k} H_t$ represents a $m \times m$ symmetric matrix, where $H = Y_t^T Y_t$. The expression for the matrix Y_t is given by:

$$Y_k = \begin{bmatrix} y_{11}^t & \cdots & y_{1m}^t \\ \vdots & \vdots & \vdots \\ y_{n1}^t & \cdots & y_{nm}^t \end{bmatrix} \quad (5)$$

Under the constraint $\delta^T \delta = 1$, the weight vector is determined by identifying the eigenvector corresponding to the maximum eigenvalue of matrix H. By normalizing this eigenvector, the weights for each indicator are obtained. Finally, the DI index is calculated based on these assigned weights.

4.1.2 Modified Gravity Model

Economic gravity theory, derived from Newton's law of universal gravitation, is widely used to analyze spatial relationships in regional economics, agricultural efficiency, and environmental performance due to its capacity to characterize inter-regional factor mobility and interaction mechanisms. The theory posits that "gravitational effects" exist between economic activities in different regions, with an intensity determined by economic scale, development level, and geographical distance. For ACP, this "gravity" manifests not only through economic and industrial interconnectedness but also via the cross-regional diffusion of low-carbon production factors. Essentially, regions with larger economic scales and more sophisticated DI exert a stronger radiative influence on surrounding areas, facilitating the transfer of low-carbon technologies, green management expertise, and knowledge resources, which potentially drives ACP improvement and convergence.

However, the traditional gravity model focuses predominantly on "physical constraints", such as economic mass and geographical distance, which limit its ability to explain the cross-regional dynamics of ACP. First, ACP enhancement depends not only on traditional inputs like capital and labor but is also increasingly contingent on technological innovation, information sharing, and the mobility of green factors under digitized conditions. Second, the advancement of DI enables regional interactions to transcend physical boundaries, allowing cross-provincial green production models and carbon-reduction technologies to diffuse rapidly. Consequently, relying solely on the standard gravity model may underestimate the role of DI in shaping the spatial convergence of regional ACP.

Accordingly, this study adopts an MGM. While retaining the fundamental framework of the classical gravity model, we adapt the variables to suit the specific context of China's ACP. In addition to economic scale and geographical distance, we incorporate the development level of DI, the degree of industrial digitalization, and regional population size. This approach provides a more comprehensive characterization of how provincial DISAN influences ACP, facilitating the identification of network characteristics and spatial linkages in the flow of agricultural carbon-reduction technologies and low-carbon factors.

Existing literature provides empirical support for applying the MGM to agricultural green development and carbon efficiency. For instance, Yang and Luo (2023) utilized an improved gravity model and social network analysis (SNA) to construct a spatial association network of agricultural carbon efficiency across Chinese provinces, identifying distinct agglomeration effects and a "core-periphery" structure. Similarly, Liu et al. (2023) combined a Super-SBM model with a modified gravity model to measure the spatial connectivity of China's ACP. Their results indicated

significant spatial association and spillover effects, with the network shifting toward a polycentric structure where eastern and central regions serve as key hubs for green technology diffusion. These studies validate the effectiveness of the MGM in characterizing spatial network features, providing a robust methodological foundation for this paper.

The specific formula is as follows:

$$R_{xy} = K_{xy} \times \frac{\sqrt{E_x P_x DE_x} \times \sqrt{E_y P_x DE_y}}{D^2_{xy}} (x \neq y) \quad (1)$$

$$K_{xy} = \frac{DE_x}{DE_x + DE_j} \quad (2)$$

In the formula, R_{xy} represents the intensity of economic association between provinces. DI_x and DI_y denote the DI of provinces x and y, respectively. E_x and E_y represent the scale of the agricultural economy in provinces x and y, measured by real GDP of the primary industry. P_x and P_y signify the total year-end population of provinces x and y. K_{xy} represents the contribution rate of province x to R_{xy}. D_{xy} is the spherical distance between provinces x and y. This study constructs a spatial association network based on the MGM model to measure the degree of connectivity in DI between provinces. Within this framework, a gravity value greater than or equal to the designated threshold is recorded as 1, while a value below the threshold is recorded as 0.

4.1.3 Social Network Analysis

DISAN is a multidimensional, complex system involving regional interactions across digital factors, including communication networks, data centers, and smart agricultural platforms. This system manifests through the localized agglomeration of elements and cross-regional diffusion, characterized by the simultaneous existence of synergy and competition. Specifically, the system exhibits three primary features: (1) Concentrated DI elements, where the clustering of broadband, 5G stations, IoT platforms, and research institutions determines regional capacity; (2) Differentiated spatial structures, where disparities in development and connectivity result in heterogeneous tie strengths and uneven centrality; and (3) Abstracted spatial associations, where network ties transcend physical distance to reflect virtualized, non-linear expansion and spillover effects.

SNA serves as a robust analytical framework for this study, enabling the identification of nodal attributes and structural patterns within inter-provincial DI connections. Previous research underscores the utility of SNA in digitalization and agricultural sustainability. For instance, Xu and Zhong (2025) characterized the DISAN, highlighting the central roles of the eastern and central regions. Similarly, Shang et al. (2022) integrated an MGM with SNA to examine the network of China's agricultural carbon emission efficiency, identifying prominent "small-world" characteristics and regional agglomeration. These studies provide a strong methodological foundation for the current research.

Accordingly, this study utilizes SNA to map inter-provincial DISANs in China using the following core indicators:

Network Density: Measures the cohesion of DI ties nationwide, defined as the ratio of actual connections to the theoretical maximum. High density indicates frequent inter-provincial flows of DI elements, facilitating the rapid dissemination of low-carbon technologies. Conversely, low

density suggests fragmented ties that hinder the cross-border diffusion of carbon-reduction expertise.

Network Efficiency: Reflects the optimization of connection paths within the network. High efficiency implies shorter transmission routes for information and technology, fostering synergistic ACP improvements. Lower efficiency indicates redundant connections, which, while potentially increasing network stability, may impede the diffusion speed of green innovations.

Clustering Coefficient: Evaluates the interconnectedness of a province's immediate neighbors. A high coefficient indicates the formation of dense local sub-groups, conducive to the localized replication of green agricultural practices. A low coefficient suggests insufficient regional collaboration and fragmented technology application.

Small-world Entropy: Quantifies the "small-world" properties of the DI network. High entropy suggests that the network maintains local cohesiveness while establishing strong long-distance linkages. This dual structure facilitates the rapid conduction of green factors and strengthens regional ACP convergence.

The specific calculation formulas are as follows:

$$D_{net} = \frac{L}{N \times (N-1)} \tag{3}$$

$$E_{net} = 1 - \frac{V}{\max(V)} \tag{4}$$

$$CC = \frac{1}{n} \sum_{x=1}^{n} \frac{2e_x}{k_x(k_x-1)} \tag{5}$$

$$PL = \frac{1}{n(n-1)} \sum_{x=2}^{n} \sum_{y=1}^{x-1} d_{xy} \tag{6}$$

$$SWQ = \frac{CC}{PL} \tag{7}$$

In the formula, N represents the number of nodes in the DISAN, L denotes the actual number of associations, and D_{net} signifies the network density. V represents the number of redundant links within the DISAN, while E_{net} denotes the network efficiency. Furthermore, k_x denotes the number of nodes associated with node x, e_x represents the number of actual associations among the neighbors of node x, and d_{xy} is the number of links in the shortest path between any two nodes x and y. CC and PL refer to the clustering coefficient and the average path length, respectively, while SWQ denotes the small-world entropy.

4.1.4 Convergence Models

Convergence theory is a standard framework in regional economics and agricultural research, used to assess whether productivity gaps between regions are narrowing and to determine if development is trending toward coordination and equilibrium. In the context of ACP, convergence testing reveals the dynamic nexus between carbon mitigation and production efficiency, reflecting whether regional disparities in low-carbon agriculture are progressively dissipating.

Existing literature identifies three primary methods for convergence analysis: σ-convergence, β-convergence, and club convergence. σ-convergence evaluates whether overall disparities shrink over time by examining the dispersion of ACP across provinces; however, its descriptive nature precludes the identification of underlying causal mechanisms. Club convergence, predicated on regional heterogeneity, groups provinces with similar economic structures and resource endowments into "convergence clubs" to analyze internal synchronization. Nevertheless, it lacks the capacity to adequately address cross-regional spillovers from DI. In contrast, the β-convergence model regresses the ACP growth rate on its initial level to test the "catch-up hypothesis"—that laggard regions grow faster than leaders. Because this model directly identifies the driving forces of regional convergence, it is the most prevalent approach in ACP research. Given its superior causal identification capabilities, this study adopts the β-convergence model to explore the spatial convergence of China's ACP under the influence of DISANs.

Furthermore, to isolate the spillover and dynamic effects inherent in spatial associations, this study incorporates spatial econometric convergence models. Specifically, we employ the Spatial Lag Model (SAR), Spatial Error Model (SEM), and Spatial Durbin Model (SDM). These models characterize the spatial interdependence of ACP through different channels: the SAR model captures the direct impact of neighboring ACP levels on local performance; the SEM model accounts for spatial autocorrelation within error terms; and the SDM incorporates the explanatory variables of neighboring regions. Consequently, the SDM provides the most comprehensive reflection of the diffusion and feedback mechanisms within the DI spatial network.

$$\ln(\frac{ACP_{i,t}}{ACP_{i,t-1}}) = \beta \ln ACP_{i,t-1} + \rho\sum_{j=1}^{n} W_{ij} \ln(\frac{ACP_{i,t}}{ACP_{i,t-1}}) + \gamma \ln X_{it} + u_i + v_i + \varepsilon_{it} \quad (8)$$

$$\ln(\frac{ACP_{i,t}}{ACP_{i,t-1}}) = \beta \ln ACP_{i,t-1} + \gamma \ln X_{it} + u_i + v_i + \varepsilon_{it}, \quad \varepsilon_{it} = \lambda\sum_{j=1}^{n} W_{it}\varepsilon_{it} + \mu_{it} \quad (9)$$

$$\begin{aligned}\ln(\frac{ACP_{i,t}}{ACP_{i,t-1}}) = {} & \beta \ln ACP_{i,t-1} + \gamma \ln X_{it} + \rho\sum_{j=1}^{n} W_{ij} \ln(\frac{ACP_{i,t}}{ACP_{i,t-1}}) \\ & + \varphi\sum_{j=1}^{n} W_{ij} \ln ACP_{i,t-1} + \eta\sum_{j=1}^{n} W_{ij} \ln X_{it} + u_i + v_i + \varepsilon_{it}\end{aligned} \quad (10)$$

In the formula, W represents the spatial weight matrix, which can be defined as a geographic distance matrix, an adjacency matrix, or a DISAN matrix. X denotes the set of control variables, while u_i and v_i represent individual and time fixed effects, respectively. Finally, ε_{it} signifies the random error term.

4.2 Variable Description

4.2.1 Digital Infrastructure

DI serves as a foundational element for the digital, intelligent, and low-carbon transformation of the agricultural sector. Its maturity dictates the technical infrastructure and development potential essential for enhancing ACP. Theoretically, DI provides the necessary hardware for information transmission, data storage, and technical applications. Moreover, it facilitates the diffusion of low-carbon technologies and the adoption of green production practices by enhancing information accessibility and optimizing resource allocation (Nie et al., 2023; Pam & Yang, 2024). Consequently, integrating DI development into the analytical framework for ACP spatial

convergence helps elucidate its pivotal role in fostering regional synergy and narrowing carbon efficiency disparities.

To empirically characterize DI development across Chinese provinces, this study adopts the methodological frameworks of Du and Wang (2024) and Yang and Zhang (2025). Aligning with the objectives of green agricultural development and carbon mitigation, we construct a comprehensive evaluation index system for provincial DI. This system encompasses three core dimensions: internet penetration, network transmission capacity, and information resource carrying capacity. These are further operationalized through six secondary indicators: internet broadband access rate, internet broadband penetration rate, mobile facility scale, long-distance optical cable length, and the volume of web pages and domain names. Collectively, these metrics provide a robust reflection of regional connectivity, communication breadth, and information resource agglomeration.

Regarding the weighting methodology, this study employs the Global Scatter-degree Analysis (G-SARA) method, also referred to as the "horizontal and vertical scatter-degree method". This approach facilitates a horizontal comparison of relative disparities between provinces at a given time and a vertical assessment of dynamic shifts within regions across periods, yielding a composite index that captures both spatial heterogeneity and temporal evolution. Unlike the traditional entropy weight method, G-SARA prioritizes both inter-regional comparability and longitudinal development trends, rendering it particularly suitable for analyzing provincial DI trajectories. The resulting DI index provides a rigorous quantitative foundation for investigating ACP spatial convergence within the context of DISANs.

Table 1: Evaluation Index System of DI

Primary Indicator	Secondary Indicator	Variable Definition	Attribute
Digital Infrastructure	Broadband Access Rate	Number of broadband access ports / Permanent population	+
	Broadband Penetration Rate	Number of broadband subscribers / Permanent population	+
	Mobile Facility Scale	Capacity of mobile telephone exchanges	+
	Optical Cable Length	Length of long-distance optical cable lines	+
	Number of Web Pages	Direct data	+
	Number of Domain Names	Direct data	+

4.2.2 Agricultural Carbon Productivity

The measurement of ACP necessitates a precise definition of the primary sources of carbon emissions stemming from agricultural activities. Drawing on existing literature and the specificities of agricultural inputs (Xiong et al., 2021; Zhang et al., 2023), this study identifies six indicators as the empirical basis for carbon emission estimation: chemical fertilizer consumption, agricultural plastic film usage, agricultural diesel consumption, pesticide usage, total sown area, and effective irrigation area. These metrics collectively reflect the carbon footprint associated with chemical application, energy consumption, and the utilization of land and water resources.

Specifically, the manufacturing and application of fertilizers and pesticides are significant sources of carbon dioxide and other greenhouse gases. Agricultural plastic film contributes to emissions during both its production and disposal phases, while its residue can disrupt the soil carbon cycle. Diesel consumption is intrinsically linked to the operational intensity of agricultural machinery and constitutes a major portion of energy-related emissions. The total sown area

represents the spatial scale of production, where tilling, fertilization, and harvesting activities drive corresponding emissions. Finally, effective irrigation area reflects the intensity of water resource utilization; the associated water extraction, pressurization, and distribution processes generate indirect carbon emissions. These six categories encompass the tripartite framework of "chemical inputs, energy consumption, and resource utilization", providing a robust profile of the structural characteristics of agricultural emissions.

To calculate total carbon emissions, this study converts these six input indicators into carbon emission equivalents using specific coefficients derived from established research. These values are then aggregated to determine the total annual carbon emissions per province. The Gross Value of Agricultural Output, adjusted to 2011 constant prices, serves as the desirable output indicator. Finally, ACP is constructed as the ratio of the Gross Value of Agricultural Output to total carbon emissions. This indicator quantifies the economic value generated per unit of carbon emission, offering a vital metric for characterizing the decoupling of agricultural growth from carbon intensity and assessing the progress of low-carbon transformation.

4.2.3 Control Variables

To mitigate omitted variable bias while investigating the impact of DISAN on the spatial convergence of ACP, this study incorporates several provincial-level control variables: ED, UL, IS, EL, and FSA.

ED is measured by per capita GDP. Higher economic development signifies superior infrastructure and enhanced investment capacity for both households and local governments. This financial strength facilitates increased expenditure on green technologies and digital systems, accelerating the transition toward intensive, low-carbon agricultural practices. Furthermore, robust economic development provides the institutional framework and funding essential for adopting digital applications and carbon-mitigation technologies.

UL is defined as the ratio of urban population to the total population. Urbanization facilitates the transfer of surplus rural labor to non-agricultural sectors, thereby optimizing factor allocation and boosting production efficiency. Additionally, it promotes mechanization, large-scale operations, and informatization, which enhance carbon resource allocation. However, because excessive urban expansion may deplete arable land and exacerbate ecological pressure, urbanization potentially exerts a dual-edged effect on ACP.

IS is quantified using an industrial structure upgrading index. Structural optimization fosters inter-sectoral linkages, promoting the diffusion of green technologies from the secondary and tertiary sectors into agriculture. For instance, modern manufacturing provides eco-friendly machinery, while the service sector drives the digitalization and decarbonization of agricultural supply chains.

EL is assessed via average years of schooling or higher education enrollment. A more educated agricultural workforce generally possesses greater environmental awareness, digital literacy, and technical proficiency. This not only improves energy conservation and emission reduction efficiency during production but also enhances the capacity for technological absorption and innovation.

FSA is calculated as the proportion of fiscal agricultural expenditure relative to the total fiscal budget. Government funding improves basic agricultural infrastructure and ecological conditions while directly stimulating the research and application of green technologies. Specifically, fiscal inputs support the promotion of low-carbon models and the construction of digital irrigation

systems, serving as a direct catalyst for ACP enhancement.

Table 2 Statistical Description

Variable	Obs	Mean	Std.Dev.	Min	Max
ACP	403	7.304	3.055	2.535	20.611
DE	403	5.672	2.777	1.612	16.661
ED	403	0.597	0.129	0.227	0.896
UL	403	0.095	0.051	0.002	0.252
IS	403	0.234	0.110	0.082	0.919
EL	403	0.115	0.034	0.039	0.204
FSA	403	0.535	0.451	0.050	2.575

4.3 Research Area and Data Sources

This study focuses on 31 provincial-level administrative units in China (excluding Hong Kong, Macao, and Taiwan) to systematically analyze the spatial convergence of ACP under the influence of DISAN. Data are primarily sourced from official publications, including the China Statistical Yearbook (2012–2024), provincial statistical yearbooks, the China Rural Statistical Yearbook, and the China Environmental Statistical Yearbook. The analysis spans 2011 to 2023, a period that encompasses China's rapid DI expansion and aligns with national strategies for agricultural green transformation and carbon mitigation.

To ensure longitudinal comparability, all GDP and agricultural output values were deflated to 2011 constant prices. Agricultural carbon emissions were estimated using the input-output accounting method, incorporating key factors such as chemical fertilizers, pesticides, agricultural films, mechanical power, irrigation water, and energy consumption. Conversion factors were derived from established carbon emission coefficients in existing literature. ACP is defined as the ratio of agricultural added value to total agricultural carbon emissions, serving as a comprehensive metric for production efficiency under carbon constraints.

To construct the spatial association framework, a modified gravity model was employed to characterize the intensity of inter-provincial DI links. The DI index—comprising internet penetration, broadband access ports, and mobile base station density—was developed using the global principal component analysis method. Geographic distances between provinces were calculated via ArcGIS based on the actual distance between provincial capitals. For cases with missing values, linear interpolation was utilized to maintain data continuity and sample integrity.

5 Measurement of ACP and DI

5.1 Agricultural Carbon Productivity

Figure 1 illustrates the spatio-temporal distribution of ACP across Chinese provinces from 2011 to 2023. Nationally, ACP followed a steady upward trajectory, with the mean value rising from 5.456 in 2011 to 10.284 in 2023. This evolution suggests that the deepening of green and low-carbon development strategies has enabled Chinese agriculture to transcend traditional high-emission models. Substantial improvements in energy efficiency and carbon mitigation signify that the agricultural green transition has yielded meaningful preliminary outcomes.

Spatially, ACP exhibits significant regional disequilibrium. Northeast China consistently maintains high productivity levels; for instance, Liaoning's ACP rose from 6.115 to 10.656, while Heilongjiang and Jilin increased to over 7.607 and 6.174, respectively. This performance stems from the region's role as a critical national grain corridor, characterized by high mechanization and

early adoption of mitigation practices like straw returning and clean energy substitution.

Conversely, Southeast coastal provinces initially recorded lower ACP levels. Shanghai, for example, stagnated around 3.821 in 2016, reflecting the carbon intensity of high-input agricultural models. However, since 2017, provinces like Fujian and Guangdong have seen ACP nearly double, reaching 13.697 and 13.826 by 2023. These breakthroughs are largely driven by the rapid expansion of DI, which has facilitated advancements in precision agriculture, smart irrigation, and clean-energy-powered facility farming.

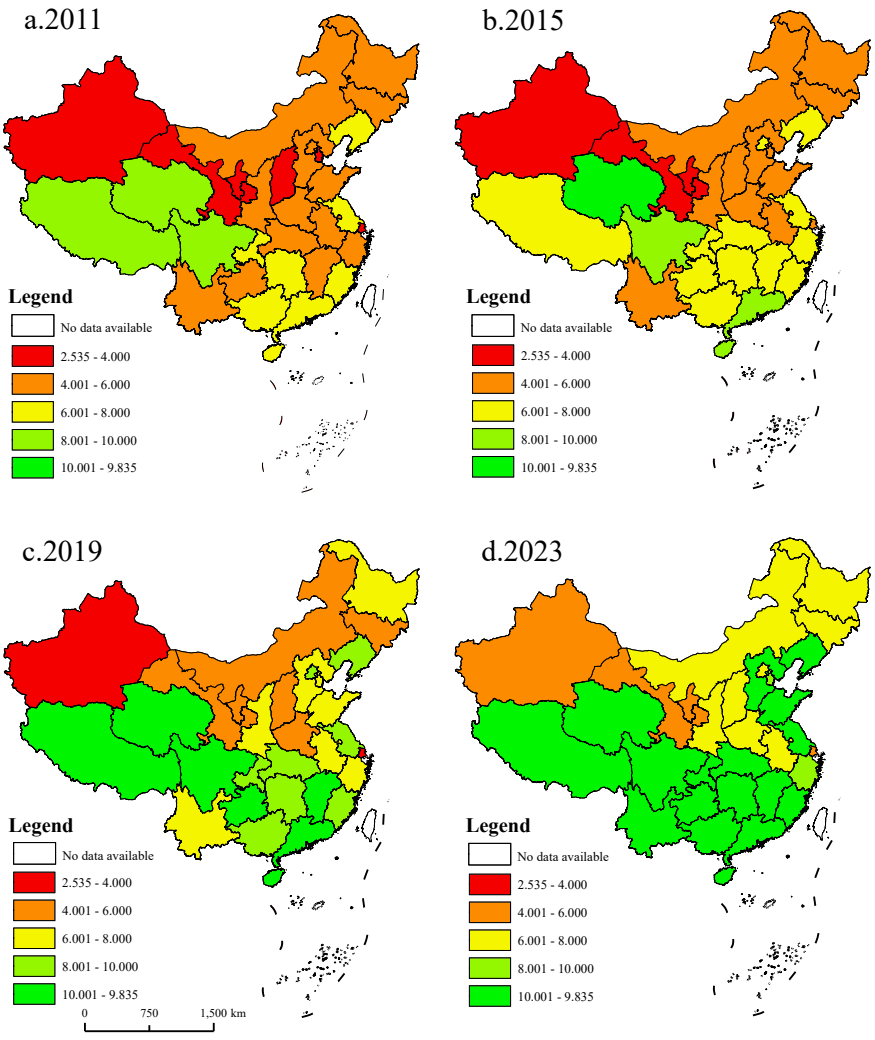


Figure 1 Spatiotemporal Distribution Pattern of China's ACP: 2011-2023

The central and western regions demonstrate a “late-mover catch-up effect”. While provinces such as Guizhou and Yunnan started below 6.000 in 2011, they achieved remarkable growth by 2023, with Guizhou surging to 14.313. This momentum is fueled by national emission-reduction initiatives, “Grain for Green” ecological policies, and the spatial spillover of green production technologies enabled by digital connectivity.

Notably, the western plateau provinces of Qinghai and Tibet far exceed national averages. By 2023, Qinghai’s ACP reached 20.611, and Tibet’s rose to 19.836. Despite their smaller agricultural scale, their reliance on abundant clean energy (e.g., hydropower and photovoltaics) and inherently ecological farming methods results in significantly higher output per unit of carbon emission. In summary, the period from 2011 to 2023 was marked by a continuous rise in national ACP and a

narrowing regional gap, characterized by the “leapfrog” development of late-mover regions.

Overall, between 2011 and 2023, national agricultural carbon productivity not only showed a continuous upward trend but also saw regional disparities gradually narrow, with some late-developing regions achieving leapfrog development.

5.2 Digital Infrastructure

Figure 2 illustrates the spatial distribution of DI development across Chinese provinces from 2011 to 2023. Nationally, DI has maintained a continuous upward trajectory. Since the “13th Five-Year Plan” period, the accelerated deployment of fiber-optic networks, mobile base stations, and cloud computing platforms in rural areas has established the essential technical foundation for enhancing ACP.

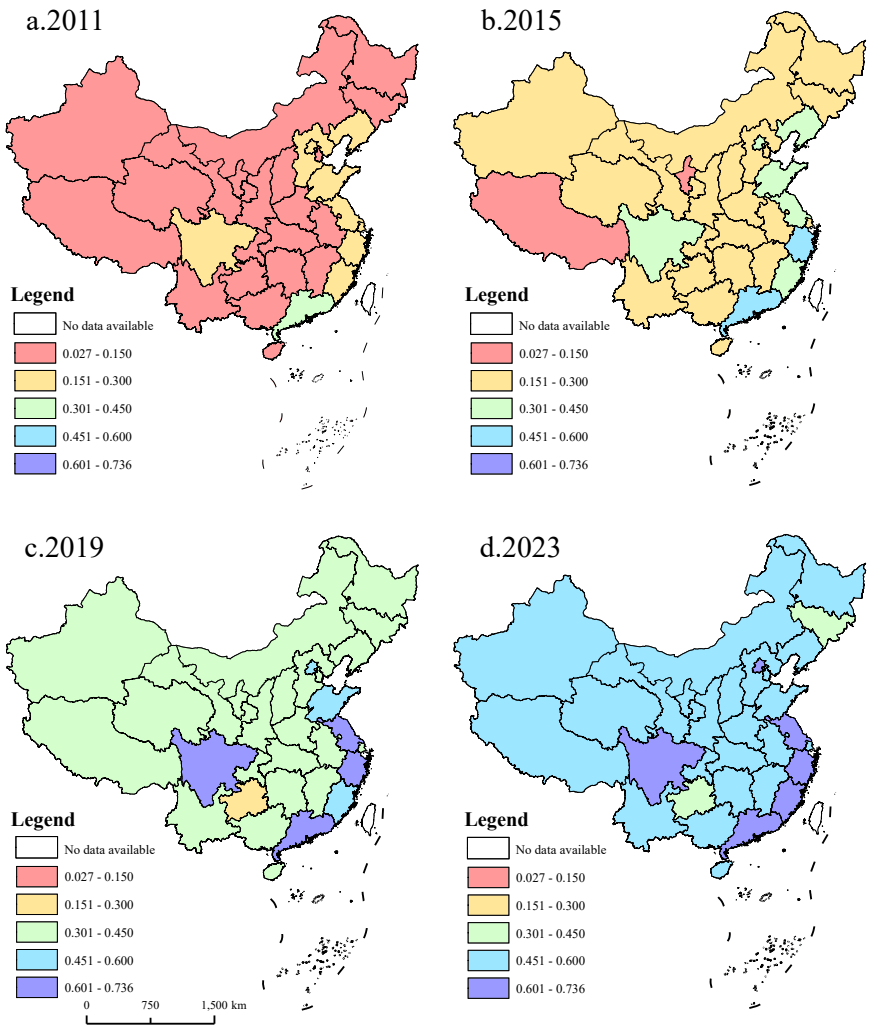


Figure 2 Spatial and Temporal Distribution Pattern of DI in China: 2011-2023

Spatially, DI development exhibits significant regional disequilibrium, following a “high-east, low-west” pattern. Beijing, for instance, saw its index rise from 0.250 in 2011 to 0.621 in 2023, consistently leading the nation. Eastern coastal provinces, including Shanghai (rising from 0.188 to 0.566), Jiangsu (0.215 to 0.736), and Zhejiang (0.231 to 0.701), have maintained similar growth momentum. Leveraging robust network foundations and advanced information service systems, these regions have established a first-mover advantage in low-carbon agricultural technology. Furthermore, they utilize digital platforms to facilitate carbon emission monitoring, disseminate

energy-saving technologies, and integrate green production practices.

In contrast, DI in central and western provinces continues to lag. Although provinces such as Guizhou (0.083 to 0.446), Yunnan (0.099 to 0.469), and Gansu (0.055 to 0.512) have improved, they still face bottlenecks in adopting smart agriculture and carbon mitigation technologies. The continued dominance of traditional input methods and insufficient digital empowerment have constrained the rapid elevation of ACP in these areas. Moreover, remote or resource-dependent regions—such as Tibet (0.027 to 0.471), Qinghai (0.057 to 0.476), and Ningxia (0.047 to 0.507)—are hindered by weak infrastructure and low levels of informatization. These areas exhibit significant path dependence, which limits their potential for a low-carbon agricultural transition.

Overall, spatial disparities in DI reflect regional economic imbalances and significantly dictate the spatial convergence of agricultural carbon productivity. While the eastern coast leads in green production efficiency due to high technology penetration, the central and western regions must prioritize accelerating infrastructure construction and optimizing policy support to foster cross-regional synergy and achieve spatial convergence in ACP.

5.3 Characteristics of the DISAN

Figure 3 illustrates the evolutionary trends of the spatial association network for China's provincial DI from 2011 to 2023. Network density rose steadily from 0.144 to 0.414, signaling a significant intensification of inter-provincial interactions. This strengthening of cross-regional collaboration and resource sharing suggests that infrastructures—such as communication networks, data centers, and digital platforms—are gradually transcending regional boundaries. This broader integration provides the robust network conditions essential for enhancing ACP.

Conversely, network efficiency declined annually from 0.793 to 0.395. This downward trend suggests that while inter-provincial connections have proliferated, information and technology transmission paths have become more complex, resulting in lower overall propagation efficiency. Effectively, the spatial network has transitioned from a highly centralized diffusion pattern toward a more decentralized, multi-centric, and balanced configuration. This shift reduces reliance on specific core provinces and enhances the resilience of the network in promoting low-carbon agricultural technologies and carbon management.

The clustering coefficient increased from 0.410 to 0.756, reflecting the continuous formation of local cooperation groups. These "regional clusters" indicate that geographically adjacent provinces, or those with similar agricultural structures, have developed tighter collaborative ties. Such clusters facilitate the localized diffusion of carbon management expertise, energy-saving measures, and sustainable agricultural practices.

The evolution of small-world entropy, which rose from 0.235 to 0.552, highlights the increasingly prominent "small-world" nature of the network. This structure implies the coexistence of dense local clusters and efficient cross-regional synergistic links, allowing digital resources and management expertise to be shared across shorter network paths. This configuration provides the institutional and structural support necessary for the collaborative improvement of national ACP.

Finally, the number of network connections increased from 139 to 399, reflecting a diversification and strengthening of inter-provincial partnerships. Given that the theoretical maximum number of connections for this provincial network is 930 (31×30), the current count indicates a "low saturation, high potential" stage. This gap suggests that network development remains anchored around several key provinces and has yet to achieve a fully integrated,

nationwide synergistic pattern.

In summary, the DISAN is characterized by rising density, significant clustering, and prominent small-world features. These attributes lay a solid foundation for the cross-regional spatial convergence of ACP while offering substantial room for future network optimization and collaborative innovation.

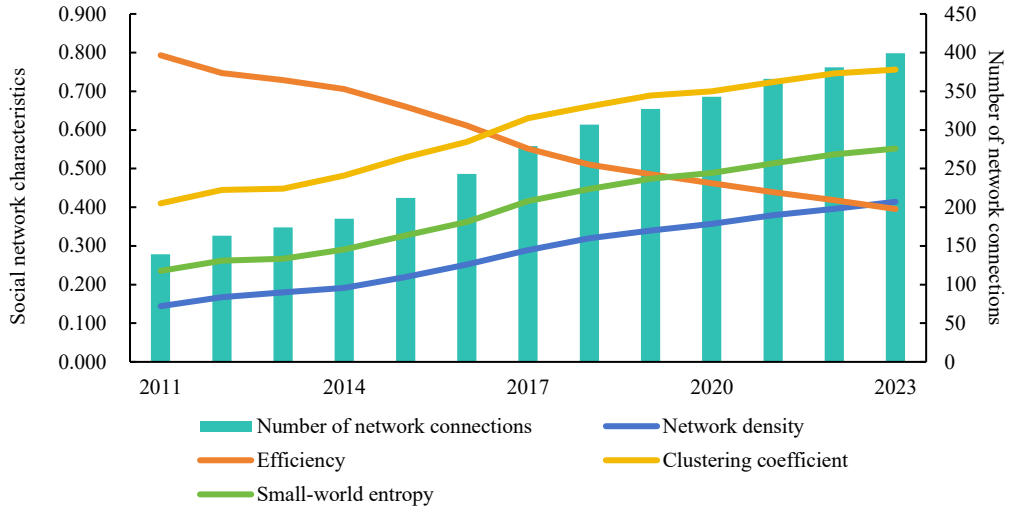


Figure 3 Characteristics of DISAN in China: 2011-2023

6. Convergence Test

6.1 Spatial Autocorrelation Test

Before analyzing the spatial convergence of ACP, this study employs Moran's I index to test for spatial correlation using Chinese provincial ACP and DI data from 2011 to 2023. The results indicate that Moran's I index for ACP is positive and statistically significant across all years, demonstrating robust spatial dependence and agglomeration effects. This suggests that ACP exhibits a distinct positive spatial clustering pattern, where provinces with high or low productivity tend to cluster with geographically similar neighbors, reflecting significant inter-provincial synergy and mutual influence. Simultaneously, while Moran's I index for DI levels shows a strengthening trend, it fails to reach significance in certain years. Overall, the spatial agglomeration of DI provides the foundational support necessary for the cross-regional collaborative development of ACP.

Regarding the specification of the spatial convergence model, this study first performed OLS regressions on the benchmark model and employed Lagrange Multiplier (LM) tests for model selection. The test results show that both LM-Error and LM-Lag are significant. However, the Robust LM-Error test failed to reach the significance threshold, whereas the Robust LM-Lag test remained significant. These findings suggest that while the SAR is partially appropriate, relying solely on the SAR may overlook the spatial spillovers of exogenous explanatory variables. Given that ACP evolution is driven not only by historical inertia and neighborhood effects but also by the spatial linkages of exogenous factors, this study prioritizes the SDM. The SDM framework facilitates the simultaneous examination of temporal, spatial, and spatio-temporal lag effects. For robustness, the SAR is also utilized for verification. Finally, based on the Hausman test results, a fixed-effects specification is adopted to control for unobservable regional heterogeneity, thereby

ensuring the reliability of the estimation results.

Table 3 Spatial Autocorrelation Test

Variables	ACP			DI		
	Moran's I	Z	P-value*	Moran's I	Z	P-value*
2011	0.089	2.499	0.006	0.050	1.705	0.044
2012	0.090	2.498	0.006	0.059	1.889	0.029
2013	0.092	2.531	0.006	0.034	1.374	0.085
2014	0.088	2.455	0.007	0.036	1.405	0.080
2015	0.096	2.619	0.004	0.038	1.457	0.073
2016	0.093	2.570	0.005	0.043	1.549	0.061
2017	0.094	2.578	0.005	0.044	1.591	0.056
2018	0.089	2.487	0.006	0.046	1.639	0.051
2019	0.091	2.538	0.006	0.039	1.494	0.068
2020	0.095	2.628	0.004	0.044	1.594	0.055
2021	0.116	3.067	0.001	0.041	1.532	0.063
2022	0.115	3.052	0.001	0.067	2.059	0.020
2023	0.108	2.898	0.002	0.084	2.408	0.008

6.2 Convergence Analysis of ACP under DISAN

Table 4 presents the regression results for the convergence of China's provincial ACP across various spatial weight matrices. Overall, excluding Model (7), the convergence coefficients across all specifications are significantly negative. This indicates a robust convergence trend in provincial ACP from 2011 to 2023, suggesting that regions with lower initial productivity levels exhibit faster growth rates—a clear "catch-up effect" that supports Hypothesis H1.

A comparison of convergence velocities reveals that in the non-spatial absolute convergence model (Model 1), the coefficient is 0.040 (significant at 1%). In the conditional convergence model (Model 2), the coefficient shifts to -0.122, and the convergence speed increases to 0.011, corresponding to a half-life of 63.929 years. This suggests that the inter-regional convergence trend becomes more pronounced upon the inclusion of control variables, highlighting their critical role in explaining regional disparities and enhancing model robustness.

Upon incorporating spatial factors, the results demonstrate that convergence speeds under both geographic distance (Models 3 and 4) and adjacency matrices (Models 5 and 6) exceed those of non-spatial models. Specifically, under geographic distance, absolute and conditional convergence speeds are 0.010 and 0.006, respectively; under the adjacency matrix, they are 0.015 and 0.004. These findings indicate that geographic proximity and inter-provincial interactions facilitate coordinated regional development through significant spatial spillover effects in agricultural production.

Notably, the convergence trend is most significant when utilizing the DISAN weight matrix (Models 7 and 8). Here, the absolute convergence speed is 0.004, while the conditional convergence speed reaches 0.011, with a convergence cycle of only 62.291 years. This confirms Hypothesis H2: DISAN effectively shortens the catch-up period for lagging regions and accelerates balanced ACP development via information flow, technology diffusion, and optimized resource allocation.

Regarding spatial spillovers, the coefficient for W·lnACP exhibits significant variation following the inclusion of control variables. Under DISAN, this coefficient is 0.131 ($P<0.1$),

indicating that digital networks promote ACP in both contiguous and non-contiguous regions. Compared to traditional geographic proximity, DI broadens cross-regional transmission paths for technology and management, accelerating the absorption of advanced production factors in lagging areas.

Analysis of control variables shows that while ED lacks a significant positive effect, the UL is positive at the 1% significance level, suggesting that urbanization effectively bolsters ACP. EL is also significantly positive, reflecting the contribution of agricultural training to carbon productivity. Conversely, IS and FSA did not pass significance tests, likely due to regional developmental variances and differing fiscal efficiencies.

In summary, DISAN significantly enhances the regional convergence and spatial diffusion of ACP. By facilitating the cross-regional flow of information and resources, it accelerates the adoption of advanced productivity in lagging regions, thereby improving the overall coordination of China's provincial ACP.

Table 4 Convergence Test

Variable	Without Spatial Factors		Distance		Adjacency		DISAN	
Model	（1）	（2）	（3）	（4）	（5）	（6）	（7）	（8）
Convergence Type	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional
Coefficient	0.040***	-0.122***	-0.074***	-0.112***	-0.061**	-0.160***	-0.044**	-0.125***
	（0.011）	（0.023）	（0.025）	（0.026）	（0.025）	（0.030）	（0.022）	（0.025）
W*lnACP			0.091***	0.291***	0.090***	0.059	0.073***	0.131*
			（0.027）	（0.082）	（0.027）	（0.043）	（0.024）	（0.074）
ED		-0.002		-0.011**		-0.022***		-0.005
		（0.003）		（0.006）		（0.008）		（0.004）
UL		0.687***		0.530***		0.346*		0.630***
		（0.118）		（0.169）		（0.196）		（0.123）
IS		-0.078		0.371		0.403		0.401
		（0.295）		（0.278）		（0.283）		（0.300）
EL		0.212***		0.216***		0.216***		0.213***
		（0.064）		（0.060）		（0.061）		（0.059）
FSA		0.414**		0.263		0.267		0.248
		（0.184）		（0.177）		（0.200）		（0.178）
Constant	-0.025	-0.216***						
	（0.022）	（0.061）						
Rho			0.614***	0.106	0.383***	0.137*	0.581***	0.356***
			（0.073）	（0.167）	（0.058）	（0.072）	（0.090）	（0.130）
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Convergence speed	-	0.011	0.006	0.010	0.005	0.015	0.004	0.011
Convergence cycle	-	63.929	108.190	70.025	132.154	47.706	184.850	62.291

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

6.3 Robustness Checks

To ensure the reliability of the findings regarding the impact of DISAN on the spatial convergence of ACP, this study conducts robustness analyses using bilateral winsorization and alternative spatial econometric specifications.

First, to mitigate the potential influence of outliers, a 5% bilateral winsorization was applied

to all variables. The regression results indicate that across all scenarios—including those omitting spatial factors and those incorporating geographic distance, adjacency, or DISAN—China's provincial ACP consistently exhibits a significant convergence trend. Taking the SDM as an example, under winsorization, the absolute and conditional convergence coefficients are 0.043 and -0.046, respectively, both significant at the 1% level. Upon introducing the DISAN weight matrix, the absolute and conditional convergence coefficients shift to -0.062 and -0.058. This confirms that the DISAN significantly accelerates the catch-up speed of lagging regions, thereby shortening the convergence cycles to 129.954 and 139.209, respectively.

Second, to address the potential limitations of a single model specification, this study employs the SAR as a supplementary check. The results show that without winsorization, the absolute and conditional convergence coefficients under the SAR model are 0.001 and -0.108, respectively. Under DISAN, these coefficients reach 0.014 and -0.113. The convergence direction remains consistent with the benchmark SDM, and the statistical significance is fundamentally stable. This indicates that the effect exerts a robust and consistent influence on regional ACP convergence, regardless of the econometric model employed.

Table 5 Robustness Check

Variable	Without Spatial Factors		Distance		Adjacency		DISAN		Distance		Adjacency		DISAN	
Type	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional	Absolute	Conditional
Model			SDM	SDM	SDM	SDM	SDM	SDM	SAR	SAR	SAR	SAR	SAR	SAR
Whether to truncate	YES	YES	YES	YES	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO
Coefficient	0.043***	-0.046***	0.045***	-0.062***	-0.036*	-0.080***	-0.025	-0.058***	0.001	-0.108***	0.017	-0.117***	0.014	-0.113***
	（0.009）	（0.018）	（0.017）	（0.018）	（0.018）	（0.019）	（0.016）	（0.018）	（0.011）	（0.021）	（0.011）	（0.022）	（0.011）	（0.022）
W*lnACP			0.061***	0.144**	0.060***	0.075**	0.043***	0.082						
			（0.019）	（0.069）	（0.019）	（0.031）	（0.017）	（0.065）						
Control variable		Controlled		Controlled		Controlled		Controlled		Controlled		Controlled		Controlled
Constant	-0.032*	-0.099*												
	（0.016）	（0.049）												
Rho			0.669***	0.020	0.451***	0.205***	0.655***	0.400***	0.647***	0.497***	0.394***	0.187***	0.630***	0.353***
			（0.063）	（0.167）	（0.052）	（0.065）	（0.074）	（0.113）	（0.070）	（0.090）	（0.058）	（0.067）	（0.086）	（0.109）
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Convergence Speed	-	0.004	0.004	0.005	0.003	0.007	0.002	0.005	-	0.010	-	0.010	-	0.010
Convergence Period	-	176.629	180.648	129.954	226.865	99.755	328.534	139.209	-	72.778	-	66.847	-	69.367

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Furthermore, the robustness tests verify the existence of spatial spillover effects across different models. Within the SDM framework, the W*lnACP coefficient under DISAN is 0.144, indicating that ACP in both contiguous and non-contiguous regions is subject to significant positive spillovers. This further corroborates that DI not only optimizes resource allocation but also facilitates the cross-regional diffusion of information, technology, and management expertise, thereby accelerating catch-up momentum in lagging areas.

In summary, the robustness tests—comprising bilateral winsorization and alternative spatial econometric modeling—consistently demonstrate that DISAN plays a significant and stable role in driving the spatial convergence of provincial ACP in China. These findings provide a reliable empirical foundation for policymakers to synchronize DI expansion with the low-carbon transition

of the agricultural sector.

7. Conclusions, Implications, and Discussion

7.1 Conclusions

Based on Chinese provincial panel data from 2011 to 2023, this study systematically evaluates ACP and DI development. By constructing a DISAN and employing convergence models, the study derives several key findings:

First, both ACP and DI in China exhibited steady growth during the sample period, despite persistent regional disequilibrium. Regarding ACP, Northeast China maintained high productivity levels, while the Southeast coastal provinces demonstrated a rapid catch-up trend. The central and western regions displayed a distinct “late-mover advantage”, with several western plateau provinces achieving superior carbon efficiency by leveraging clean energy resources. Conversely, DI development in the eastern coastal regions significantly leads the nation, whereas central, western, and remote provinces continue to exhibit a marked lag.

Second, the DISAN has become increasingly integrated. Rising network density and clustering coefficients, alongside strengthened “small-world” characteristics, indicate a continuous expansion of inter-provincial digital partnerships. This evolutionary shift from a “core-node dominated” hierarchy toward a “multi-centric collaborative” network has enhanced system resilience. Furthermore, it has facilitated the cross-regional diffusion of low-carbon agricultural technologies and management models, thereby bolstering the overall synergy of ACP.

Third, China's ACP demonstrates a significant spatial convergence trend. Compared to traditional geographic proximity models, convergence under DISAN is faster, with a significantly shorter convergence cycle. This suggests that DI transcends geographical constraints, reinforcing the cross-regional flow of information and resources while accelerating the absorption of advanced production factors in lagging regions. Consequently, the DISAN plays a pivotal role in facilitating ACP spillover effects, broadening collaboration between non-contiguous regions, and promoting balanced regional development. Additionally, urbanization and education levels significantly enhance ACP, suggesting that population agglomeration and human capital are vital pillars for agricultural decarbonization. In contrast, economic development, industrial structure, and fiscal support for agriculture do not exert significant effects in this study, likely due to regional variations in developmental stages and fiscal efficiency.

7.2 Policy Recommendations

First, expand DI to elevate overall ACP. Empirical findings reveal significant regional disparities in China’s provincial ACP; although lagging regions exhibit a “catch-up effect”, the rate of convergence remains insufficient. Therefore, policy efforts must prioritize addressing DI deficits by accelerating the deployment of broadband networks, 5G communications, data centers, and the Agricultural IoT within rural production systems. Specifically, strengthening real-time monitoring, intelligent control, and carbon tracking is essential. Simultaneously, the adoption of precision farming equipment and low-carbon machinery should be incentivized to optimize resource efficiency. By unifying technical standards and data collection mechanisms, the government can provide the institutional safeguards necessary for robust carbon accounting and green agricultural development.

Second, strengthen spatial association to foster regional synergy in carbon mitigation. This study demonstrates that spatial spillovers from DI narrow the regional ACP gap; however,

digitalization remains imbalanced. To drive cross-regional cooperation, digital platforms should be developed to facilitate the exchange of emission data, green technologies, and management expertise, establishing a "leading-to-lagging" linkage mechanism. Eastern regions should be encouraged to export their digital agriculture experiences to the central and western provinces, fostering regional complementarity. Furthermore, advancing the application of big data, cloud computing, and artificial intelligence will accelerate the cross-regional diffusion of monitoring and accounting innovations.

Third, leverage spatial externalities to accelerate ACP convergence. Empirical evidence indicates that digital spatial association significantly shortens the catch-up period for lagging regions. Consequently, policy frameworks should maximize the spatial externalities of infrastructure. This includes establishing national and regional carbon monitoring and trading platforms to achieve data interconnectivity between production and markets. Additionally, research institutions and leading enterprises should be incentivized to conduct cross-regional R&D, promoting practices like low-carbon tillage and straw returning in underdeveloped areas. Finally, integrating ACP metrics into local government performance evaluations and channeling green finance toward agricultural digitalization will ensure a sustained transition.

7.3 Policy Implications

First, optimize top-level design to build a systematic policy framework. Current policies often emphasize end-of-pipe emission reduction over process optimization, leading to structural inefficiencies. A governance logic centered on DISAN can reshape the strategic framework for agricultural carbon mitigation. National planning should integrate carbon intensity targets with DI, utilizing remote sensing and blockchain for lifecycle carbon tracking. At the implementation level, a dedicated fund for the digital transformation of agriculture can help unify carbon accounting standards and bridge regional information gaps.

Second, enhance regional coordination to dismantle imbalanced application patterns. While spatial association facilitates knowledge diffusion, a stark divide persists between the digital-intensive East and the infrastructure-poor West. To bolster synergy, policymakers should identify regional comparative advantages and establish "National Agricultural Low-Carbon Digital Infrastructure Demonstration Zones". Supporting cross-regional laboratories and talent exchange programs will help dismantle "carbon information silos" and technical barriers, thereby enhancing the collective governance of agricultural carbon productivity.

Third, facilitate convergence mechanisms for a balanced mitigation pathway. Existing policies rely heavily on localized fiscal subsidies, often ignoring the potential of spatial association to drive provincial convergence. By prioritizing digital interconnectivity, the catch-up cycle for lagging regions can be markedly reduced. Implementation should involve establishing a digitalized monitoring and evaluation system alongside incentives for technology absorption in underdeveloped provinces. This "diffusion-absorption-convergence" pathway will accelerate spatial convergence, ensuring that China's agricultural sector achieves green, coordinated development in line with its "dual carbon" (carbon peaking and neutrality) objectives.

7.4 Limitations and Future Research Directions

Utilizing panel data from 31 Chinese provinces, this study investigates the impact of DISAN on ACP. By constructing spatial weight matrices and convergence models, it elucidates the mechanisms through which DI drives carbon efficiency and facilitates regional convergence. These findings offer theoretical insights and policy references for advancing China's low-carbon

agricultural transition and optimizing regional development under the “dual carbon” objectives. Despite these contributions, several limitations persist, highlighting avenues for future research.

First, the analysis is restricted to the provincial level. While this reflects macro-level national patterns, it may obscure granular heterogeneities and micro-spatial spillover effects at the municipal or county levels. As data accessibility improves, future research should leverage more disaggregated data to uncover the spatial differentiation of ACP and the micro-mechanisms of DI more precisely.

Second, although this study focuses on spatial convergence and association, the specific transmission pathways between DI and ACP enhancement require further elucidation. Specifically, the mechanisms by which DI operates—such as the integration of intelligent machinery, the dissemination of precision fertilization techniques, the implementation of carbon monitoring systems, and cross-regional green technology diffusion—merit deeper investigation. Future studies could integrate econometric modeling with qualitative case studies to identify key operational chains in the digitalization and decarbonization of agriculture, providing more targeted, actionable policy guidance.

Finally, given the rapid pace of agricultural digitalization and decarbonization, ACP evolution is characterized by significant dynamic and long-term complexities. This study’s reliance on 2011–2023 panel data may not fully capture the long-term evolutionary impact of DISAN. Future research should incorporate real-time monitoring data and longitudinal analysis to explore long-term convergence trajectories, stage-specific characteristics, and the interaction between ACP and the spatial diffusion of digital networks. Such efforts would establish a more systematic and enduring empirical foundation for green agricultural development and cross-regional collaborative governance.

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