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Spatiotemporal Evolution and Driving Factors of Coupling Coordination Between New-Type Urbanization and Digital Village Construction

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Abstract

Coordinating new-type urbanization and digital village construction supports urban–rural integration. Using 2012–2023 panel data for 30 Chinese provincial-level regions, this study constructs subsystem indices, calculates the coupling coordination degree (CCD) to summarize joint development, and assesses relative balance separately. The analysis combines kernel density estimation, Dagum Gini decomposition, traditional and spatial Markov chains, spatial autocorrelation tests, and a two-way fixed-effects spatial Durbin model. Both indices increased, and relative balance improved despite a widening absolute index gap. CCD rose as provincial disparities narrowed, but eastern leadership persisted alongside rapid western catch-up, steady central improvement, and slower northeastern progress. East–west and coastal–inland gradients persisted, with interregional disparities remaining dominant. CCD transitions were persistent and gradual, with conditional probabilities varying by initial levels and neighborhood conditions. Provincial CCD showed significant positive spatial dependence. Human capital and fiscal expenditure on science and technology had significant positive local and spatial indirect associations with CCD, while the positive association of fiscal support for agriculture was mainly local. Some estimated effects of openness, industrial structure upgrading, and agricultural machinery intensity were significantly negative. The findings support investment in human capital and technology, cross-regional collaboration, and region-specific policies.

Keywords: new-type urbanization; digital village construction; coupling coordination degree; regional disparities; spatial Markov chain; spatial Durbin model

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1. Introduction

Urban–rural relations constitute a foundational structure of socioeconomic development, and their coordinated evolution is a significant concern for Chinese modernization [1]. Since China embarked on reform and opening up, the share of its permanent residents living in urban areas rose from 17.92% in 1978 to 67.00% in 2024. While promoting economic and social growth, urbanization has also given rise to problems such as urban–rural development imbalances, the one-way movement of factors of production out of rural areas, and uneven allocation of public services [2,3], leading to challenges including insufficient development quality and weak urban–rural linkages [4]. Against this background, people-centered new-type urbanization places greater emphasis on coordinated progress

across demographic, economic, social, and ecological dimensions [5], while highlighting how urban areas can propel rural development and promote urban–rural integration [6]. Meanwhile, conventional policy instruments have gradually shown diminishing marginal effectiveness in addressing the misallocation of urban–rural resources. Consequently, how digitalization can improve urban–rural factor allocation, industrial linkages, and the coordination of public services has become a key question for strengthening coordinated urban–rural development [7].

Digital village construction offers a new technological pathway for improving rural development conditions. Since China's 2018 Central No. 1 Document proposed implementing the digital village strategy, digital technologies have continued to penetrate the agricultural and rural sectors, injecting new impetus into rural development by improving production methods, enabling factor mobility, and optimizing governance and service provision [8]. The 2025 Central No. 1 Document further called for deeper implementation of the Digital Village Development Action, promoting a shift in digital village construction from infrastructure expansion toward higher-quality, more efficient development. Digital village construction helps strengthen rural areas' capacity to absorb industries, technologies, and service resources from urban areas, while the market demand, talent agglomeration, and public service systems generated by new-type urbanization also create conditions for rural applications of digital technologies [9]. Therefore, although new-type urbanization and digital village construction emphasize development in cities and rural areas, respectively, both serve urban–rural integration, and whether their development levels can become relatively aligned matters for the broader process of coordinated urban–rural development.

Existing research on new-type urbanization has examined its conceptual foundations, measurement, spatial disparities, and development effects. With people-centered development as its core orientation, new-type urbanization represents a systemic development process marked by the coordinated advancement of industrialization, informatization, urbanization, and agricultural modernization [10]. As resource and environmental constraints and social equity have received increasing attention, research has gradually shifted from individual indicators, such as the percentage of residents living in urban areas, toward multidimensional assessments of sustainability and overall development quality [11]. Accordingly, ecological conditions, healthcare, communications, and public services have been incorporated into the measurement framework [12]. Existing studies commonly construct indicator systems covering demographic, economic, spatial, social, and ecological dimensions [13] and derive indicator weights through approaches including the entropy weight method and principal component analysis [14]. The findings indicate that China's new-type urbanization has continued to advance; however, substantial regional disparities remain, with an overall development gradient in which the eastern region leads the central and western regions, alongside a certain degree of spatial agglomeration [15]. New-type urbanization may also promote increases in farmers' income and rural development through industrial structure upgrading, improved resource allocation, and expanded public services [16]. Research on digital village construction largely focuses on transformations in production, governance, and lifestyles brought about as digital technologies become embedded in rural socioeconomic systems [17]. Regarding the measurement of development levels, existing studies generally construct comprehensive evaluation systems covering digital infrastructure, the digital transformation of industries, capacity for digital governance, and digital inclusion in everyday life [18]. Existing work also applies the Dagum Gini coefficient, kernel density estimation, and spatial analysis to assess differences across regions, changes over time, and spatial patterns [19]. Regarding development effects, digital village construction may help advance urban–rural integration by facilitating factor flows between urban and rural areas, promoting industrial restructuring, and fostering entrepreneurship

in emerging business activities, while potentially generating positive spatial spillover effects in neighboring regions [20]. Meanwhile, financial constraints, the urban–rural digital divide, talent shortages, and inadequate institutional support may continue to restrict the application and effective utilization of digital technologies [21].

Building on these studies, scholars have increasingly examined how digitalization develops in coordination with new-type urbanization. Existing work, however, mainly examines coordination between the digital economy and new-type urbanization or investigates only how the rural digital economy affects new-type urbanization. Relevant studies suggest that the digital economy and new-type urbanization are closely linked in their development, with technological innovation, industrial structure, fiscal expenditure on science and technology, and infrastructure conditions potentially shaping their coordination [22,23]. Chen (2025) further found that the rural digital economy can advance new-type urbanization by contributing to human capital accumulation, agricultural economic growth, and industrial restructuring [24]. Rural e-commerce can expand the market for agricultural products and create local employment, thereby providing industrial and employment support for new-type urbanization [25]; digital infrastructure may also foster rural revitalization and, in turn, further promote the coordinated development of new-type urbanization [26]. A limited number of studies have begun to examine this relationship from both directions, finding that new-type urbanization and the rural digital economy are dynamically linked and interconnected in factor allocation and industrial coordination [27,28].

Prior studies have laid important groundwork for understanding the relationship between digitalization and new-type urbanization, but three limitations remain. First, the digital economy includes digital activity in cities and rural areas, while rural revitalization involves multiple dimensions, including industry, ecology, culture, and governance. Consequently, the relevant literature cannot fully capture whether digital village construction is coordinated with the process of new-type urbanization. Second, previous studies have generally examined overall evolution, regional disparities, or spatial agglomeration separately, with limited integrated analysis of the sources of regional disparities, transitions between coordination levels, and the neighborhood conditions associated with those transitions. Third, studies of influencing factors have frequently employed cross-sectional data or non-spatial models, making it difficult to distinguish the local effects of individual factors from their spatial indirect effects.

Accordingly, this study uses observations from 30 Chinese provincial-level regions spanning 2012–2023, develops comprehensive evaluation indicator systems for new-type urbanization and digital village construction, and uses the coupling coordination degree (CCD) to summarize their joint development, alongside separate analyses of subsystem development levels and relative balance. First, kernel density estimation is combined with spatial distribution analysis to examine the overall evolution, while the Dagum Gini coefficient quantifies regional disparities and decomposes them by source. Second, Markov chain analysis is conducted to investigate transitions between coordination levels and the associated neighborhood conditions. Finally, following the global Moran's I test, this study specifies a spatial Durbin model incorporating province and year fixed effects and estimates each influencing factor's direct, indirect, and total effects using a spatial contiguity matrix and a geographic distance matrix.

The study makes three marginal contributions. First, in contrast to research focused on broad concepts such as the digital economy or rural revitalization, this study directly examines the state of coordination between digital village construction and new-type urbanization, thereby emphasizing the alignment between digital applications in agriculture and rural areas and the urbanization process. Second, regarding the research content, this study incorporates overall evolution, the sources of regional disparities, and transitions

between coordination levels into a unified framework. It not only identifies the composition of coordination disparities but also examines the persistence of different coordination states and their relationships with neighborhood conditions, thereby broadening understanding of the formation and evolution of provincial-level coordination disparities. Third, regarding the analysis of influencing factors, this study uses long-term provincial panel data to distinguish the local effects of individual factors from their spatial indirect effects and compares the estimation results obtained using two spatial weight matrices, offering new empirical evidence for understanding the spatial linkages associated with the coordinated development of the two systems.

2. Coupling Coordination Mechanism

New-type urbanization and digital village construction are interrelated core subsystems of urban–rural development, connected through bidirectional flows of labor, capital, technology, data, and other factors. Three foundations underpin the coupled development of the two systems. First, a shared set of objectives encompasses the dismantling of the urban–rural dual structure, the advancement of urban–rural integration, and the pursuit of common prosperity [29]. Second, the systems have complementary functions: drawing on industrial agglomeration and market scale, urban areas provide rural areas with technology, capital, talent, and public services, whereas rural areas support urban development through the provision of agricultural products, ecological products, and space for industrial development [30]. Third, factor flows are mutually coordinated: digital technologies lower information barriers and transaction costs between urban and rural areas, creating conditions for cross-regional factor allocation and the realization of value from rural resources [31].

2.1. The Empowering Effects of Digital Village Construction on New-Type Urbanization

2.1.1. Industrial Digitalization and Industrial Integration Strengthen the Industrial Foundation for New-Type Urbanization

By integrating digital technologies into every stage of agricultural production and management, industrial digitalization transforms conventional agricultural production methods [32]. In the production process, technologies such as intelligent agricultural machinery and precision crop and livestock farming substantially increase land productivity and resource-use efficiency, facilitating a shift toward intensive and efficient agriculture; in the management process, digital systems convert information from different stages into data for decision support, thereby improving production and operational efficiency. Building on this foundation, digital village construction brings farming, rural manufacturing, and services into closer integration [33] and gives rise to emerging forms of rural business, including smart agriculture, rural cultural tourism, and agricultural product processing and distribution. The resulting gains in manufacturing and service efficiency support the upgrading of the industrial structure associated with new-type urbanization toward higher-end and service-oriented development. At the same time, nearby employment opportunities in counties and townships enable surplus rural labor to find work locally, forming a flexible employment pattern in which workers "leave the land but not the countryside" [34,35]. This pattern helps alleviate traffic congestion and pressure on public services arising from the excessive one-way concentration of rural residents in large cities—problems associated with "big-city diseases"—and supports a shift in new-type urbanization from a narrow focus on population expansion toward multidimensional improvements in development quality.

2.1.2. Digital Technologies Support Green Agricultural Production and Ecological Urbanization

Ecological livability is a core dimension of new-type urbanization, and digital village construction promotes a shift in agriculture toward resource-conserving and environmentally friendly development through agricultural production monitoring and refined management [36]. Monitoring enabled by the Internet of Things (IoT), together with intelligent irrigation and precision fertilization, can improve the efficiency with which land and water are used, reduce excessive use of chemical fertilizers and pesticides, and lower agricultural non-point source pollution. This process not only improves rural production and living environments but also helps ease pressures on water and soil environments faced by urban and rural areas alike and increases the capacity to supply green agricultural and ecological products. Consequently, improved rural ecological conditions can provide ecological safeguards for new-type urbanization through better regional environmental quality and a greater supply of green products, thereby supporting a green transition in modes of production and living across urban and rural areas.

2.1.3. Data-Driven Factor Allocation Improves Development Efficiency

Digital platforms can reduce information search and transaction costs in urban–rural resource allocation and facilitate connections between rural business entities and urban markets, technical services, and sources of capital [37]. Rural e-commerce and platforms offering digital services extend market linkages, allowing distinctive rural products and resources to enter broader transaction networks; meanwhile, big data and artificial intelligence enable more precise matching between supply and demand and reduce resource idleness and misallocation caused by information asymmetry. As urban–rural information linkages and transaction channels gradually improve, capital, technology, and labor gain more opportunities for cross-regional allocation, helping transform rural resource advantages into industrial development capacity and thereby supporting new-type urbanization through greater resource-use efficiency and stronger urban–rural collaboration.

2.2. Supporting Effects of New-Type Urbanization on Digital Village Construction

2.2.1. Industrial Agglomeration and Technology Diffusion Consolidate the Foundation for Digital Village Construction

New-type urbanization brings together population, industries, and innovation resources, thereby providing a foundation for digital technology research and development, specialized services, and business model innovation [23]. As urban and rural infrastructure becomes more integrated and industrial linkages strengthen, network connectivity, digital services, and related supporting facilities can gradually extend to county-level areas and villages, creating better conditions for applying digital technologies in rural areas. Meanwhile, urban digital service enterprises, technology extension agencies, and specialized service organizations can introduce technological solutions and management experience into rural areas through industrial cooperation and service extension, thereby reducing technology adoption and maintenance costs for rural business entities. Inflows of industrial capital and the expansion of service networks also help alleviate the funding and service constraints on rural digitalization and bring digital technologies into closer alignment with agricultural production and rural business needs.

2.2.2. Green Demand and the Spread of Governance Experience Drive Green Transformation

Green development is an important direction of new-type urbanization [38]. Urban residents' demand for green agricultural products, ecological products, and rural leisure services provides market opportunities for the development of rural industries while imposing higher requirements for quality control, environmental protection, and traceability.

To meet these demands, rural business entities need to strengthen production monitoring, quality traceability, and business management, thereby increasing their demand for digital technology applications. Meanwhile, the diffusion of urban ecological governance experience and green technologies to rural areas helps advance the digitalization of environmental monitoring, pollution control, and resource management. The combined improvement of market demand and governance capacity can expand the application scenarios for green digitalization in rural areas and promote closer alignment between ecological protection and industrial development.

2.2.3. Institutional Innovation for Urban–Rural Integration Expands the Scope for Development

Institutional reforms concerning the household registration system, rural property rights, and public services can lower barriers to urban–rural factor mobility, improve conditions for employment, entrepreneurship, and business operations that span urban and rural areas, and provide institutional support for rural products entering urban markets and for technology, capital, and talent moving to rural areas [39]. Population mobility and return migration for employment and entrepreneurship during urbanization provide channels through which knowledge, skills, and business experience can spread to rural areas [40]. Under appropriate institutional and service conditions, returnees with relevant experience can combine the market knowledge, management capabilities, and digital skills acquired through urban employment with rural resources and participate in rural e-commerce, production services, and industrial operations. Therefore, institutional coordination and the return of talent can work together to expand the market opportunities and human resource base for digital village construction.

Taken together, digital village construction contributes to new-type urbanization by upgrading industries, fostering green production, and improving factor allocation, while new-type urbanization promotes rural digitalization through technology and capital provision, green demand, and institutional innovation. These six pathways constitute a theoretical framework for bidirectional interaction between the two systems. The operation of these pathways depends on infrastructure, industrial support conditions, and the institutional environment. This framework underpins the subsequent analysis of spatial disparities in CCD and its driving factors; the overall mechanism is presented in Figure 1.

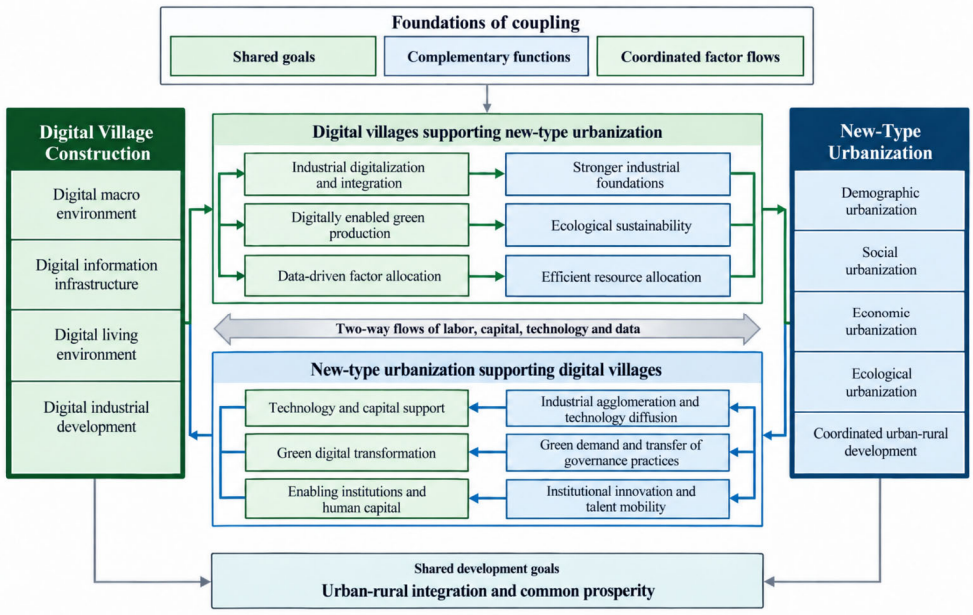


Figure 1. Mechanisms of coupling coordination between new-type urbanization and digital village construction.

3. Materials and Methods

3.1. Data Sources and Preprocessing

The analysis uses a 2012–2023 panel of 30 provincial-level administrative units in China; Tibet, Hong Kong, Macao, and Taiwan are excluded because of data limitations. The sampled units are assigned to eastern, central, western, and northeastern China under the regional classification of the National Bureau of Statistics of China. Data are compiled mainly from the *China Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Urban–Rural Construction Statistical Yearbook*, Wind, and provincial statistical yearbooks. The Digital Financial Inclusion Index comes from Peking University's Institute of Digital Finance, whereas $PM_{2.5}$ concentrations come from Columbia University's SEDAC Global $PM_{2.5}$ Concentration Dataset. Statistics for "National Modern Agricultural Demonstration Projects" are obtained from the Ministry of Agriculture and Rural Affairs and other government departments.

A small number of missing values were imputed by linear interpolation. To place indicators expressed in different units on a common scale across provinces and years, min–max normalization was applied using the full-sample maximum and minimum values. Equations (1) and (2) specify the calculations:

Positive indicators are normalized as follows:

$$X'_{ij} = \frac{X_{ij} - \min X_{ij}}{\max X_{ij} - \min X_{ij}} \quad (1)$$

Negative indicators are normalized as follows:

$$X'_{ij} = \frac{\max X_{ij} - X_{ij}}{\max X_{ij} - \min X_{ij}} \quad (2)$$

In these equations, X'_{ij} denotes the normalized indicator value, which lies in $[0, 1]$; $\max X_{ij}$ and $\min X_{ij}$ denote, respectively, the highest and lowest observed values of indicator j over the full province–year sample.

3.2. Construction of the Evaluation Indicator System

People-centered development is the defining feature of new-type urbanization. With reference to the *National New-Type Urbanization Plan (2014–2020)* and related studies [41–43], this study selects 18 indicators in accordance with the principles of scientific rigor, systematic coverage, and comparability. These indicators form an evaluation system spanning five dimensions: population urbanization, social urbanization, economic urbanization, ecological urbanization, and coordinated urban–rural development (Table 1).

Digital village construction is deeply integrated into rural socioeconomic development, driving transformations in agricultural production methods, rural lifestyles, and industrial development patterns. Based on the Outline of Digital Countryside Development Strategy, the *Digital Countryside Development Action Plan (2022–2025)*, and related studies [44–46], this study selects 14 indicators to evaluate digital village construction. As shown in Table 2, the indicator system covers rural digital access and services together with the conditions supporting their development. Per capita rural electricity consumption represents rural energy-use conditions relevant to the operation of digital equipment and services, while per capita provincial e-commerce sales and purchases characterize the wider digital market environment surrounding rural economic activities.

Table 1. New-type urbanization indicator system.

Dimension	Subdimension	Operational Measure	Attribute	Weight
Population Urbanization	Level of Permanent-Resident Urbanization	Permanent Residents Living in Urban Areas/All Permanent Residents	+	0.049
	Level of Population Agglomeration	Urban Population Density	+	0.078
	Level of Non-agricultural Employment	Employment in Secondary and Tertiary Sectors/Total Employment	+	0.038
Social Urbanization	Level of Urban Transport Infrastructure	Per Capita Urban Road Area	+	0.040
	Level of Public Cultural Services	Public Library Collections per Permanent Resident	+	0.152
	Level of Medical and Health Services	Beds in Healthcare Institutions per 1000 People	+	0.056
	Level of Social Security Coverage	Basic Pension Insurance Coverage Rate for Urban and Rural Residents	+	0.051
Economic Urbanization	Level of Economic Development	Per Capita Gross Regional Product	+	0.099
	Level of Industrial Non-agriculturalization	Combined Value Added in Secondary and Tertiary Sectors/Gross Regional Product	+	0.028
	Level of Residents' Income	Average Disposable Income per Urban Resident	+	0.091
	Level of Consumer Market Development	Consumer Goods Retail Sales/Total Population	+	0.094
Ecological Urbanization	Level of Urban Greening	Per Capita Area of Park Green Land	+	0.042
	Level of Sewage Treatment	Urban Sewage Treatment Rate	+	0.011
	Level of Environmental Sanitation Infrastructure	Number of Public Toilets per 10,000 Persons	+	0.063
	Level of Air Quality	Annual Mean $PM_{2.5}$ Concentration	−	0.020
Urban–Rural Coordinated Development	Level of Urban–Rural Income Coordination	Urban–Rural Ratio of Per Capita Disposable Income	−	0.036
	Level of Urban–Rural Consumption Coordination	Urban–Rural Ratio of Per Capita Consumption Expenditure	−	0.040
	Level of Urban–Rural Living-Standard Coordination	Urban–Rural Ratio of Engel Coefficients	−	0.013

Note: "+" indicates that higher values are favorable, whereas "−" indicates that lower values are favorable.

Table 2. Digital village construction indicator system.

Dimension	Subdimension	Operational Measure	Attribute	Weight
Digital Macro Environment	Digital Agricultural Talent	Agricultural Technicians per 1000 Persons	+	0.038
	Investment in Digital Development	Per Capita Fixed Asset Investment in Information Transmission, Software and Information Technology Services	+	0.058
	Energy Support Conditions for Rural Digitalization	Per Capita Rural Electricity Consumption	+	0.244
Digital Information Infrastructure	Level of Rural Broadband Access	Number of Rural Broadband Access Users/Rural Population	+	0.072
	Rural Cable Radio and Television Penetration Rate	Number of Rural Cable Radio and Television Users/Number of Rural Households	+	0.062
	Rural Mobile Phone Penetration Rate	Number of Mobile Phones Owned per 100 Rural Households at Year-End	+	0.016
	Rural Computer Penetration Rate	Number of Computers Owned per 100 Rural Households at Year-End	+	0.035
Digital Living Environment	Rural Delivery Route Density	Rural Delivery Routes/Administrative Area	+	0.087
	Level of Agricultural Meteorological Service Support	Number of Agricultural Meteorological Observation Stations/Administrative Area	+	0.057
	Level of Rural Digital Service Consumption	Per Capita Transport and Communications Expenditure of Rural Residents	+	0.041
	Convenience of Rural Postal Services	Average Population Served per Rural Postal Business Outlet	−	0.006
Digital Industry Development	Development Level of Digital Financial Inclusion	Rural Digital Financial Inclusion Index	+	0.027
	Development Level of Regional E-commerce	Per Capita E-commerce Sales and Purchases	+	0.213
	Foundation for Agricultural Industrial Modernization	Numbers of National Modern Agricultural Demonstration Parks and Industrial Parks, National Rural Industrial Integration Development Demonstration Parks, and National Key Leading Enterprises in Agricultural Industrialization	+	0.045

3.3. Research Methodology

3.3.1. Entropy Weight Method

This study applies the entropy weight method separately to the two subsystems using a pooled sample of 360 province–year observations covering 30 provincial-level regions over 2012–2023. The weights reflect differences in the information redundancy of the normalized indicators. Normalized values equal to zero are replaced with 0.0001 before calculating indicator proportions and entropy values. The calculation proceeds as follows:

(1) For indicator j, determine the share of evaluation unit i:

$$P_{ij} = \frac{X'_{ij}}{\sum_{i=1}^{n} X'_{ij}} \tag{3}$$

(2) Compute the entropy of indicator j:

$$e_j = -k \sum_{i=1}^{n} P_{ij} \times \ln(P_{ij}) \tag{4}$$

where e_j ranges from 0 to 1, and $k = \frac{1}{\ln n}$.

(3) Determine the information redundancy for indicator j:

$$d_j = 1 - e_j \tag{5}$$

(4) Compute the weight of indicator j:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \tag{6}$$

(5) Each evaluation unit's composite score is

$$U_i = \sum_{j=1}^{m} w_j X'_{ij} \tag{7}$$

3.3.2. Coupling Coordination Degree Model

The CCD model combines the composite development indices of new-type urbanization and digital village construction into a descriptive score. The coupling degree, comprehensive development index, and CCD are calculated as follows [47]:

$$C = 2\sqrt{\frac{U_1 \times U_2}{(U_1 + U_2)^2}} \tag{8}$$

$$T = \alpha U_1 + \beta U_2 \tag{9}$$

$$D = \sqrt{C \times T} \tag{10}$$

In these equations, U_1 and U_2 denote the composite development indices of new-type urbanization and digital village construction, respectively. C measures relative balance on the constructed index scales, approaching one as the two index values become more similar, while T represents their weighted development level. D denotes the CCD. With equal subsystem weights ($\alpha = \beta = 0.5$), Equations (8)–(10) simplify to $D = (U_1 U_2)^{\frac{1}{4}}$. Equal products therefore yield identical CCD values even when the ratios between the subsystem indices differ. Accordingly, CCD summarizes joint development, while the separate trajectories of U_1, U_2, and C describe subsystem development and relative balance. CCD values are classified according to Table 3 [48].

Table 3. Classification criteria for the coupling coordination degree (CCD) levels.

Value Range	Incoordination Stage	Value Range	Coordination Stage
[0.00, 0.10]	Extreme incoordination	(0.50, 0.60]	Barely coordinated
(0.10, 0.20]	Severe incoordination	(0.60, 0.70]	Primary coordination
(0.20, 0.30]	Moderate incoordination	(0.70, 0.80]	Intermediate coordination
(0.30, 0.40]	Mild incoordination	(0.80, 0.90]	Good coordination
(0.40, 0.50]	Near incoordination	(0.90, 1.00]	High-quality coordination

With $\alpha = \beta = 0.5$, sensitivity is assessed using dimension-balanced weighting, joint ±20% weight adjustments for rural electricity consumption and provincial e-commerce transactions, and exclusion of both indicators. Under exclusion, the remaining weights are renormalized, while indicator normalization, the urbanization index, and CCD classification thresholds remain unchanged. The dimension-balanced and ±20% specifications yield Spearman correlations of 0.9953–0.9999 with the baseline. Exclusion yields Pearson and Spearman correlations of 0.9725 and 0.9944, respectively, with annual provincial rank correlations of 0.9889–0.9969. National mean CCD rises from 0.465 to 0.641, compared with 0.407 to 0.573 at baseline, and annual regional rankings remain unchanged. CCD values shift upward overall, with category changes confined to adjacent levels. Thus, temporal trends and relative rankings remain stable.

3.3.3. Kernel Density Estimation

Kernel density estimation (KDE) describes the shape of a variable's distribution and how it evolves over time through a continuous density curve. This nonparametric method requires no prespecified distributional form and is relatively robust [49]. This study uses KDE to examine the evolution of CCD distributions for China as a whole and within each of its four major regions. The formula is as follows:

$$f(x) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{X_i - x}{h}\right) \tag{11}$$

For Equation (11), N denotes the sample size; the bandwidth h governs the smoothness of the density curve; the Gaussian kernel function is represented by $K(\cdot)$; and X_i gives the value of the ith observation.

3.3.4. Dagum Gini Coefficient

To examine the structure of regional CCD disparities, this study applies the Dagum Gini coefficient. It measures differences across regions and separates overall disparity into intraregional disparity, interregional disparity, and transvariation density, thereby identifying the sources of disparity and the contribution of each component. Compared with the conventional Gini coefficient, it better accounts for overlap between regional sample distributions [50]. The calculation is as follows:

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\left|y_{ji} - y_{hr}\right|}{2n^2\overline{y}} \tag{12}$$

$$G = G_w + G_{nb} + G_t \tag{13}$$

Equations (12) and (13) use G for the overall Gini coefficient. The dataset consists of 30 provincial-level units ($n = 30$), classified into k regions. The counts for regions j and h are n_j and n_h; y_{ji} and y_{hr} give the corresponding provincial CCD scores, while $\bar{y}$ denotes the nationwide average CCD. Finally, G_w, G_{nb}, and G_t indicate how much intraregional disparity, interregional disparity, and transvariation density contribute to overall disparity, respectively.

3.3.5. Markov Chains

Markov chain analysis assigns successive random states to k discrete categories and identifies patterns of evolution from the transition probabilities among these categories [51]. Separate traditional and spatial Markov transition matrices are constructed to examine level transitions under two settings: without spatial constraints and conditional on spatial lag.

(1) Traditional Markov Chain

Traditional Markov chain analysis examines transitions between CCD states without accounting for spatial neighborhood conditions. All observations in the 30-province panel for 2012–2023 are combined into one sample; its 25th, 50th, and 75th percentiles provide fixed thresholds for four contiguous, non-overlapping CCD states: low (I), medium–low (II), medium–high (III), and high (IV). The transition probabilities are calculated as follows:

$$P_{ij} = \frac{n_{ij}}{n_i} \tag{14}$$

In this equation, P_{ij} denotes the probability that a province moves from CCD level i at time t to level j at $t + 1$; n_{ij} is the number of such provincial transitions observed during the study period; and n_i is the total number of observations initially classified at level i.

(2) Spatial Markov Chains

The spatial Markov chain extends the traditional Markov chain by adding a spatial lag, allowing CCD-state transition probabilities to be compared under different spatial neighborhood conditions. The spatial lag takes the following form:

$$Lag_a = \sum p_b W_{ab} \tag{15}$$

For province a, Lag_a gives the spatially lagged value; p_b is the attribute value for province b before spatial weighting; and W_{ab} is the (a,b) element of the spatial contiguity matrix. The row-standardized spatial contiguity matrix described in Section 3.3.6 is used in this calculation.

3.3.6. Spatial Econometric Model

Spatial econometric models extend conventional panel data models by accounting for spatial linkages across regions. This study employs a spatial contiguity matrix and a geographic distance matrix to characterize interprovincial spatial linkages. In the spatial contiguity matrix, a province pair receives 1 if the provinces share a land boundary and 0 otherwise; because Hainan shares no land border with any other province, it is linked to Guangdong following the nearest-neighbor principle. The geographic distance matrix assigns each pair of provinces a weight equal to the reciprocal of the great-circle distance between their capitals, so closer capitals receive larger weights. Each matrix has zeros on its diagonal, and both matrices are row-standardized.

(1) Spatial Autocorrelation Analysis

Prior to spatial econometric estimation, global Moran's I is applied to test whether the CCD between new-type urbanization and digital village construction exhibits overall spatial autocorrelation. The statistic is calculated as follows [52]:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} (x_i - \bar{x}) (x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}) \sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{16}$$

where I refers to the global Moran's I statistic; n indicates the province count; x_i and x_j give the CCD values for provinces i and j, respectively; $\bar{x}$ is the average CCD value; and W_{ij} is the corresponding entry in the spatial weight matrix.

(2) Spatial Durbin Model

Building on the spatial autocorrelation analysis, this study specifies a spatial Durbin model (SDM) with province and year fixed effects to examine the explanatory variables' local and spatial indirect associations with CCD. The model takes the following form [53]:

$$Y_t = X_t\delta + WX_t\theta + \rho WY_t + \mu + \gamma_t\iota_N + \varepsilon_t \quad (17)$$

Here, Y_t collects the CCD values of all provinces in year t, and X_t is the matrix of their corresponding driving-factor values; W is the spatial weight matrix specified above. The coefficient vectors δ and θ correspond to the driving factors and their spatially lagged values, respectively, while ρ is the coefficient on the spatial lag of the dependent variable. Province fixed effects are denoted by μ, time fixed effects by γ_t, and the random error vector by ε_t; ι_N is an N-dimensional column vector of ones. Because the SDM includes spatial lags of both the dependent and explanatory variables, its estimated coefficients cannot be interpreted directly as marginal effects. Partial derivatives are therefore used to decompose the effects into direct, indirect, and total components.

4. Results

4.1. Analysis of Subsystem Development Levels and Relative Balance

Figure 2 presents the temporal evolution of the national mean indices of new-type urbanization and digital village construction, together with the mean relative balance between the two subsystems. Between 2012 and 2023, the new-type urbanization index increased from 0.296 to 0.465, while the digital village construction index rose from 0.103 to 0.241. Their compound annual growth rates were 4.189% and 7.980%, respectively. The digital village construction index remained below the new-type urbanization index throughout the observation period, despite its faster proportional growth.

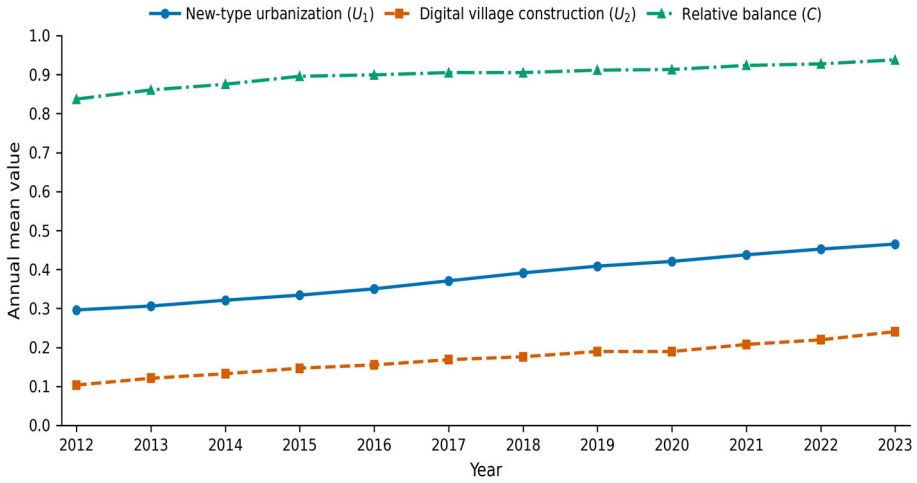


Figure 2. Temporal evolution of the two subsystem indices and their relative balance, 2012–2023.

The annual trajectories differed in their continuity and pace. The new-type urbanization index increased every year, whereas the digital village construction index exhibited minor fluctuations. The latter reached approximately 0.190 in 2019, remained nearly unchanged in 2020, and subsequently resumed growth through 2023. Over the full period, the ratio of the national mean digital village construction index to the national mean new-type urbanization index increased from 0.349 to 0.517, indicating relative catch-up on the constructed index scales.

The national mean of province-level C increased from 0.837 in 2012 to 0.938 in 2023, indicating improved relative balance between the subsystem indices. Mean C reached

approximately 0.905 in 2017. The increase during 2012–2017 was therefore 0.068, compared with 0.033 during 2017–2023, showing that improvements in proportional balance were greater in the earlier period and more gradual thereafter. Meanwhile, the absolute difference between the national mean subsystem indices widened from 0.193 to 0.225. This pattern reflects their different initial levels: although digital village construction grew faster proportionally, its lower starting value meant that its absolute increase remained smaller than that of new-type urbanization. Consequently, digital village construction narrowed its proportional gap with new-type urbanization while the absolute difference between the two mean indices increased.

4.2. Analysis of the Spatiotemporal Patterns of the CCD

4.2.1. Temporal Evolution Characteristics

Based on the estimated CCD values, kernel density estimation is applied to trace changes in the CCD distribution over time for China as a whole and for its four major regions.

Figure 3 shows how the nationwide kernel density distribution of CCD between new-type urbanization and digital village construction changed from 2012 to 2023. In terms of its position, the main peak of the kernel density curve moved steadily rightward over the study period, while the national mean CCD rose from approximately 0.407 to 0.573; the low-value end also shifted markedly rightward, indicating that the increase in CCD extended across the provincial distribution rather than being confined to a few high-CCD provinces. In terms of shape, the main peak generally grew taller and narrower, and the distribution became more concentrated, especially after 2020, suggesting some narrowing of interprovincial differences. The curves generally maintained a unimodal pattern throughout the study period; although slight shoulders or low secondary peaks appeared in some years, no pronounced polarization emerged. Regarding distributional tails, the kernel density curves consistently exhibited a right-hand tail, but it did not lengthen continuously, indicating that a small number of high-CCD provinces maintained their leading positions without further widening their gaps with most other provinces. In sum, the nationwide pattern combined an overall rise in CCD with catch-up among low-CCD provinces and continued leadership among high-CCD provinces.

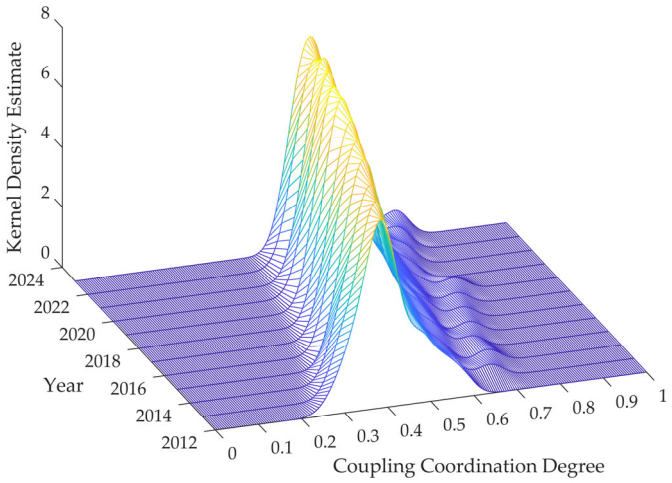


Figure 3. Kernel density distributions of the CCD between new-type urbanization and digital village construction in China from 2012 to 2023.

For the four major regions (Figure 4), the kernel density curves generally shifted rightward from 2012 to 2023, although the magnitude of the shifts and the distributional

patterns differed markedly. In the eastern, central, western, and northeastern regions, mean CCD rose from 0.484, 0.389, 0.345, and 0.418 to 0.639, 0.566, 0.532, and 0.519, respectively; the corresponding increases were 0.156, 0.177, 0.187, and 0.101. The largest increase occurred in the western region, followed by the central region, whereas the northeastern region recorded a comparatively small increase.

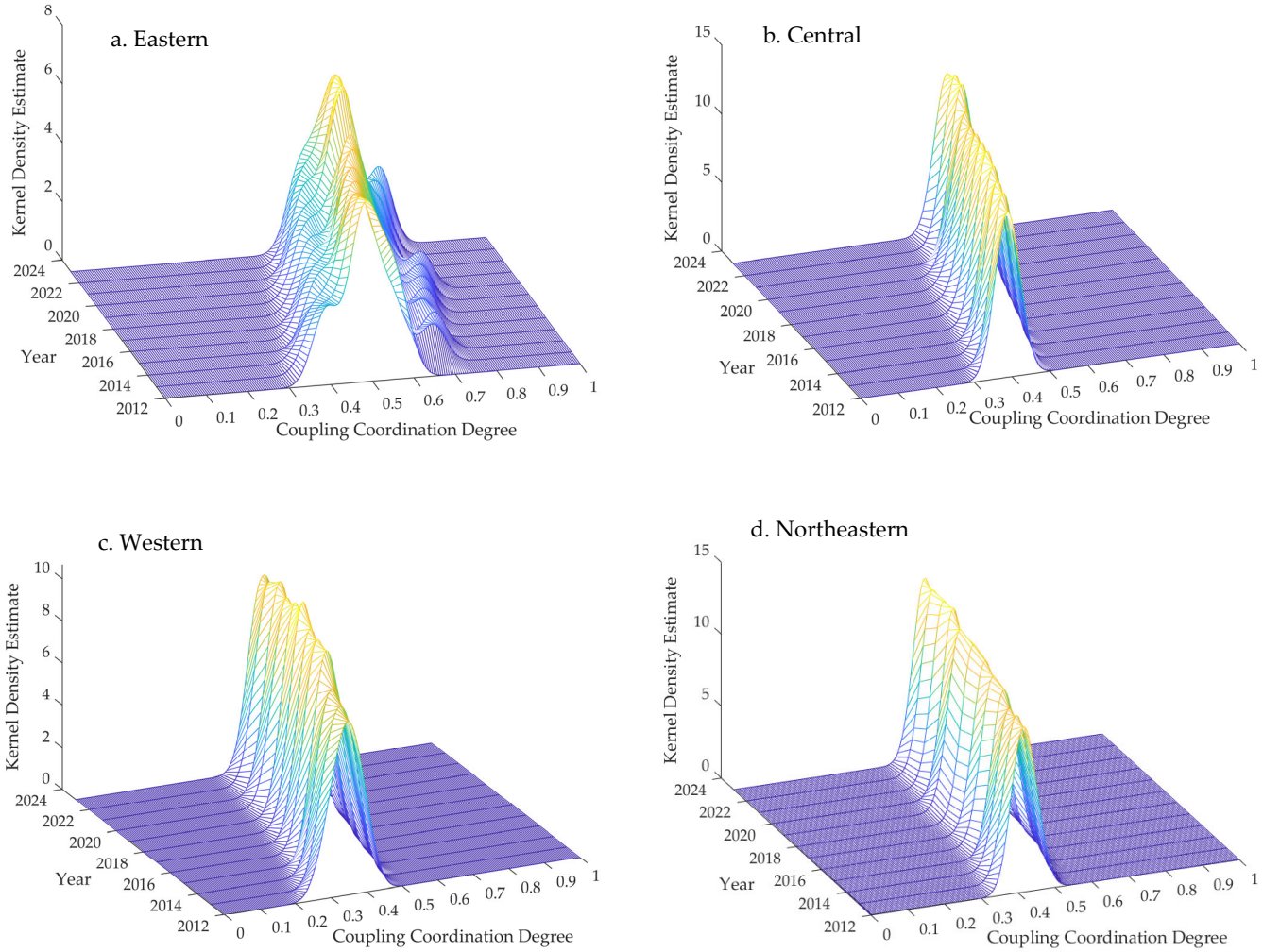


Figure 4. Kernel density distributions of the CCD between new-type urbanization and digital village construction across China's four major regions from 2012 to 2023. Panels (**a**–**d**) correspond to the eastern, central, western, and northeastern regions, respectively.

Among the four regions, the eastern region's kernel density curve remained relatively far to the right, indicating that its CCD retained a leading position throughout the study period. Its distribution covered a relatively wide range, with a main peak that varied somewhat in height, a modest shoulder, and a relatively pronounced rightward extension. This pattern suggests continued improvement from an already high level while internal development levels remained distinctly differentiated. The central region's curve progressed rightward over time and maintained a concentrated unimodal shape, indicating continuous CCD improvement and relatively limited intraregional disparities. Despite beginning at the lowest level, the western region's kernel density curve exhibited the largest rightward shift, while its main peak gradually increased in height and its width generally narrowed. These changes indicate relatively rapid improvement and narrowing intraregional disparities, consistent with a marked catch-up trend. However, its distribution at the close of the observation period still lagged behind those of eastern and central China, leaving its relative

development level low. The kernel density curve for the northeastern region was relatively concentrated and exhibited the smallest rightward shift, indicating that CCD changes across its provinces were relatively synchronized, although the overall pace of improvement was comparatively slow. Overall, the regional trajectories were distinct: the eastern region retained its lead at a high level, the central region improved steadily, the western region showed relatively rapid catch-up, and the northeastern region progressed more slowly.

4.2.2. Spatial Evolution Characteristics

To clarify how the CCD between new-type urbanization and digital village construction evolved spatially, this study maps the calculated values for 2012, 2016, 2020, and 2023 using ArcGIS 10.8 (Figure 5) and combines these maps with a provincial-level heat map for 2012–2023 to assess transitions between CCD levels and the extent of improvement (Figure 6).

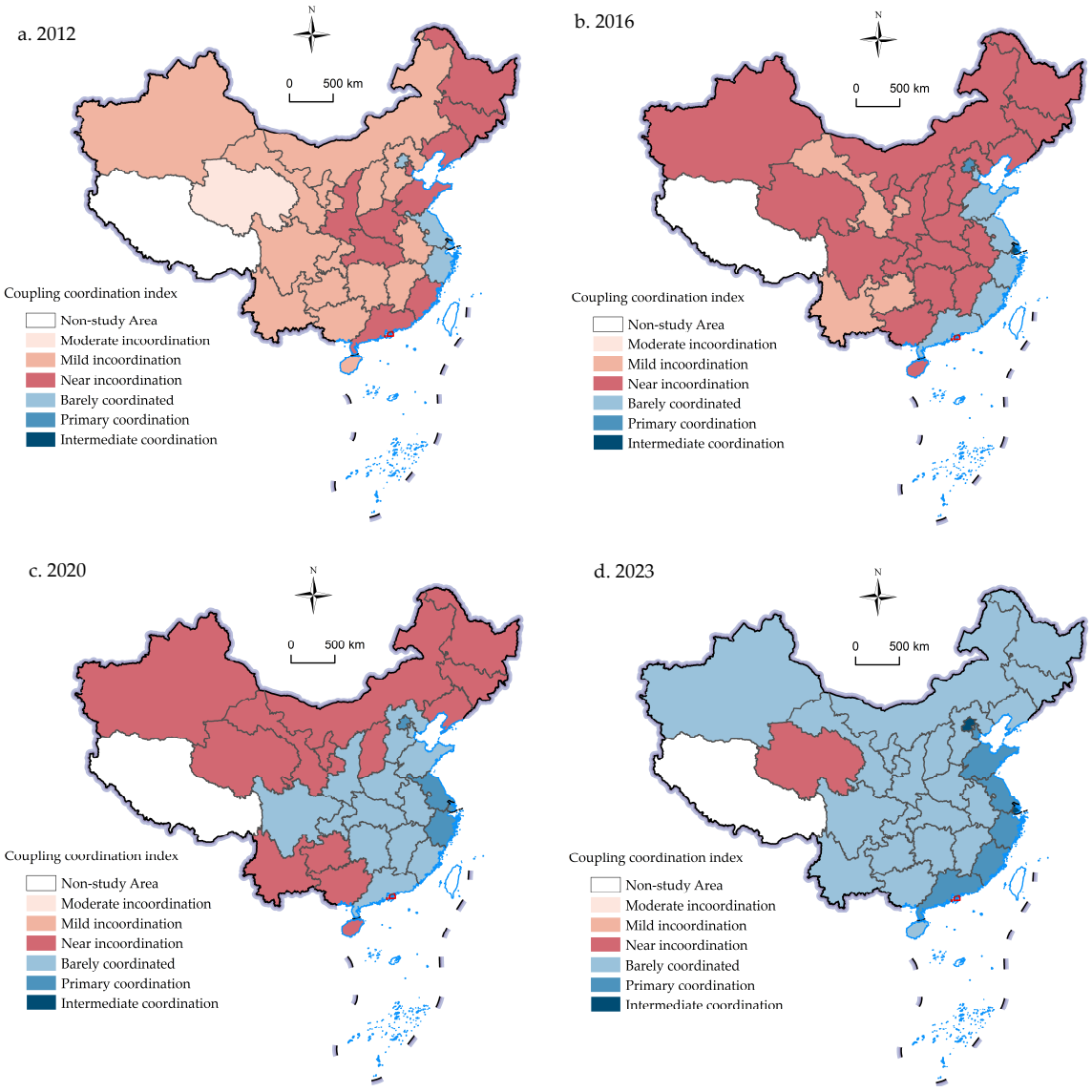


Figure 5. Spatial distribution of the CCD between new-type urbanization and digital village construction. Panels (**a**–**d**) represent 2012, 2016, 2020, and 2023, respectively.

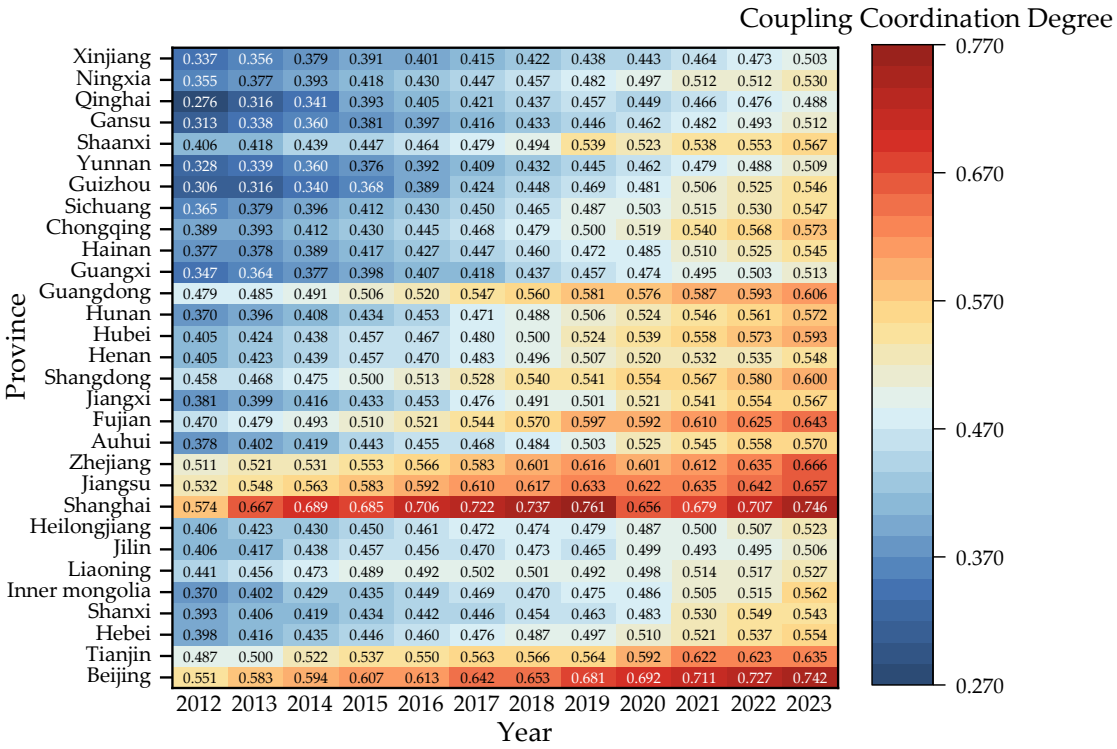


Figure 6. Heat map of the CCD between new-type urbanization and digital village construction from 2012 to 2023.

Figure 5 shows a sustained nationwide rise in CCD from 2012 to 2023, with higher-level areas spreading from a few nodes on the eastern coast into eastern and central China; throughout, the spatial pattern remained "higher in the east than in the west and higher along the coast than inland." In 2012, most provinces were at the mild or near incoordination stage, and only Beijing, Shanghai, Jiangsu, and Zhejiang reached the barely coordinated stage, with higher-level areas concentrated primarily in Beijing and the Yangtze River Delta. By 2016, near incoordination had become the predominant category; Shanghai was the first to attain intermediate coordination, Beijing reached primary coordination, and Guangdong, Fujian, Jiangsu, Zhejiang, Shandong, and Tianjin along the eastern coast reached the barely coordinated stage, indicating a shift in higher-level areas from a few isolated nodes to multiple coastal nodes. In 2020, barely coordinated areas expanded further into central China and parts of western China, with a high-value node in Beijing and a high-value cluster in the Yangtze River Delta; a contiguous pattern of improvement across central and eastern China gradually emerged, whereas near incoordination remained predominant in western and northeastern China. By 2023, all provinces except Qinghai had reached at least the barely coordinated stage; Beijing and Shanghai had attained intermediate coordination, while Tianjin, Jiangsu, Zhejiang, Fujian, Shandong, and Guangdong had reached primary coordination, making the eastern coastal region's lead more apparent.

Overall, CCD improved across provinces, although the eastern coastal provinces maintained their leading positions. This pattern may be associated with population and industrial agglomeration, close urban–rural market linkages, and stronger county-level industrial foundations in the eastern coastal region, which facilitate the integration of digital technologies into rural production and business operations. In contrast, some inland provinces are constrained by dispersed rural settlements and the relatively high operating costs of digital services; consequently, despite a widespread catch-up trend, provinces with higher CCD levels remain concentrated primarily along the eastern coast.

Regarding province-level evolutionary trajectories (Figure 6), all 30 provinces had higher CCD levels in 2023 than in 2012, forming six types of evolutionary pathways. Among them, fifteen provinces moved from mild incoordination to the barely coordinated category, while six moved from near incoordination to the barely coordinated category; together, these two pathways accounted for 70.00% of the sampled provinces. By 2023, 21 provinces were classified as barely coordinated, six as having primary coordination, and Beijing and Shanghai as having intermediate coordination, while Qinghai remained in the near-incoordination category. These results indicate that the principal change in provincial CCD levels during the study period was the widespread crossing of the threshold from incoordination to coordination, whereas sustained progress toward higher coordination levels had not yet become widespread.

Although the provinces generally followed a similar upward trajectory, the magnitude of improvement varied. Guizhou's CCD increased from 0.306 to 0.546, representing the largest increase nationwide at 0.240. In Guizhou, engagement with the digital economy can improve rural households' production and business operations and raise their incomes through digital production, sales, and services; the province's relatively rapid CCD growth may therefore be linked to the broader uptake of digital technologies by rural industries [54]. In contrast, the three northeastern provinces exhibited relatively slow improvement, with Heilongjiang, Jilin, and Liaoning recording increases of 0.117, 0.100, and 0.086, respectively, all below the national provincial average of 0.166. This may be related to the lengthy digital transformation of traditional industries, while population outflows and a limited capacity to attract talent may also have constrained county-level industrial development and the use of digital technology in rural areas [55]. Although Qinghai recorded an increase of 0.212, its initial value was only 0.276, leaving it below the coordination threshold at the end of the study period. Thus, provincial changes in CCD level reflect both baseline development conditions and the capacity to build sustained momentum for improvement over the observation period, resulting in an evolutionary pattern characterized by widespread upgrading alongside persistent interprovincial differentiation.

4.3. Analysis of Regional Disparities in the CCD

4.3.1. Overall and Intraregional Disparities

This study employs the Dagum Gini coefficient to measure nationwide and intraregional CCD disparities across the four major regions from 2012 to 2023, as shown in Figure 7. The overall national Gini coefficient decreased from 0.098 in 2012 to 0.060 in 2023, representing a decline of 39.22% and indicating a marked narrowing of interprovincial CCD disparities.

Regarding intraregional disparities, the mean Gini coefficients for the eastern, western, central, and northeastern regions were 0.0699, 0.0357, 0.0143, and 0.0139, respectively, exhibiting an overall pattern of "eastern > western > central > northeastern." The Gini coefficient for the eastern region reached 0.086 in 2013 and subsequently declined overall to 0.057 in 2023; however, it remained higher than those of the other regions throughout the study period, indicating that its internal development gradient remained pronounced. In the western region, the Gini coefficient decreased from 0.060 in 2012 to 0.029 in 2023, representing a decline of 50.76%. Combined with the continuous increase in its CCD, this result indicates a pronounced catch-up trend among low-CCD provinces. This trend may be attributable to gradual improvements in digital infrastructure and urban–rural public services across western provinces, as well as the narrowing of disparities in basic development conditions. The Gini coefficient for the central region generally exhibited a W-shaped pattern, indicating that although its intraregional disparities remained relatively small, convergence and divergence occurred alternately, and a stable convergence trend had not yet emerged. Its relatively limited overall disparities may be related to the location of

several provinces along the key axes and at major nodes of the national urbanization framework combining two horizontal axes and three vertical axes; meanwhile, differences among provinces in the pace of undertaking industrial transfers, developing digital infrastructure, and translating such development into tangible outcomes resulted in periodic changes in intraregional disparities. The Gini coefficient for the northeastern region remained generally low and fell to only 0.009 in 2023, the lowest among the four regions, indicating relatively similar provincial CCD levels within the region.

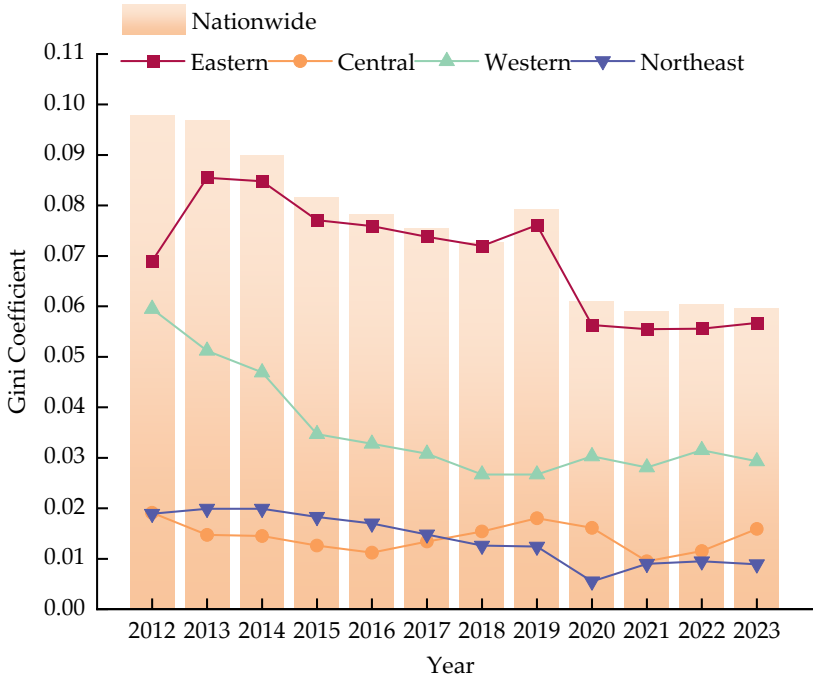


Figure 7. Overall and intraregional disparities in the CCD, 2012–2023.

4.3.2. Interregional Disparities

Figure 8 illustrates the interregional disparities in the CCD between new-type urbanization and digital village construction across the four major regions from 2012 to 2023. Based on the mean values over the study period, the interregional Gini coefficients were ranked as follows: eastern–western (0.128) > eastern–northeastern (0.094) > eastern–central (0.090) > western–northeastern (0.049) > central–western (0.047) > central–northeastern (0.029). The three regional pairs involving the eastern region generally exhibited relatively large disparities, indicating that the gaps between the eastern region and the other regions were the principal manifestation of interregional disparities. Among them, the eastern–western disparity was the most pronounced, possibly reflecting the eastern region's relative advantages in urbanization, digital infrastructure, and industrial support.

Regarding the temporal trends, except for the eastern–northeastern and central–northeastern pairings, the Gini coefficients of the other four regional pairings declined overall, indicating that the disparities between most regional pairings narrowed. In particular, the western–northeastern Gini coefficient decreased from 0.096 in 2012 to 0.025 in 2023, representing a decline of 73.59% and the most pronounced interregional convergence among all regional pairings. By contrast, the eastern–northeastern Gini coefficient increased from 0.087 to 0.105 and surpassed the eastern–western coefficient in 2022, becoming the regional pairing with the largest interregional disparity; meanwhile, the central–northeastern Gini coefficient exhibited a distinct U-shaped trajectory, declining from 0.036 in 2012 to 0.017 in 2017 before increasing to 0.043 in 2023. Overall, interregional disparities among the four major regions were characterized by an overall narrowing accompanied by localized diver-

gence, with the most prominent disparity gradually shifting from the eastern–western gap to the eastern–northeastern gap. Going forward, while efforts should continue to narrow the disparities between the eastern region and the central and western regions, greater attention should be given to the relatively lagging development of the northeastern region to prevent its disparities with the eastern and central regions from widening further.

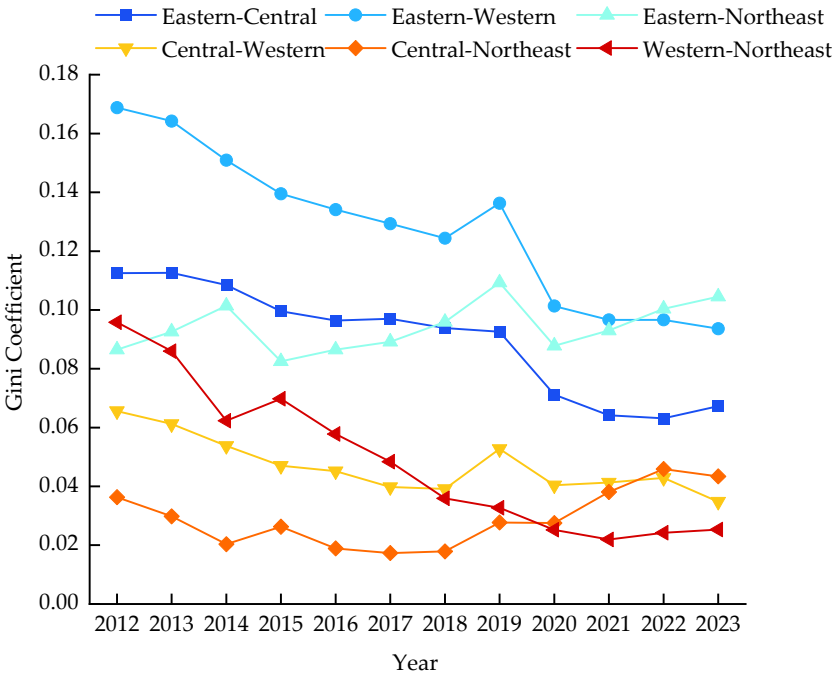


Figure 8. Interregional disparities in CCD among China's four major regions, 2012–2023.

4.3.3. Sources of Disparities and Their Contributions

Figure 9 presents the composition of overall disparities in CCD between new-type urbanization and digital village construction in China, together with each component's contribution, for 2012–2023. During the study period, the share attributable to intraregional disparities rose modestly from 17% to 19%, whereas the interregional share fell from 80% to 76% but remained the largest contributor to overall disparities, indicating that the development gradient among the four major regions had not fundamentally changed. The continued predominance of interregional disparities may reflect persistent regional differences in industrial foundations, infrastructure provision, and human capital. Unequal capacities to adopt digital technologies and translate related investment into development outcomes may contribute to uneven progress in the two subsystems and the persistence of regional CCD disparities. Transvariation density accounted for 3% of overall disparity in 2012 and 5% in 2023, peaking at 6% in 2021; this suggests greater overlap among provincial CCD distributions across regions, with some provinces in lower-mean regions surpassing certain provinces in higher-mean regions. Overall, the sources of CCD disparities were characterized by the continued dominance of the regional development gradient and increasing cross-regional overlap. Therefore, narrowing the overall disparities requires not only promoting coordinated interregional development but also addressing interprovincial differentiation within regions, thereby gradually establishing a policy framework that combines regional coordination with province-specific measures.

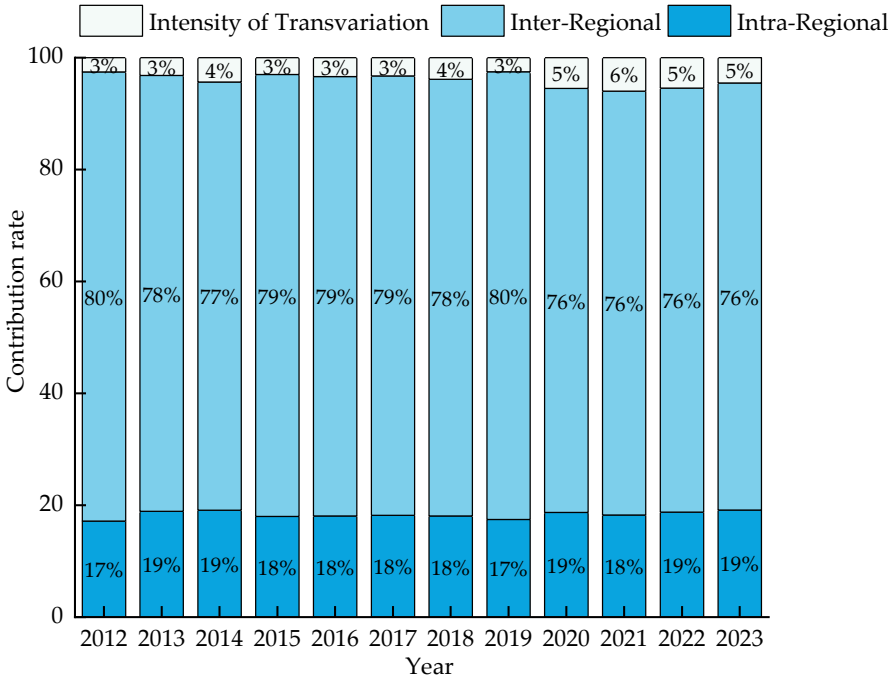


Figure 9. Percentage contributions of the components to the overall Gini coefficient for CCD, 2012–2023.

4.4. Dynamic Evolution of the CCD

4.4.1. Traditional Markov Chain Transition Probabilities

Table 4 reports the traditional Markov transition matrix for the CCD between new-type urbanization and digital village construction. The matrix contains 330 state-transition observations between adjacent years, with 90, 90, 79, and 71 observations originating from the low, medium–low, medium–high, and high states, respectively. Three patterns emerge from the traditional Markov chain results. First, the CCD exhibits strong state persistence. The probabilities of remaining in the same state, represented by the main-diagonal elements, range from 0.711 to 0.986 and are substantially higher than the off-diagonal probabilities in the corresponding rows. In particular, the high state has a persistence probability of 0.986, suggesting that provinces reaching this level are unlikely to fall back in the short term. Second, CCD states show an overall tendency to move upward. The probabilities for transitions from low to medium–low, medium–low to medium–high, and medium–high to high are 0.233, 0.289, and 0.228, respectively; the only downward transition observed is from high to medium–high, with a probability of 0.014. This indicates that upward transitions are generally more likely than downward transitions. Third, the evolution of CCD states is distinctly gradual. All transition probabilities between non-adjacent states are zero, indicating that state changes occur primarily between adjacent levels and that no leapfrogging transitions were observed. Overall, without conditioning on spatial neighborhood characteristics, CCD transitions show strong path dependence, a general upward tendency, and stepwise upgrading.

Table 4. Traditional Markov transition probability matrix.

Spatial Lag Type	t/(t + 1)	I (Low)	II (Medium–Low)	III (Medium–High)	IV (High)	Observations
No lag	I	0.767	0.233	0.000	0.000	90
	II	0.000	0.711	0.289	0.000	90
	III	0.000	0.000	0.772	0.228	79
	IV	0.000	0.000	0.014	0.986	71

4.4.2. Spatial Markov Chain Transition Probabilities

Table 5 presents CCD transition probabilities under different spatial lag conditions. Compared with the traditional Markov matrix, probabilities for the same initial CCD category vary across neighborhood conditions, indicating conditional spatial associations in provincial CCD evolution.

Table 5. Spatial Markov chain transition probability matrix.

Spatial Lag Type	t/(t + 1)	I (Low)	II (Medium–Low)	III (Medium–High)	IV (High)	Observations
I	I	0.862	0.138	0.000	0.000	65
	II	0.000	0.778	0.222	0.000	9
	III	0.000	0.000	1.000	0.000	1
	IV	0.000	0.000	0.000	0.000	—
II	I	0.500	0.500	0.000	0.000	22
	II	0.000	0.772	0.228	0.000	57
	III	0.000	0.000	0.875	0.125	16
	IV	0.000	0.000	0.000	1.000	4
III	I	0.667	0.333	0.000	0.000	3
	II	0.000	0.500	0.500	0.000	20
	III	0.000	0.000	0.765	0.235	51
	IV	0.000	0.000	0.050	0.950	20
IV	I	0.000	0.000	0.000	0.000	—
	II	0.000	0.750	0.250	0.000	4
	III	0.000	0.000	0.636	0.364	11
	IV	0.000	0.000	0.000	1.000	47

Persistence in the low CCD category differs across neighborhood levels. Under low spatial lag conditions, the persistence probability is 0.862, exceeding the traditional probability of 0.767 by 9.5 percentage points, while the probability of moving to the medium–low category decreases from 0.233 to 0.138. Under medium–low spatial lag conditions, the probability of moving from low to medium–low reaches 0.500, which is 26.7 percentage points above the traditional estimate. These contrasts show different allocations of probability between persistence and upward movement among observations with the same initial CCD category.

Upward transitions from the intermediate categories exhibit distinct conditional patterns. For the medium–low initial category, the upward transition probability is 0.228 under medium–low spatial lag conditions but reaches 0.500 under medium–high conditions, exceeding the traditional probability of 0.289 by 21.1 percentage points. For the medium–high initial category, probabilities of moving to the high category under medium–low, medium–high, and high spatial lag conditions are 0.125, 0.235, and 0.364, respectively. The maximum difference is 23.9 percentage points, revealing an ascending conditional gradient across these neighborhood categories within the sample.

Persistence remains high at the upper end of the CCD distribution. The probabilities of retaining the high category under medium–high and high spatial lag conditions are 0.950 and 1.000, respectively, consistent with the strong persistence observed in the traditional matrix. All observed movements in the conditional matrices occur between adjacent categories, preserving the gradual character of CCD transitions.

CCD transitions combine category persistence with differences across neighborhood conditions. Low-level neighborhoods correspond to greater persistence among low-CCD observations, while some higher-level neighborhood conditions coincide with higher upward transition probabilities for intermediate categories. These associations vary with the initial CCD level. Estimates for conditional groups containing only one to four observations are interpreted descriptively and alongside the observation counts reported in Table 5.

4.5. Analysis of the Drivers of CCD

4.5.1. Selection of Driving Factors

Following earlier studies [42,56,57], this study develops an empirical framework with one dependent variable and seven explanatory variables to investigate the drivers of the CCD between new-type urbanization and digital village construction. CCD is the dependent variable, and the seven explanatory variables are degree of openness, industrial structure upgrading, human capital level, intensity of fiscal support for agriculture, agricultural land productivity, intensity of fiscal expenditure on science and technology, and agricultural machinery intensity. Table 6 details their measurement methods. The spatial Durbin model is subsequently used to estimate each factor's direct and spatial indirect associations with CCD under the specified spatial weight matrices. The analysis relies chiefly on the *China Statistical Yearbook*, *China Rural Statistical Yearbook*, *China Finance Yearbook*, and *statistical yearbooks* issued by the sampled provinces, autonomous regions, and municipalities.

Table 6. Driving factors of the CCD between new-type urbanization and digital village construction.

Driving Factor	Measurement	Unit
Degree of openness (X_1)	Aggregate value of imports and exports/Gross regional product	%
Industrial structure upgrading (X_2)	Tertiary-sector value added/Secondary-sector value added	Ratio
Human capital level (X_3)	(Number of enrolled higher-education students/Total population) × 10,000	Persons per 10,000 population
Intensity of fiscal support for agriculture (X_4)	Expenditure on agriculture, forestry, and water affairs/General public budget expenditure	%
Agricultural land productivity (X_5)	Gross value of agricultural output/Total crop-sown area	10^4 CNY/ha
Intensity of fiscal expenditure on science and technology (X_6)	Local fiscal spending on science and technology/Gross regional product	%
Agricultural machinery intensity (X_7)	Total agricultural machinery power/Total crop-sown area	kW/ha

4.5.2. Spatial Econometric Model Tests

(1) Spatial Autocorrelation Analysis

Prior to the spatial econometric analysis, this study computes global Moran's I for the CCD between new-type urbanization and digital village construction using both the spatial contiguity matrix and the geographic distance matrix (Table 7). From 2012 to 2023, the statistic ranges from 0.462 to 0.547 with the spatial contiguity matrix and from 0.119 to 0.168 with the geographic distance matrix. Every value is positive and significant at the 1% level. Despite year-to-year fluctuations, the positive sign and statistical significance persist, indicating sustained positive spatial autocorrelation in provincial CCD and spatial clustering of provinces with similar development levels. The consistent findings across the two spatial weight matrices support the robustness of this pattern. Accordingly, the analysis of driving factors needs to account for spatial dependence through a spatial econometric model.

Table 7. Global Moran's I statistics for the CCD between new-type urbanization and digital village construction.

Matrix	Spatial Contiguity Matrix		Geographic Distance Matrix	
Year	Moran's I	Z-statistic	Moran's I	Z-statistic
2012	0.547 ***	4.736	0.168 ***	5.630
2013	0.515 ***	4.623	0.160 ***	5.582
2014	0.510 ***	4.627	0.159 ***	5.588
2015	0.534 ***	4.793	0.163 ***	5.661
2016	0.526 ***	4.765	0.158 ***	5.561
2017	0.509 ***	4.614	0.146 ***	5.213
2018	0.508 ***	4.620	0.142 ***	5.106
2019	0.462 ***	4.239	0.119 ***	4.472
2020	0.513 ***	4.528	0.141 ***	4.931
2021	0.527 ***	4.660	0.146 ***	5.099
2022	0.528 ***	4.666	0.142 ***	4.974
2023	0.500 ***	4.463	0.144 ***	5.067

Note: *** indicates statistical significance at the 1% level.

(2) Spatial Econometric Model Selection

To select the spatial econometric specification, LM, LR, Wald, and Hausman tests are conducted separately using the spatial contiguity matrix and the geographic distance matrix (Table 8). Under both matrices, the LM tests for spatial lag and spatial error dependence, including their robust counterparts, are significant at the 1% level, suggesting that both forms of spatial dependence are present. The LR and Wald results reject the restrictions that would simplify the SDM to an SAR or SEM specification, while the Hausman result favors fixed effects. Further LR comparisons support jointly accounting for individual and time effects. As the model-selection results agree across the two spatial weight matrices, a spatial Durbin model with two-way fixed effects for provinces and years is adopted.

Table 8. Spatial econometric model selection tests.

Test Category		Spatial Contiguity Matrix	Geographic Distance Matrix
		Test Statistic	Test Statistic
LM test	LM-lag	34.612 ***	655.974 ***
	Robust LM-lag	10.193 ***	187.136 ***
	LM-error	227.360 ***	608.597 ***
	Robust LM-error	202.941 ***	139.759 ***
LR test	LR-SDM/SAR	35.81 ***	35.81 ***
	LR-SDM/SEM	42.66 ***	41.82 ***
Wald test	Wald-SDM/SAR	34.90 ***	34.92 ***
	Wald-SDM/SEM	41.60 ***	40.22 ***
Hausman test	Fixed versus random effects	23.42 ***	40.72 ***
Fixed-effects test	LR-both/ind	43.75 ***	38.63 ***
	LR-both/time	313.27 ***	353.03 ***

Note: *** indicates statistical significance at the 1% level.

4.5.3. Results of the Driving-Factor Analysis

Table 9 presents the effect decomposition from a spatial Durbin model estimated with province and year fixed effects using each of the two spatial weight matrices. The principal effect directions for the driving factors are broadly consistent across the two matrices, although the statistical significance and estimated magnitudes of some effects differ, indicating that the findings are generally robust but remain somewhat sensitive to the choice of spatial weights. With the spatial contiguity matrix, the estimated spatial autoregressive coefficient is $\rho = 0.379$ (significant at the 1% level), indicating significant positive spatial

dependence in provincial CCD. For brevity, the following discussion considers the driving factors' direct and indirect effects estimated with the spatial contiguity matrix; estimates from the geographic distance matrix are used for robustness testing.

Table 9. Effect decomposition results of the two-way fixed-effects spatial Durbin model.

Explanatory Variable	Spatial Contiguity Matrix			Geographic Distance Matrix		
	Direct Effect	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect
Degree of openness (X_1)	0.016 (0.015)	−0.089 ** (0.041)	−0.073 (0.051)	0.00359 (0.0157)	−0.435 ** (0.179)	−0.432 ** (0.187)
Industrial structure upgrading (X_2)	−0.018 *** (0.005)	−0.002 (0.017)	−0.021 (0.020)	−0.0241 *** (0.00551)	−0.200 *** (0.0682)	−0.224 *** (0.0707)
Human capital level (X_3)	2.286 *** (0.604)	8.899 *** (1.959)	11.185 *** (2.286)	2.713 *** (0.718)	17.75 * (9.565)	20.463 ** (9.953)
Intensity of fiscal support for agriculture (X_4)	0.152 ** (0.071)	0.161 (0.165)	0.314 * (0.185)	0.125 * (0.0714)	0.393 (0.709)	0.518 (0.718)
Agricultural land productivity (X_5)	0.018 (0.012)	0.029 (0.044)	0.047 (0.046)	0.0321 *** (0.0109)	0.159 (0.114)	0.191 (0.117)
Intensity of fiscal expenditure on science and technology (X_6)	1.648 *** (0.435)	3.055 *** (1.182)	4.702 *** (1.460)	1.820 *** (0.407)	12.180 *** (4.278)	14.00 *** (4.438)
Agricultural machinery intensity (X_7)	0.00004 (0.00093)	−0.00845 *** (0.00266)	−0.00841 *** (0.00301)	−0.00109 (0.00102)	−0.0313 *** (0.0105)	−0.0324 *** (0.0108)
Spatial autoregressive coefficient (ρ)		0.379 *** (0.067)			0.329 ** (0.152)	
Province fixed effects		Yes			Yes	
Year fixed effects		Yes			Yes	
R^2		0.498			0.441	

Note: Standard errors are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

(1) Degree of Openness. The indirect effect of the degree of openness is −0.089 and statistically significant at the 5% level, whereas its direct and total effects are not significant, indicating that its negative association is primarily reflected in the indirect spatial effect. This may be related to the uneven distribution of the benefits of openness across regions. When export-oriented industries and market opportunities become concentrated in advantaged regions, other regions lacking the corresponding industrial capacity may find it difficult to share these benefits simultaneously, potentially further differentiating the regional allocation of resources required for urban–rural development.

(2) Industrial Structure Upgrading. The estimated direct effect of industrial structure upgrading is −0.018 ($p < 0.01$); neither its indirect nor its total effect reaches statistical significance. Expansion of the tertiary industry relative to the secondary industry does not necessarily imply a simultaneous strengthening of urban–rural industrial linkages. When service-sector growth is primarily oriented toward urban markets but the provision of services supporting agricultural production and county-level business operations remains relatively insufficient, an increasingly service-oriented industrial structure may become misaligned with the development needs of rural industries, thereby limiting its benefits for coordinated development.

(3) Human Capital. The estimates for human capital are 2.286 for the direct effect, 8.899 for the indirect effect, and 11.185 for the total effect (all $p < 0.01$), indicating positive local and spatial indirect associations. Human capital is complementary to knowledge-intensive inputs such as research and development, facilitating the conversion of accumulated knowledge into technological applications and productivity gains [58]. Stronger capacities for talent development and knowledge provision can support the use of digital technologies

across urban and rural areas, while interregional talent flows and research collaboration may facilitate knowledge circulation and help explain the positive spatial indirect association.

(4) Intensity of Fiscal Support for Agriculture. The intensity of fiscal support for agriculture has a direct effect of 0.152, significant at the 5% level; its indirect effect does not reach statistical significance, whereas its total effect does at the 10% level, indicating that the positive relationship is primarily manifested within the local region. Fiscal support for agriculture can strengthen the endogenous capacity of rural development by promoting agricultural innovation and improving basic public services in rural areas [59]. These investments may improve the conditions for rural areas to access urban resources and digital services, while implementation through local projects may help explain the predominantly local association.

(5) Agricultural Land Productivity. Under the spatial contiguity matrix, none of the estimated direct, indirect, or total effects of agricultural land productivity is statistically significant. Output value per unit of sown area is influenced by production technologies, agricultural product prices, and cropping structures; a higher value of this indicator cannot, by itself, be equated with improvements in agricultural digitalization or urban–rural factor-allocation efficiency. Over the sample period, agricultural land productivity shows no statistically significant association with CCD under this specification.

(6) Intensity of Fiscal Expenditure on Science and Technology. Estimates for this variable are 1.648 for the direct effect, 3.055 for the indirect effect, and 4.702 for the total effect (all $p < 0.01$). These public expenditures can finance research and development activities, enhance technological innovation capacity, and provide technological support for improvements in development quality [60]. With respect to new-type urbanization and digital village construction, such investment helps expand the local supply of technology and promotes the application of technological achievements in urban and rural production and business operations. Meanwhile, scientific research collaboration and industrial linkages may provide channels for technological achievements to be disseminated across regions, allowing the positive effects of this fiscal investment to reach other spatially connected regions.

(7) Agricultural Machinery Intensity. The direct effect of agricultural machinery intensity is not statistically significant. Its indirect and total effects are −0.00845 and −0.00841, respectively (both $p < 0.01$), indicating that the negative association with CCD is primarily reflected in the spatial indirect effect. Agricultural machinery density reflects equipment allocation rather than actual operational efficiency and service accessibility; agricultural machinery service markets and equipment sharing mean that the benefits of mechanization depend not only on the local stock of machinery but also on how services are organized and equipment is utilized [61]. Cross-regional operations further create a mismatch between the regions in which equipment is owned and those in which service benefits accrue; therefore, an increase in machinery power density does not necessarily correspond to a simultaneous rise in gains from urban–rural coordination.

5. Discussion

From 2012 to 2023, the CCD between new-type urbanization and digital village construction increased steadily. The national kernel density curves shifted to the right and became increasingly concentrated, while the overall Gini coefficient declined markedly, indicating higher CCD values and narrowing interprovincial disparities. The expansion of rural digital infrastructure, the digitalization of public services, and stronger county-level industrial linkages can facilitate rural access to urban capital, technology, and market resources. However, the potential of digitalization to reduce regional inequalities remains conditioned by infrastructure, education, and industrial development [62]. The continued

leadership of eastern China, relatively rapid western catch-up, and slower improvement in northeastern China show that the nationwide increase in CCD coexisted with distinct regional development trajectories. Differences in industrial foundations, human capital, and the capacity to translate resources into development gains provide a possible explanation for this regional variation. County-level digital village development also exhibits a pronounced east–west gradient and spatial clustering [63], consistent with the persistence of regional differentiation observed in this study. These findings suggest that efforts to narrow the digital access gap should be accompanied by improvements in the effective application of digital technologies in agricultural production, county-level industries, and rural public services.

The national CCD kernel density curves became increasingly concentrated, while the traditional Markov matrix showed high probabilities of remaining in the same category. Narrowing interprovincial disparities was therefore compatible with incremental increases in CCD within existing categories. Infrastructure development, industrial restructuring, human capital accumulation, and improvements in public services involve cumulative adjustments, which may help explain the gradual upgrading observed during the study period. Related research on digital village construction and rural economic resilience has also documented latecomer catch-up and heterogeneous development trajectories [46]. Transition patterns also differed across neighborhood conditions. Low-level neighborhoods were associated with greater persistence among low-CCD provinces, while upward transition probabilities for provinces initially in the medium–high category increased across higher neighborhood categories. This gradient was not consistent across all initial categories, indicating that the association between neighborhood conditions and CCD transitions varied with the initial CCD level.

The spatial Durbin model further reveals differences in the roles of the various resources. Human capital and fiscal expenditure on science and technology exhibit significant direct and indirect effects, indicating positive associations within provinces and in spatially connected provinces. Talent mobility, research collaboration, and industrial connections are possible channels. Human capital can facilitate more efficient conversion of digital resources into gains for rural development [64], while interregional digital economic linkages also facilitate knowledge diffusion and regional collaboration [65]. The positive association of fiscal support for agriculture is largely confined to the local region, possibly because the relevant funding is mainly channeled through local agricultural projects and initiatives to develop rural public services. The estimated associations for the degree of openness, industrial structure upgrading, agricultural land productivity, and agricultural machinery intensity are not uniformly positive, indicating differences in their relationships with CCD across factors and model specifications.

Several limitations remain. First, this study uses data for 30 Chinese provincial-level regions. Provincial aggregates may obscure county- and household-level differences, and the original indicator series contained a small number of missing observations. Future research could use more complete county-level panels and household surveys. Second, the digital village construction index includes indicators of supporting conditions, some of which do not directly measure the use of digital technologies in rural areas. Digital governance and digital literacy are also not fully captured. More targeted rural indicators and micro-level evidence could refine the index. Third, the SDM estimates conditional spatial associations but does not establish causal effects or identify specific transmission pathways. The limited number of provincial spatial units also leaves few observations in some conditional spatial Markov groups, restricting the generalizability of their estimated probabilities. Finer geographic data, longer panels, and research designs supporting causal identification could aid further examination of mechanisms and transition patterns.

6. Conclusions and Policy Implications

6.1. Conclusions

Drawing on a 2012–2023 panel of 30 provincial-level regions in China, this study investigates the CCD between new-type urbanization and digital village construction in terms of its spatiotemporal evolution, regional disparities, level transitions, and driving factors. The main conclusions are presented below:

(1) Both subsystem indices increased over the study period, with faster proportional growth in digital village construction. The national mean of province-level *C* rose from 0.837 to 0.938, indicating improved relative balance on the constructed index scales, although the difference between the national mean subsystem indices widened from 0.193 to 0.225. Nationwide, CCD continued to increase, as the kernel density curves moved rightward overall and the distribution gradually became more concentrated. Low-CCD provinces improved concurrently, and no stable polarization emerged. Regionally, the eastern region remained ahead, the western region caught up relatively quickly, the central region improved steadily, and the northeastern region improved more slowly. Spatially, CCD remained higher in eastern than western China and in coastal than inland areas, while areas at higher CCD levels gradually spread from the eastern coast into eastern and central China.

(2) Interprovincial CCD disparities generally narrowed, while intraregional disparities ranked eastern > western > central > northeastern. The eastern region exhibited relatively pronounced internal development disparities, whereas the western region demonstrated strong catch-up convergence. Interregional disparities continued to account for the largest share of overall CCD disparity. The mean gap between the eastern and western regions was relatively large, whereas the eastern–northeastern gap widened, indicating the coexistence of overall convergence and localized divergence.

(3) CCD transitions exhibited strong persistence and gradual upward movement, with observed changes confined to adjacent categories. Spatial conditioning revealed differences in transition probabilities for the same initial CCD category across neighborhood conditions. Low-level neighborhoods corresponded to greater persistence among low-CCD observations, while some higher-level neighborhood conditions coincided with higher upward transition probabilities for intermediate categories. High-CCD observations generally retained their original category. These conditional associations varied with the initial CCD level.

(4) Provincial CCD exhibited significant positive spatial dependence. Spatial Durbin model estimates showed that human capital and fiscal expenditure on science and technology each had a significant positive association with CCD within the province and in other spatially connected regions, whereas the positive association of fiscal support for agriculture was mainly local. Some effects of the degree of openness, industrial structure upgrading, and agricultural machinery intensity were significantly negative, while the results for agricultural land productivity were sensitive to the spatial weight matrix specification. Overall, knowledge, talent, and technological innovation provide important support for greater coordination between the two systems, and driving factors differ markedly in their modes of influence and spatial effects.

6.2. Policy Implications

Drawing on these findings and taking account of the evolutionary patterns and driving factors of the coupled and coordinated development of new-type urbanization and digital village construction, this study proposes the following policy recommendations:

First, differentiated support should be implemented according to each region's development stage. Given the strong stability and gradual progression of CCD levels, regions should determine their development priorities based on their existing foundations and prac-

tical needs. Regions with relatively low coordination levels should prioritize improvements in rural digital infrastructure and basic public services to enhance the accessibility and actual use of digital services; regions in the transitional stage should improve the conditions for urban–rural factor mobility and promote the integration of rural e-commerce, smart agriculture, and other applications with local industries; and regions with relatively high coordination levels should deepen the sharing of digital services and industrial collaboration between urban and rural areas while exploring development models with potential for wider application.

Second, regional resource allocation should be optimized and cross-regional collaboration strengthened. Given that interregional disparities remain the primary source of overall disparities, mechanisms for fiscal transfer payments and public resource allocation should be improved, with priority given to relatively disadvantaged areas in northeastern, central, and western China. Digital infrastructure and public services should also be extended to underserved counties. Meanwhile, considering the association between CCD transition probabilities and the development levels of neighboring regions, interprovincial coordination in planning and cooperation in technology, industry, and talent development should be strengthened. By leveraging city clusters, regional hub cities, and county-level nodes, regions should jointly establish digital agricultural service platforms, share technology extension resources, and strengthen the capacity of less-developed regions to absorb technological advances and accommodate industrial development.

Third, policy efforts should bolster talent development and technological support while making the coordination of fiscal measures more effective. Mechanisms for training and recruiting rural digital talent and facilitating professional exchange should be improved, and technological collaboration among research institutions, enterprises, and rural business entities should be promoted. Fiscal expenditure on science and technology should place greater emphasis on translating digital technologies into practical applications in agricultural production and rural business operations. Fiscal funds supporting agriculture should prioritize rural infrastructure, technology extension, and public service provision. Meanwhile, industrial restructuring and opening-up should be aligned with the industrial absorption capacity of counties and the practical needs of rural areas, rather than focusing solely on expanding the scale of development.

Fourth, the application efficiency of digital technologies and agricultural machinery should be improved in accordance with local agricultural foundations. Regions should promote digital applications in precision agricultural production, quality traceability, processing and distribution, and rural e-commerce by focusing on locally competitive agricultural products and distinctive industries, while selecting appropriate development approaches according to the scale of operations, technological conditions, and market demand. Agricultural machinery-sharing schemes and digital agricultural services for small- and medium-scale farmers should be encouraged to improve machinery utilization efficiency and service accessibility. The digitalization of rural industries should also be integrated with county-level employment, skills training, and industrial development to strengthen the capacity of rural industries to support coordinated urban–rural development.

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