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Terrain Constraints on Agricultural Development and Water Resource Coordination in China

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Abstract

To address the mismatch between agricultural development and water resource conditions, this study examined 22 provinces and four municipalities in China over the period 2014–2023 and incorporated terrain factors into the analytical framework. An integrated evaluation system was developed for the Agricultural Development Index (ADI) and Water Resource Condition Index (WCI). The entropy weight method, coupling coordination degree model, standard deviation ellipse model, spatial difference coefficient, and two-way fixed-effects model were employed to characterize the spatiotemporal dynamics and coordination between agricultural development and water resource conditions. The results indicate that the ADI increased steadily throughout the study period, whereas the WCI remained relatively stable, reflecting distinct evolutionary trajectories of the two systems. Although the coordination level of the Agriculture–Water Resources System improved overall, pronounced regional disparities persisted. Plain regions exhibited stronger coordination, whereas mountainous and plateau regions showed lower coordination levels because of terrain constraints and limited resource endowments. Spatial mismatches between agricultural and water resource advantage regions were evident, although the overall matching relationship between the two systems gradually strengthened. The proposed evaluation framework provides a scientific basis for optimizing regional agricultural layouts, improving water resource allocation, and promoting coordinated agricultural and water resource development.

Keywords: agricultural development index; water resource condition; coupling coordination; terrain factors; spatiotemporal characteristics

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Academic Editor: Georgios Koubouris

Received: 22 July 2026
Revised: 5 August 2026
Accepted: 18 August 2026
Published: 20 August 2026

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1. Introduction

Frequent climate anomalies and rapid urbanization in China have increased concerns regarding food security and sustainable water resource management [1–3]. Despite limited cultivated land resources, China must support the food demand of a large population [4], while agricultural water use accounts for more than 70% of total water consumption [5,6]. Uneven spatial and temporal distributions of water resources [7], low per capita water availability [8], and regional disparities in agricultural investment [9,10] have resulted in increasing mismatches between agricultural development and water resource conditions [11]. For instance, plain regions often support intensive agricultural production but face water scarcity [12], whereas mountainous regions generally possess greater water resources but have limited agricultural development potential due to complex terrain [13]. Existing studies have mainly focused on agricultural systems or water resource systems

separately [14], with insufficient consideration of the role of terrain in regulating their coordination. Terrain affects the Agriculture–Water Resources System by influencing cultivated land distribution, infrastructure development, agricultural production patterns, and water resource allocation [15–17]. To address this gap, this study incorporates terrain types as a spatial stratification framework to investigate regional differences in agriculture–water coordination under different terrain constraints and to explore the factors associated with spatial disparities between agricultural development and water resource conditions.

Existing studies have examined the relationship between agriculture and water resources from multiple perspectives, including technological optimization [18], resource assessment [19], and system coordination [20]. International research has primarily focused on precision irrigation [21,22], improving water-use efficiency [23], and optimizing decision-making approaches [24], providing important theoretical and technical support for efficient agricultural resource utilization and integrated resource assessment [25]. In China, research has mainly emphasized coupling coordination analysis at the scales of urban agglomerations and river basins [26,27], while also investigating the multidimensional drivers of agricultural production systems [28]. Despite these advances, several gaps remain. Agricultural development inputs and hydrological conditions are often assessed separately, limiting systematic evaluations of the Agriculture–Water Resources System. A standardized framework for national-scale interprovincial comparison remains lacking. Moreover, terrain is usually treated as a background factor rather than an active constraint, and its role in agriculture–water coordination remains insufficiently understood. Quantitative characterization of spatial mismatches between agricultural and water resource advantage regions also requires further improvement. To address these gaps, this study analyzed balanced panel data from 22 provinces and four municipalities in China covering the period 2014–2023. Autonomous regions, Hong Kong, Macao, and Taiwan, were excluded because of substantial differences in statistical systems, data availability, and indicator definitions relative to the provincial data for mainland China [29,30]. The study encompasses plain, hilly, mountainous, and plateau terrain types. Integrated evaluation systems were developed for agricultural development and water resource conditions. The entropy weight method [31], coupling coordination degree model [32], standard deviation ellipse model [33], spatial difference coefficient [34], and two-way fixed-effects model [35] were then employed to evaluate the coordination between the two systems under different terrain constraints.

This study incorporates terrain classification as a spatial stratification dimension to systematically examine how terrain constraints influence the spatial patterns, temporal evolution, and regional heterogeneity of the Agriculture–Water Resources System. It clarifies the geographic mechanisms underlying regional differences in coordination [36–38]. From a practical perspective, the findings provide guidance for optimizing agricultural investment, water resource allocation, and water-saving infrastructure according to terrain conditions, thereby promoting balanced agricultural development and sustainable water resource management [39]. Theoretically, this study proposes a three-dimensional human–land coordination framework of "human investment–hydrological endowment–terrain foundation [40]," addressing the limited consideration of terrain in large-scale agriculture–water resource coupling studies and providing a methodological reference for regional coordination research.

2. Materials and Methods

2.1. Data Sources

The province was adopted as the basic analytical unit because consistent data on agricultural production, water resource utilization, and socioeconomic development were avail-

able throughout the study period, enabling comprehensive comparisons of the Agriculture–Water Resources System across regions.

Terrain types were classified using a 30 m spatial-resolution digital elevation model (DEM) dataset obtained from the Geospatial Data Cloud, together with existing national-scale geomorphological classification datasets of China.

The data were obtained from authoritative official statistical yearbooks and reports. The primary data sources for evaluating agricultural development and water resource conditions are summarized in Table 1.

Table 1. Summary of Data Sources.

Target Layer	Data Sources	Year
Agricultural Development	China Statistical Yearbook and provincial statistical yearbooks	2014–2023
Water Resource Conditions	China Water Resources Bulletin, provincial water resources bulletins, China Environmental Statistical Yearbook, and China Statistical Yearbook	2014–2023

Although the data are derived from authoritative official sources, limitations remain, including time lags in data availability and incomplete coverage of some indicators. To reduce these effects, indicator screening and calibration were performed, and the coupling coordination analysis was integrated with the standard deviation ellipse model. Data processing and visualization were conducted using SPSS (Version 31.0.0), ArcGIS (Version 10.8.2), Microsoft Office (Version 16.0.17932.20360), and OriginPro (Version 2024).

2.2. Evaluation of the Dual-System Indices and Determination of Indicator Weights

The agricultural development evaluation system [41] comprised four dimensions: agricultural foundation, economic development, agricultural investment, and development quality. Agricultural foundation indicators characterize resource endowments and production capacity, economic development indicators reflect agricultural vitality and farmers' income, agricultural investment indicators measure the level of agricultural modernization, and development quality indicators assess production stability and green development performance. Indicators representing cultivated land resources, production capacity, economic benefits, and investment support were classified as positive because they promote agricultural development, whereas excessive fertilizer application and disaster impacts were treated as negative indicators owing to their adverse effects on agricultural sustainability. The water resource condition evaluation system [42,43] consisted of water resource endowment, utilization structure, and utilization efficiency. Endowment indicators represent regional water supply capacity, utilization structure indicators describe water allocation patterns, and utilization efficiency indicators reflect resource-use performance and ecological pressure. Indicators associated with water availability and agricultural water supply were defined as positive, whereas high proportions of domestic and ecological water use, excessive water exploitation, and pollutant emissions were classified as negative because they increase resource pressure and reduce sustainable utilization capacity. The complete indicator system is presented in Table 2. A unified coding scheme was adopted, in which A denotes the ADI, B denotes the WCI, and the numerical suffix identifies individual indicators (e.g., A11 and A12 represent the first two indicators under the Agricultural

Foundation criterion). This coding system facilitates indicator management and ensures consistency in subsequent model calculations.

Table 2. Indicator System for Agricultural Development and Water Resource Conditions.

Target Layer	Criterion Layer	Indicator Layer	Attribute
Agricultural Development	Agricultural Status	A11 Proportion of cultivated land area to total land area	+
		A12 Per capita output of major agricultural products	+
		A13 Proportion of agricultural value added	+
	Economic Development	A21 Employment proportion in the primary industry	+
		A22 Agricultural Economic Growth Dynamism	+
		A23 Proportion of farmers' disposable income	+
	Agricultural investment	A31 Agricultural Mechanization Level	+
		A32 Agricultural fixed asset investment	+
		A33 Rural healthcare level	+
	Development Quality	A41 Proportion of effective irrigated area	+
		A42 Fertilizer consumption per unit cultivated land area	−
		A43 Disaster impact	−
Water Resource Conditions	Water Resource Endowment	B11 Total water resources	+
		B12 Per capita water resources	+
		B13 Annual average precipitation	+
	Water Resource Utilization Structure	B21 Proportion of agricultural water use to total water use	+
		B22 Proportion of ecological water use to total water use	−
		B23 Proportion of domestic (urbanization-related) water use to total water use	−
	Water Resource Utilization Efficiency	B31 Water consumption per 10,000 yuan of output value	−
		B32 Water resource development and utilization rate	−
		B33 Wastewater pollutant emissions	−

Based on the coordination between agricultural development and water resource conditions, a dual-system evaluation framework was developed (Figure 1). The framework integrates multidimensional indicators and classifies them as positive or negative to facilitate subsequent quantitative analysis.

Based on the above indicator system, the entropy weight method was employed to determine indicator weights objectively according to the information provided by data variation, thereby reducing subjective bias. Although entropy weighting does not directly reflect theoretical importance, it captures the relative contribution of each indicator based on its variability across regions and years and has been widely applied in regional sustainability assessment and composite index construction. Before weighting, all indicators were normalized using the min–max method and classified as positive (+) or negative (−) according to their attributes. To improve the stability of the weighting results, comprehen-

sive weights were calculated using the full panel dataset rather than estimating weights separately for each year. This procedure eliminated differences in measurement units and scales, ensuring the reliability of subsequent analyses while reducing potential weighting bias.

$$x\prime_{ij} = \frac{x_{ij} - \min x_j}{\max x_j - \min x_j} \text{ (Positive Indicators)} \quad (1)$$

$$x\prime_{ij} = \frac{\max x_j - x_{ij}}{\max x_j - \min x_j} \text{ (Negative Indicators)} \quad (2)$$

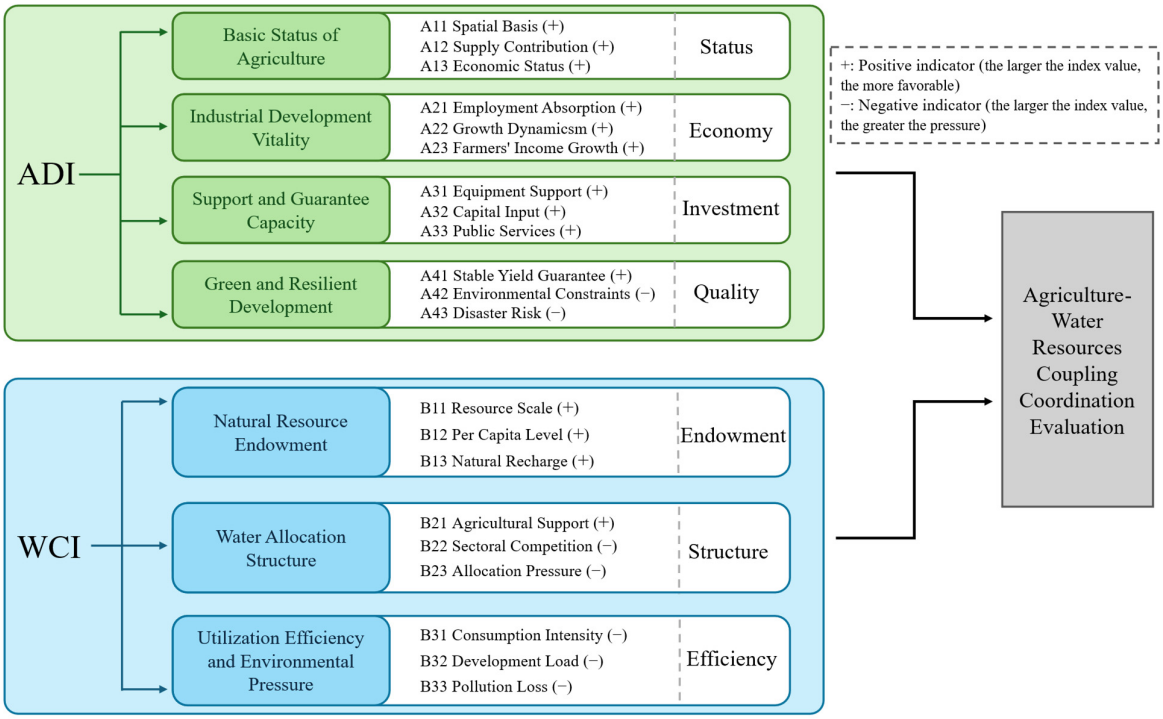


Figure 1. Framework of the Dual-System Evaluation System.

Based on the standardized indicator values and previous studies, the ADI and WCI were calculated as follows:

$$ADI = \sum_{i=1}^{4} x\prime_{ij} \times \omega_i \quad (3)$$

$$WCI = \sum_{i=1}^{3} x\prime_{ij} \times \omega_i \quad (4)$$

The weight ω_i was calculated as follows:

$$p_{ij} = \frac{x\prime_{ij}}{\sum x\prime_{ij}} \quad (5)$$

$$e_i = -\frac{\sum p_{ij} \cdot \ln\left(p_{ij}\right)}{\ln(m)} \quad (6)$$

$$w_i = 1 - \frac{e_j}{\sum(1 - e_j)} \quad (7)$$

where ADI and WCI denote the Agricultural Development Index and Water Resource Condition Index, respectively; ω_i is the weight assigned to the i-th criterion, and x_{ij} is the standardized value of the j-th indicator. The entropy weight method was consistently

adopted to determine indicator weights throughout the evaluation models, ensuring an objective weighting process.

2.3. Comprehensive Evaluation Method Based on the Coupling Coordination Degree

2.3.1. Coupling Coordination Degree Model

Based on the composite indices of the ADI and WCI, the coupling coordination degree (CCD) model was employed to quantify the coupling relationship and coordination status between the two systems. Unlike structural equation modeling (SEM) and geographically weighted regression (GWR), which focus on variable relationships and spatial heterogeneity, the CCD model evaluates the coordinated development of integrated systems and is therefore well suited to assessing the coordination between agricultural development and water resource conditions [44].

The comprehensive development level of the two systems was first calculated and denoted as T, which represents their overall development status. The calculation is given by:

$$T = \alpha \times AEI + \beta \times WCI \quad (8)$$

where ADI and WCI denote the Agricultural Development Index and Water Resource Condition Index, respectively. The parameters α and β represent the contribution coefficients of the two systems. Because agricultural development and water resource conditions constitute two equally important subsystems of the Agriculture–Water Resources System, equal weights were assigned to avoid subjective bias, with $\alpha = \beta = 0.5$.

Based on the comprehensive development level T, the coupling coordination degree (D) was calculated as follows:

$$D = \sqrt{C \times T} \quad (9)$$

where C denotes the coupling degree and T is the comprehensive development index of the dual systems. The coupling coordination degree is the primary evaluation indicator in this study, ranging from 0 to 1. Higher values of D indicate stronger coordination between agricultural development and water resource conditions, whereas lower values reflect greater mismatch and more severe imbalances between the two systems.

Because the CCD is mathematically derived from ADI and WCI, the regression results should be interpreted as statistical associations rather than strict causal effects. Accordingly, the two-way fixed-effects model was used to examine the relationships between the component systems and the overall coordination level.

2.3.2. Model Classification Criteria

The CCD was classified according to widely adopted criteria in previous studies and the development characteristics of the study area [45]. This classification facilitates the interpretation of regional spatial differentiation. The classification criteria are presented in Table 3.

2.4. Spatiotemporal Characteristics Analysis and Mechanism Analysis

The ADI and WCI exhibit distinct spatiotemporal patterns and complex interactions. The CCD model alone cannot fully characterize their spatial distribution, migration trends, or regional heterogeneity. Therefore, the standard deviation ellipse (SDE) [46] model was employed to identify the spatial evolution of the two systems, while the spatial non-overlap coefficient [47] was used to quantify their spatial correspondence. The spatiotemporal characteristics were analyzed from two perspectives: spatial configuration and spatial non-overlap.

2.4.1. Standard Deviation Ellipse Model

The SDE is a global spatial statistical method used to characterize the spatial distribution of geographic phenomena by describing their centroid, spatial extent, directional trend, and dispersion. Compared with single spatial indices, it provides a more comprehensive representation of overall spatial patterns. In this study, the ADI and WCI were used as weighting variables to construct SDEs for the two systems. The spatial evolution of each system was characterized using the ellipse centroid, major and minor axes, and azimuth angle.

Table 3. Classification Criteria for Coupling Coordination Degree.

Coupling Coordination Degree (D) Interval	Coordination Level	Coupling Coordination Status
[0.0–0.1]	1	Extreme imbalance
[0.1–0.2]	2	Severe imbalance
[0.2–0.3]	3	Moderate imbalance
[0.3–0.4]	4	Slight imbalance
[0.4–0.5]	5	Near imbalance
[0.5–0.6]	6	Barely coordinated
[0.6–0.7]	7	Primary coordination
[0.7–0.8]	8	Intermediate coordination
[0.8–0.9]	9	Good coordination
[0.9–1.0]	10	Excellent coordination

Changes in ellipse area indicate the expansion or contraction of high-value regions, whereas variations in azimuth reflect shifts in the dominant spatial orientation. The relative lengths of the major and minor axes describe the balance and directional dispersion of the spatial distribution. Together, these parameters characterize the spatial differentiation of agricultural development and water resource conditions. The corresponding equations are given as follows:

$$S_{xx} = \sum_{n-1}^{n} W_i^2 (x_i - \bar{x}_w)^2 \quad (10)$$

$$S_{yy} = \sum_{n-1}^{n} W_i^2 (y_i - \bar{y}_w)^2 \quad (11)$$

$$S_{xy} = \sum_{n-1}^{n} W_i^2 (x_i - \bar{x}_w)(y_i - \bar{y}_w) \quad (12)$$

where S_{xx} and S_{yy} denote the weighted second-order central moments along the x- and y-axes, respectively, describing the spatial dispersion of the observations around the weighted centroid. S_{xy} is the weighted mixed second-order central moment (covariance), which is used to determine the overall orientation of the spatial distribution. W_i is the weight assigned to province i, and x_w and y_w denote the coordinates of the weighted centroid.

Based on these parameters, the azimuth angle (θ) of the ellipse major axis was calculated as follows:

$$\tan\theta = \frac{(S_{xx} - S_{yy}) + \sqrt{(S_{xx} - S_{yy})^2 + (2S_{xy})^2}}{2S_{xy}} \quad (13)$$

The azimuth angle (θ) describes the orientation of the ellipse major axis, and its temporal variation reflects changes in the dominant spatial distribution of agricultural development and water resource conditions. To further characterize the spatial distribution, the standard deviations along the x- and y-axes were calculated as follows:

$$\delta_x = \sqrt{\frac{\sum_{i=1}^{n} [W_i (x_i' \cos\theta - y_i' \sin\theta)]^2}{\sum_{i=1}^{n} W_i^2}} \quad (14)$$

$$\delta_y = \sqrt{\frac{\sum_{i=1}^{n}[W_i(x_i\prime\sin\theta - y_i\prime\cos\theta)]^2}{\sum_{i=1}^{n} W_i^2}} \quad (15)$$

where δx and δy denote the standard deviations of the ellipse along the x- and y-axes, corresponding to the lengths of the minor and major axes, respectively. Annual variations in these parameters were used to characterize changes in centroid migration, spatial expansion or contraction, and the directional evolution of agricultural development and water resource conditions.

2.4.2. Spatial Non-Overlap Coefficient

The SDE describes the spatial distribution of the ADI and WCI individually but cannot quantify the spatial correspondence between the two systems. To address this limitation, the spatial coefficient of variation (sCoV) was introduced as a complementary indicator. Based on the intersection and union areas of the two SDEs, the sCoV quantifies the degree of spatial overlap and mismatch between agricultural development and water resource conditions. Unlike conventional coefficients of variation that measure only numerical differences, the sCoV incorporates spatial topological relationships to characterize spatial heterogeneity. The corresponding equations are given as follows:

$$A = \frac{P \cap I}{P \cup I} \quad (16)$$

$$R = 1 - A \quad (17)$$

where P and I denote the areas of the standard deviation ellipses for the ADI and WCI, respectively. $P \cap I$ and $P \cup I$ represent the intersection and union areas of the two ellipses. A denotes the spatial overlap coefficient, and R denotes the spatial non-overlap coefficient, with values ranging from 0 to 1. Higher R values indicate weaker spatial correspondence and greater spatial mismatch between agricultural development and water resource conditions, whereas lower values indicate stronger spatial overlap and correspondence between the two systems.

The spatial non-overlap coefficient was combined with the annual changes in the standard deviation ellipses to characterize the spatiotemporal evolution of the Agriculture–Water Resources System.

3. Results

3.1. Comprehensive Evaluation of the Dual Systems and Terrain-Based Regional Classification

Using panel data from 22 provinces and four municipalities in China during 2014–2023, the ADI and WCI were evaluated to examine their spatiotemporal characteristics under different terrain conditions. As shown in Figure 2, panel (A) presents the geographical and terrain classifications, panel (B) compares the ten-year mean values of ADI and WCI across terrain types, panel (C) illustrates their temporal evolution, and panel (D) depicts the spatial correspondence between the two systems. These analyses provide the basis for the subsequent evaluation of coupling coordination and spatial evolution.

3.1.1. Spatial Patterns of Geographical and Terrain-Based Regional Classification

As shown in Figure 2A, the study area was divided into seven geographical regions: East, Northeast, North, Northwest, South, Southwest, and Central China. According to the dominant landform, the provinces were further classified into four terrain types: plains, hills, plateaus, and mountains. Because socioeconomic, agricultural, and water resource data were consistently available at the provincial level, the province was adopted as the

basic analytical unit. For provinces with mixed terrain, the dominant terrain type was used to represent the overall terrain constraint.

The geographical classification reflects differences in location and regional development, whereas the terrain classification is based on landform characteristics and their influence on agricultural production and water resource distribution. Plains generally provide favorable conditions for large-scale agriculture and water infrastructure, while mountainous and plateau regions are more constrained by complex terrain. Hills exhibit intermediate characteristics between these two terrain types. These terrain differences underpin the spatial heterogeneity of agricultural development and water resource conditions and provide the basis for subsequent analyses of regional coordination.

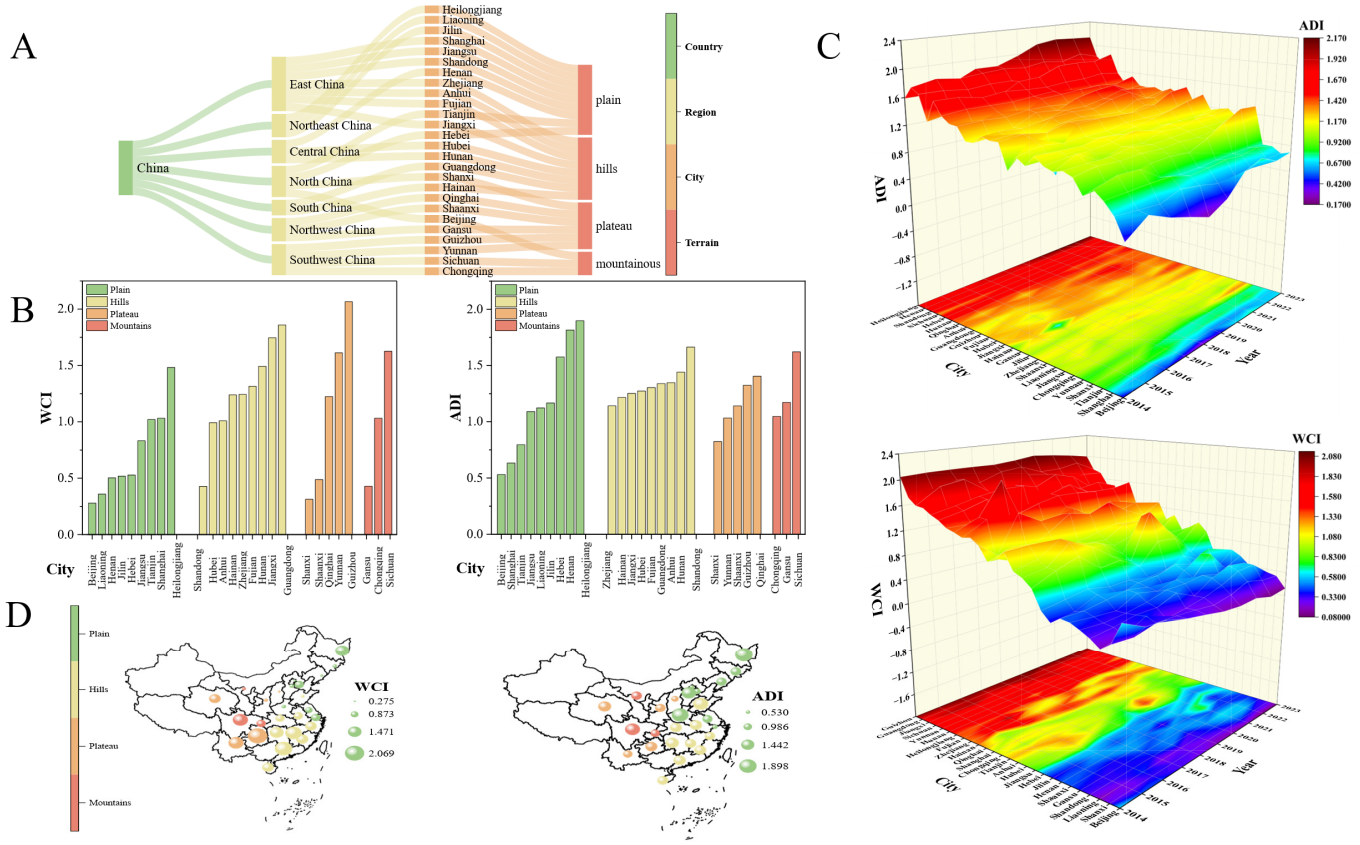


Figure 2. Integrated analysis of the Agriculture–Water Resources System. (**A**) Spatial classification of geographical regions and terrain types. (**B**) Provincial mean ADI and WCI across different terrain types. (**C**) Three-dimensional surface plot showing the temporal evolution of ADI and WCI (2014–2023). (**D**) Terrain-based spatial distribution of the mean ADI and WCI.

3.1.2. Spatial Zoning of Dual-System Mean Values and Static Terrain-Coupling Characteristics

Figure 2B compares the ten-year mean values of the ADI and WCI across provinces under different terrain types. ADI was generally higher in plain-dominated provinces, particularly in the major grain-producing regions of East, North, and Central China. These regions benefited from extensive cultivated land, higher levels of agricultural mechanization, and greater fixed-asset investment. In contrast, mountainous and plateau regions in Northwest and Southwest China exhibited lower ADI values, reflecting the constraints of complex terrain on high-standard farmland construction and large-scale agricultural production. Hilly regions showed intermediate ADI levels. WCI displayed a distinct north–south gradient. Humid regions in South and Southwest China recorded the highest values because of abundant precipitation and water resources, whereas arid and semi-arid regions

in North and Northwest China showed the lowest values owing to limited water availability and greater agricultural water demand. Northeast, East, and Central China exhibited intermediate WCI levels. Overall, three regional patterns were identified: a high-ADI–low-WCI resource-constrained pattern in the North China Plain, a high-WCI–low-ADI underutilized pattern in mountainous Southwest China, and a high-ADI–high-WCI coordinated pattern in the plains of the middle and lower Yangtze River Basin.

Figure 2D further illustrates the spatial distributions of ADI and WCI under different terrain conditions. ADI showed a clear pattern of higher values in plains and lower values in mountainous and plateau regions, whereas WCI exhibited a pronounced north–south gradient, with clear water-resource advantages in southern hilly and mountainous areas. Although the North China Plain maintained relatively high agricultural development, its water resource support remained comparatively weak, indicating a persistent spatial mismatch between agricultural development and water resource conditions. These contrasting patterns suggest that terrain and resource endowments jointly shape the spatial differentiation of the Agriculture–Water Resources System.

Across different terrain types, plains generally combined high agricultural development with comparatively limited water resources, whereas mountainous regions exhibited contrasting characteristics depending on climatic conditions. Humid mountainous areas possessed relatively favorable water resources but lower agricultural development, while arid mountainous regions showed relatively low levels of both ADI and WCI. These findings highlight the role of terrain in regulating the regional spatial differentiation of agricultural development and water resource conditions.

3.1.3. Temporal Evolution of the Agricultural Development Index and Water Resource Condition Index

Figure 2C illustrates the annual changes in the ADI and WCI across provinces from 2014 to 2023. ADI increased steadily throughout the study period, with no province showing a sustained decline. Growth was most pronounced in the eastern plains and central hilly regions, reflecting continued improvements in agricultural investment, mechanization, and rural infrastructure. In contrast, western mountainous regions exhibited slower growth because of terrain constraints. In the major grain-producing areas of North China, the growth rate gradually slowed during the later years, partly owing to increasing fertilizer inputs and the impacts of agricultural meteorological disasters.

Compared with ADI, WCI exhibited much smaller interannual variation and remained spatially stable throughout the study period. Southern humid provinces showed modest improvements in WCI, whereas North China and the Huang–Huai–Hai Plain remained at relatively low levels despite slight gains associated with water-saving measures and inter-basin water transfer projects. In Southwest China, WCI fluctuated only slightly, although increasing domestic water demand reduced the relative advantage of agricultural water availability.

The contrasting temporal trajectories indicate that agricultural development progressed more rapidly than improvements in water resource conditions. As a result, the spatial relationship between the two systems evolved differently across regions. In the major grain-producing plains, agricultural development outpaced improvements in water resource support, intensifying resource constraints. By contrast, water-abundant mountainous regions in Southwest China maintained relatively favourable water resource conditions but comparatively low agricultural development. Overall, the asynchronous evolution of the two systems provides the temporal basis for subsequent analyses of coupling coordination and spatial differentiation.

3.2. Coupling Coordination Analysis of the Dual Systems

The CCD was calculated to evaluate the coordination between the ADI and WCI across 22 provinces and four municipalities in China during 2014–2023 (Figure 3). Figure 3A presents the annual average CCD across different terrain types, Figure 3B illustrates the temporal evolution of coordination levels, Figure 3C shows provincial changes in CCD, and Figure 3D depicts the relationships among ADI, WCI, and CCD. These results characterize the regional coordination patterns of the Agriculture–Water Resources System and provide the basis for subsequent spatial analyses.

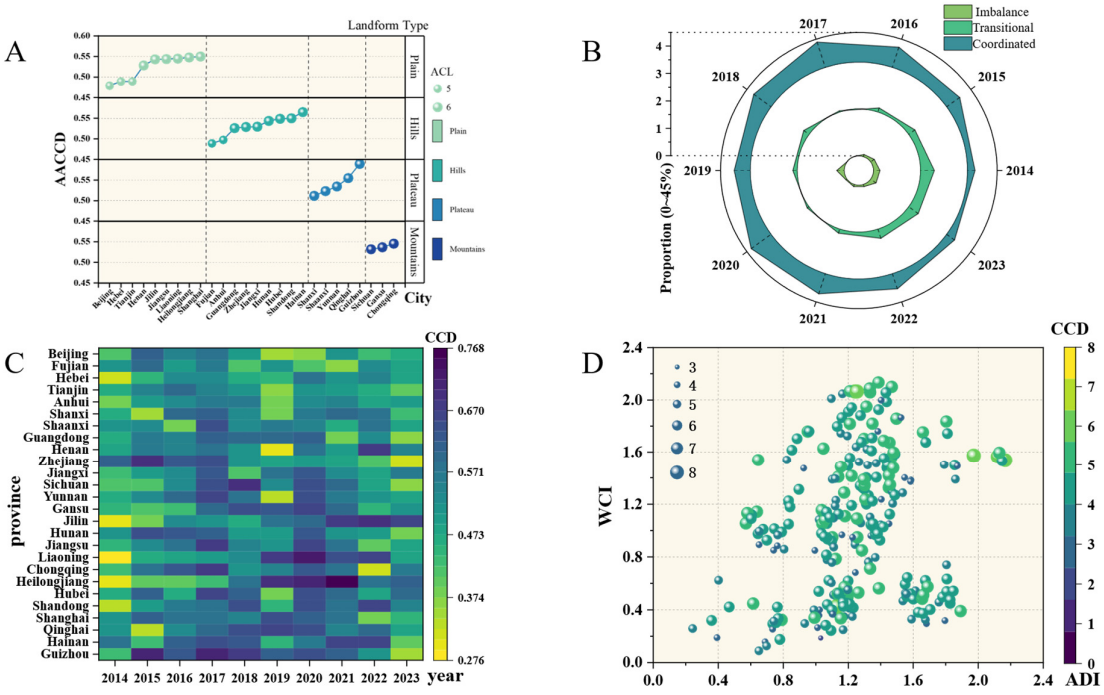


Figure 3. Integrated analysis of the coupling coordination characteristics of the Agriculture–Water Resources System. (**A**) Annual average CCD across different terrain types. (**B**) Annual distribution of coupling coordination levels. (**C**) Temporal variation in provincial CCD during 2014–2023. (**D**) Relationships among the ADI, WCI, and CCD.

3.2.1. Differences in Coupling Coordination Levels Among Different Terrain Regions

Figure 3A compares the annual average coupling coordination degree (AACCD) among four terrain types: plains, hills, plateaus, and mountains. Significant differences in coordination levels were observed across terrain regions.

Plain regions exhibited the highest coordination levels, benefiting from flat terrain, concentrated cultivated land, and relatively developed agricultural infrastructure. Major grain-producing areas in East, North, and Northeast China showed particularly high AACCD values. Hilly regions displayed intermediate coordination levels. Although these regions generally possess favorable water resource conditions, fragmented terrain limits large-scale agricultural development and infrastructure construction, reducing the efficiency of resource utilization.

Plateau and mountainous regions showed relatively lower coordination levels because complex terrain restricts agricultural expansion, high-standard farmland construction, and mechanization. Mountainous Southwest China exhibited a high-WCI–low-ADI pattern, indicating insufficient transformation of water resource advantages into agricultural development capacity, whereas some arid plateau regions experienced coordination constraints due to limited water availability. Overall, terrain influences regional coordination

differences by shaping agricultural development capacity and water resource utilization efficiency.

3.2.2. Overall Evolution Characteristics of the Coupling Coordination Degree of the Dual Systems

At the national scale, the CCD between agricultural development and water resource conditions showed an overall increasing trend during 2014–2023. The Agriculture–Water Resources System gradually transitioned from a relatively imbalanced state toward improved coordination. As shown in Figure 3B, low-coordination categories accounted for a relatively large proportion during the early study period, whereas coordinated categories gradually increased over time, indicating an overall improvement in system coordination.

This temporal evolution was consistent with the contrasting changes in ADI and WCI. ADI increased rapidly, whereas WCI exhibited relatively limited variation due to the influence of natural hydrological conditions. The asynchronous development of the two systems affected regional CCD changes, highlighting the importance of balancing agricultural development with water resource carrying capacity.

The coordination level increased rapidly during 2015–2017, followed by a more stable evolution after 2018, when coordinated categories became dominant in most regions. Nevertheless, certain areas continued to exhibit coordination constraints due to disparities between agricultural development and water resource conditions. These results indicate the need for region-specific agricultural development strategies considering local resource conditions.

3.2.3. Spatial Differentiation Characteristics of the Coupling Coordination Degree

The CCD of the Agriculture–Water Resources System exhibited clear spatial heterogeneity among provinces. As shown in Figure 3C, CCD values generally increased across all provinces during 2014–2023, although substantial regional differences remained. Eastern coastal provinces and regions along the middle and lower reaches of the Yangtze River maintained relatively high coordination levels throughout the study period. Provinces such as Jiangsu, Zhejiang, and Shandong consistently exhibited high CCD values, reflecting their relatively strong agricultural foundations and water resource support capacities.

Central China showed continuous improvements in coordination, with CCD gradually increasing over time. In contrast, Northwest and Southwest China generally exhibited lower coordination levels, characterized by different constraint patterns. Northwest regions were primarily affected by limited water availability, whereas Southwest regions were influenced by complex terrain conditions, resulting in resource-constrained and low-agricultural-utilization patterns, respectively.

Temporally, most provinces in Figure 3C shifted from darker to lighter colors, indicating an overall improvement in coordination levels. However, regional disparities persisted due to differences in natural conditions and agricultural development processes.

3.2.4. Analysis of the Driving Factors of Dual-System Coupling Coordination

Figure 3D illustrates the relationships among the ADI, WCI, and CCD to explore the factors associated with coordination development. Overall, ADI and WCI showed a positive relationship, with high CCD values mainly occurring in regions characterized by both high agricultural development and favorable water resource conditions. This indicates that the coordination of agricultural development capacity and water resource support provides an important basis for improving system coordination.

Regions with advantages in only one subsystem generally exhibited limited coordination improvement because of constraints from the other subsystem. For example, the North China Plain showed high agricultural development but faced water resource

constraints, whereas Southwest China possessed relatively favorable water resources but insufficient agricultural development capacity. These results suggest that the coordination of the Agriculture–Water Resources System depends on the combined effects of agricultural development capacity, water resource support, and terrain constraints rather than a single factor.

Overall, the coupling coordination degree of China's Agriculture–Water Resources System improved during 2014–2023, although regional disparities remained. Eastern regions maintained higher coordination levels, central regions showed continuous improvement, and western regions exhibited differentiated coordination patterns. These differences reflect the combined influence of agricultural foundations, water resource conditions, and terrain constraints.

3.3. Spatiotemporal Characteristics Analysis of the Dual Systems

The previous results demonstrate distinct spatiotemporal patterns between the ADI and WCI. To further characterize their spatial distributions, centroid migration, and spatial correspondence, the SDE model and spatial non-overlap analysis were applied. The spatiotemporal characteristics of the Agriculture–Water Resources System were examined from two perspectives: spatial pattern evolution and inter-system spatial correspondence. The results are presented in Figure 4. Specifically, Figure 4a,b show the SDE characteristics of ADI, Figure 4c,d present those of WCI, and Figure 4e illustrates the spatial overlap and non-overlap characteristics between the two systems.

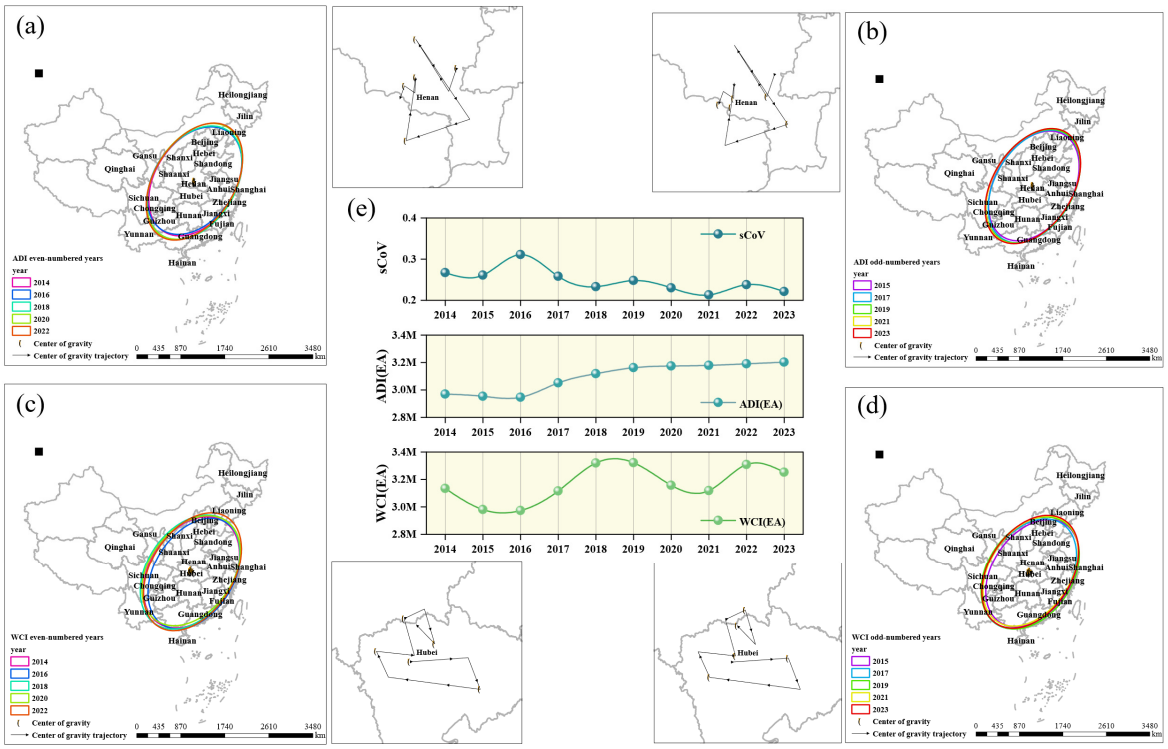


Figure 4. Spatiotemporal characteristics of the Agriculture–Water Resources System. (**a**) Standard deviation ellipses (SDEs) of the ADI in even-numbered years. (**b**) SDEs of ADI in odd-numbered years. (**c**) SDEs of the WCI in even-numbered years. (**d**) SDEs of WCI in odd-numbered years. (**e**) Temporal changes in ellipse areas of ADI and WCI and their spatial non-overlap characteristics. The small square in the Figure 4 represents an enlarged view of the centroid migration of the standard deviation ellipse. The arrows indicate the movement direction of the standard deviation ellipse centroid over time.

3.3.1. Analysis of the Standard Deviation Ellipse Model

As shown in Figure 4a,b, the spatial distribution of the ADI remained relatively stable during 2014–2023. The major axis of the ADI ellipse consistently extended along the northeast–southwest direction, covering the North China Plain, Huang–Huai–Hai Plain, and the agricultural core areas along the middle and lower reaches of the Yangtze River. This indicates that agricultural development advantages remained concentrated in traditional grain-producing regions throughout the study period. The spatial centroid of ADI remained around Henan and its surrounding areas, with only minor interannual fluctuations, indicating limited migration of the agricultural development center. Provinces such as Henan, Shandong, Hebei, Jiangsu, and Anhui maintained relatively high ADI values. Meanwhile, the ellipse area generally expanded, suggesting a gradual increase in the spatial extent of high-agricultural-development regions. Overall, the ADI exhibited a pattern characterized by a stable core and an expanding spatial range.

Compared with ADI, the spatial distribution of WCI showed stronger dependence on natural conditions. As shown in Figure 4c,d, the WCI ellipse generally exhibited a northeast–southwest orientation and extended toward southern regions. The ellipse mainly covered the Yangtze River Basin, South China, and Southwest China, while its centroid remained near Hubei and surrounding areas during the study period. This pattern corresponds to the overall distribution of China's water resources, characterized by greater availability in the south and lower availability in the north. The WCI centroid exhibited larger fluctuations than that of ADI, indicating greater temporal variability in the spatial distribution of water resource conditions. However, the overall distribution pattern remained stable, and changes in ellipse area reflected adjustments in the spatial extent of water resource advantages.

A comparison of the two systems reveals a clear spatial mismatch between agricultural development and water resource conditions. The ADI centroid remained concentrated in agricultural core regions around Henan, whereas the WCI centroid was located closer to water-resource-rich regions in central and southern China. The North China Plain represents a high-ADI–low-WCI pattern with limited water resource support, while parts of Southwest China exhibit a high-WCI–low-ADI pattern characterized by insufficient transformation of water resource advantages into agricultural development capacity.

3.3.2. Analysis of the Spatial Non-Overlap Coefficient

As shown in Figure 4e, the spatial non-overlap coefficient (R) exhibited a fluctuating downward trend during 2014–2023. The index increased from approximately 0.27 in 2014 to a peak of about 0.315 in 2016, indicating a temporary increase in spatial mismatch between agricultural development and water resource conditions. Subsequently, R declined continuously, reaching a minimum value of approximately 0.21 in 2021. After a short-term increase in 2022, it decreased again to about 0.225 in 2023. Overall, R ranged from 0.21 to 0.32, suggesting a gradual improvement in the spatial correspondence between agricultural development and water resource conditions.

The ellipse area of ADI showed a pattern of initial adjustment followed by continuous expansion. It decreased slightly from approximately 2.96 million km^2 in 2014 to 2.94 million km^2 in 2016, then increased steadily to about 3.20 million km^2 in 2023, indicating an expansion of the spatial extent of high-agricultural-development regions. In contrast, the ellipse area of WCI exhibited stronger fluctuations. It declined from approximately 3.14 million km^2 in 2014 to the lowest value in 2016, increased to a peak of about 3.33 million km^2 in 2022, and remained relatively high in 2023.

Overall, ADI exhibited continuous spatial expansion, whereas WCI showed periodic fluctuations. The asynchronous evolution of the two systems resulted in temporal variations in their spatial correspondence. The spatial non-overlap coefficient effectively

characterizes changes in spatial mismatch between agricultural development and water resource conditions, but it does not independently explain the underlying mechanisms or causal relationships.

3.4. Construction and Analysis of the Coordinated Development Response Model

3.4.1. Construction of the Response Model

The previous sections established the ADI, WCI, and CCD to evaluate the development status and coordination level of the Agriculture–Water Resources System across 22 provinces and four municipalities in China. However, index-based assessments mainly characterize regional differences in coordination levels and cannot further examine the factors influencing coordination outcomes. Therefore, a coordinated development response model was constructed to investigate the determinants of Agriculture–Water Resources System coordination.

Given the panel structure of the dataset, persistent regional heterogeneity exists in natural conditions, agricultural foundations, water resource endowments, and socioeconomic characteristics. Meanwhile, temporal variations caused by policy changes and macroeconomic fluctuations may also affect coordination levels. Therefore, a two-way fixed effects model was employed to control for province-specific effects and time-specific effects, thereby reducing the influence of unobserved heterogeneity. The model is expressed as follows:

$$D_{it} = \alpha + \beta_1 AEI_{it} + \beta_2 WCI_{it} + \beta_3 CV_t + \mu_i + \lambda_t + \varepsilon_{it} \quad (18)$$

In the model, D_{it} represents the CCD of region i in year t and serves as the dependent variable. ADI_{it} denotes the Agricultural Development Index, reflecting the regional agricultural development level. WCI_{it} represents the Water Resource Condition Index, indicating the regional water resource support capacity. CV_t denotes the spatial non-overlap indicator, which characterizes temporal variations in the spatial correspondence between agricultural development and water resource conditions. μ_i represents the regional fixed effect controlling for time-invariant provincial heterogeneity, while λ_t represents the year fixed effect controlling for common temporal shocks. ε_{it} denotes the random error term.

Before model estimation, descriptive statistics and Pearson correlation analysis were conducted to examine variable distributions and correlation patterns. Subsequently, ordinary least squares (OLS), one-way fixed effects, and two-way fixed effects models were estimated, and the preferred specification was selected based on model performance. The variance inflation factor (VIF) test was applied to assess multicollinearity among explanatory variables. Model performance was further evaluated using R^2, adjusted R^2, root mean square error (RMSE), and mean absolute error (MAE).

3.4.2. Model Fitting Results and Variable Relationship Analysis

The descriptive statistics of the variables are presented in Table 4. During 2014–2023, the mean coupling coordination degree of the Agriculture–Water Resources System was 0.5314, indicating an overall moderate coordination level. However, the considerable gap between the maximum and minimum values demonstrates substantial spatial heterogeneity in coordination development among provinces. The mean value of ADI was 1.2374, with a standard deviation of 0.3405, reflecting differences in regional agricultural development levels. The WCI had a mean value of 1.0259 and a higher standard deviation of 0.5353, indicating greater spatial variation in water resource conditions compared with agricultural development. The spatial non-overlap indicator (CV) showed a relatively limited variation range, suggesting that the overall spatial relationship between agricultural development and water resource conditions changed within a relatively stable range during the study period.

Table 4. Descriptive Statistics of Variables.

Variable	Sample Size	Mean	Standard Deviation	Minimum	Maximum
D (Coupling Coordination Degree)	260	0.5314	0.0972	0.277	0.768
ADI (Agricultural Development Index)	260	1.2374	0.3405	0.2434	2.1667
WCI (Water Resource Condition Index)	260	1.0259	0.5353	0.0881	2.1323
CV (Spatial Difference Indicator)	260	0.2479	0.0269	0.2131	0.3109

The Pearson correlation analysis results are presented in Table 5. The coupling coordination degree was positively correlated with both the ADI and WCI, with correlation coefficients of 0.1218 and 0.2128, respectively. These results indicate that higher agricultural development levels and stronger water resource support capacities were associated with higher coordination levels of the Agriculture–Water Resources System. In contrast, D showed a negative correlation with the spatial non-overlap indicator (CV), suggesting that increased spatial mismatch was associated with lower system coordination. Overall, the correlation results provide preliminary evidence for the relationships among variables and support the subsequent multivariate regression analysis.

Table 5. Pearson Correlation Coefficient Matrix.

Variable	D	ADI	WCI	CV
D	1	0.1218	0.2128	−0.0483
ADI	0.1218	1	0.2172	−0.1429
WCI	0.2128	0.2172	1	0.026
CV	−0.0483	−0.1429	0.026	1

After controlling for regional and year effects, the regression results are presented in Table 6. Standard errors in all three models were clustered at the provincial level to account for potential heteroskedasticity and serial correlation. Model 1 was estimated using ordinary least squares (OLS) and showed relatively limited explanatory power, indicating that the selected variables alone could not fully capture regional differences in coordination levels. Model 2 introduced regional fixed effects, resulting in improved model performance, suggesting that time-invariant provincial heterogeneity plays an important role in explaining coordination differences. Model 3 further incorporated year fixed effects, with R^2 increasing to 0.5416 and adjusted R^2 reaching 0.4675. The Hausman test was conducted to compare fixed-effects and random-effects specifications, and the results supported the selection of the two-way fixed-effects model. Therefore, Model 3 was adopted as the final response model. The fitting performance of the selected model is shown in Figure 5, and the final model is expressed as follows:

$$D_{it} = \alpha + 0.1874AEI_{it} + 0.3636WCI_{it} - 0.0141CV_t + \mu_i + \lambda_t + \varepsilon_{it} \quad (19)$$

Standard error refers to the province-clustered standard errors.

In addition, given the limited cross-sectional dimension of the panel dataset and the inclusion of year fixed effects, common temporal shocks across provinces were partially controlled. Future studies could further examine potential cross-sectional dependence using specialized panel data tests.

Table 6. Regression Results of the Coordinated Development Response Model.

Variable	Model 1 OLS	Model 2 Regional Fixed Effects	Model 3 Two-Way Fixed Effects
ADI	0.0207	0.1818 ***	0.1874 ***
Standard Error	0.0181	0.051	0.0468
WCI	0.0360 ***	0.3889 ***	0.3636 ***
Standard Error	0.0115	0.04	0.039
CV	−0.1560	−0.0474	−0.0141
Standard Error	0.2228	0.211	0.0133
Constant	0.4255	0.1445	—
Regional Fixed Effects	No	Yes	Yes
Year Fixed Effects	No	No	Yes
Sample Size	260	260	260
R^2	0.0531	0.3767	0.5416
Adjusted R^2	0.042	0.3012	0.4675

Note: *** indicates significance at the 1% level ($p < 0.01$).

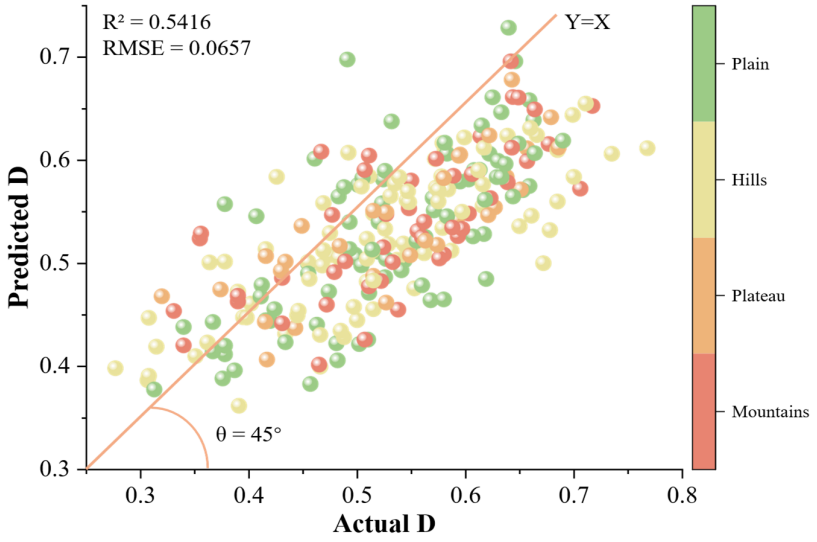


Figure 5. Scatter Plot of the Fitting Performance of the Coordinated Development Response Model.

3.4.3. Comprehensive Analysis of the Effects of Agricultural, Water Resource, and Spatial Conditions

The two-way fixed-effects model results indicate that the coefficient of ADI is 0.1874 and statistically significant, suggesting a positive association between agricultural development level and the coordination degree of the Agriculture–Water Resources System. Higher agricultural development levels are generally associated with improved agricultural infrastructure, production capacity, and resource utilization efficiency, which contribute to higher coordination levels.

The coefficient of WCI is 0.3636 and is also statistically significant. Its estimated effect is larger than that of ADI, indicating that water resource conditions have a stronger association with system coordination. Regions with higher water resource support capacity generally exhibit stronger resource support for agricultural production and fewer constraints on agricultural–water coordination.

The coefficient of the spatial non-overlap indicator (CV) is negative, indicating that increased spatial mismatch between agricultural development and water resource conditions is associated with lower coordination levels. Greater spatial mismatch may increase pressure on resource allocation and weaken the coordination efficiency of the Agriculture–Water

Resources System. Overall, agricultural development level, water resource conditions, and spatial correspondence jointly influence regional coordination patterns, with water resource support capacity showing a relatively stronger association.

3.4.4. Model Robustness and Discussion of the Coordinated Development Response Characteristics

To evaluate the robustness of the model, a multicollinearity test was conducted. The VIF values of ADI, WCI, and CV were 1.074, 1.053, and 1.024, respectively, all below the commonly accepted threshold of 5. These results indicate that no significant multicollinearity exists among the explanatory variables, supporting the stability of the model estimation.

The model comparison results show that the explanatory power improved substantially after incorporating regional and year fixed effects. This indicates that coordination levels of the Agriculture–Water Resources System are associated not only with agricultural development levels and water resource conditions but also with regional heterogeneity and temporal variations. Differences in natural conditions, agricultural development stages, and resource utilization patterns jointly contribute to regional disparities in coordination levels.

Overall, the coordinated development of agricultural and water resources reflects the combined influence of agricultural development capacity, water resource support conditions, and spatial allocation characteristics. The response model provides quantitative evidence for examining the relationships between regional agricultural development and water resource coordination and offers a basis for understanding variations in coordination levels.

4. Discussion

4.1. Spatiotemporal Patterns of Agriculture–Water Resources Coupling Coordination

This study demonstrates that the coupling coordination degree of the Agriculture–Water Resources System in China generally improved during 2014–2023, although substantial regional disparities remained. This finding is consistent with previous studies reporting gradual improvements in agricultural–water resource coordination. Furthermore, the results highlight the contribution of terrain heterogeneity to regional differences in coordination levels. Plain regions generally exhibited higher coordination levels than plateau and mountainous regions, suggesting that terrain conditions influence agricultural production capacity, infrastructure development, and water resource accessibility.

Previous studies have also emphasized the role of terrain heterogeneity in agricultural water resource management, although many have focused primarily on river basins or irrigation districts [48]. By conducting a provincial-scale analysis, this study extends existing research by providing broader empirical evidence on the spatial differentiation of agriculture–water resource coordination.

4.2. Terrain Constraints and the Mechanisms Underlying Coordination Differences

The coordination level of the Agriculture–Water Resources System was generally higher in plain regions than in hilly, plateau, and mountainous regions, indicating the important role of terrain heterogeneity in shaping regional coordination differences. Flat terrain in plains provides favorable conditions for irrigation infrastructure development, agricultural mechanization, and large-scale farming. In contrast, plateau and mountainous regions often face challenges associated with complex topography, fragmented water resource distribution, and higher infrastructure construction costs, which increase the difficulty of achieving coordinated agricultural and water resource development.

These findings are consistent with previous studies showing that terrain complexity influences agricultural water resource utilization efficiency [49], suggesting that terrain-related constraints represent an important factor affecting agriculture–water coordination.

4.3. Spatial Pattern Characteristics

This study found that the spatial centroid of agricultural development advantages remained near Henan Province during 2014–2023, whereas the spatial distribution of water resource conditions exhibited periodic fluctuations. The overall spatial mismatch between agricultural development advantages and water resource conditions remained relatively stable, indicating a persistent inconsistency between regions with strong agricultural development capacity and those with favorable water resource endowments.

These findings are consistent with previous studies reporting long-term spatial disparities between agricultural development centers and water-resource-abundant regions [50]. By integrating provincial panel data, this study further quantified the temporal evolution of this spatial mismatch pattern.

4.4. Study Limitations and Future Perspectives

This study has several limitations that should be addressed in future research. First, the provincial-scale analysis may introduce spatial aggregation bias, as internal variations in terrain, climate, and resource conditions within provinces may not be fully captured. Future studies could further examine these patterns using finer-scale datasets, such as county-level or gridded data. Second, although the entropy weight method provides an objective weighting approach based on data variability, it may not fully represent the theoretical importance of individual indicators. Future research could improve the robustness of the evaluation framework by integrating subjective and objective weighting methods such as PCA and CRITIC. Third, since the CCD is mathematically derived from the ADI and WCI, the regression results should be interpreted as statistical associations rather than strict causal effects. The impacts of policy interventions and other external factors require further investigation using appropriate causal identification strategies. Finally, the standard deviation ellipse model and spatial non-overlap index are descriptive approaches that characterize spatial patterns but cannot identify spatial dependence. Future studies could incorporate spatial statistical methods, such as Moran's I and spatial econometric models, to further explore spatial autocorrelation and local spatial interactions.

5. Conclusions

This study investigated the coupling coordination between agricultural development and water resource conditions across 22 provinces and four municipalities in China during 2014–2023, incorporating terrain classification as a spatial stratification framework.

Three main findings were identified. First, agricultural development showed a continuous increasing trend, whereas water resource conditions exhibited greater temporal fluctuations, indicating divergent evolutionary patterns between the two subsystems. Second, the coupling coordination degree generally improved, but significant regional disparities remained. Plain regions maintained higher coordination levels than plateau and mountainous regions, highlighting the influence of terrain heterogeneity on regional coordination differences. Third, agricultural development advantages remained concentrated in central agricultural regions, while water resource advantages showed greater spatial variability, resulting in persistent spatial mismatch between the two systems.

The proposed framework integrating agricultural development, water resource conditions, and terrain stratification provides a transferable approach for regional agriculture–water coordination assessment. Future studies should incorporate finer-scale spatial

datasets and policy-related variables to further improve the understanding of coordination mechanisms.

Author Contributions: Conceptualization, Q.L. and J.Z.; methodology, Q.L., Y.W. and J.Z.; software, Q.L., Y.W., J.S., Y.Z. and B.Y.; validation, J.S. and Y.Z.; formal analysis, Q.L. and J.S.; data curation, Q.L., Y.W., J.S., Y.Z. and B.Y.; writing—original draft preparation, Q.L., Y.Z. and J.Z.; writing—review and editing, Q.L., Y.W. and J.Z.; visualization, Q.L.; supervision, J.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the United Nations Educational, Scientific and Cultural Organization (UNESCO, Grant No. 4500469020), the Sichuan Province Natural Science Foundation of China (Grant No. 2022NSFSC1123), the Free Exploration Research Project of Sichuan Agricultural University (2521993049), the Key Research Base of Social Sciences in Sichuan Province–Tuo jiang River Basin High-quality Development Research Center Project (Grant No. TJGZL2022–23) and the National Undergraduate Training Program for Innovation and Entrepreneurship of China (No. S202610626120). The funders played no role in study design, data collection and analysis, decision to publish, or manuscript preparation.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: These data were derived from the following resources available in the public domain: China Statistical Yearbook: https://www.stats.gov.cn/sj/ndsj/ (accessed on 18 July 2026); China Water Resources Bulletin: http://www.mwr.gov.cn/sj/tjgb/szygb/ (accessed on 18 July 2026); China Environmental Statistical Yearbook: https://www.mee.gov.cn/hjzl/sthjzk/sthjtjnb/ (accessed on 18 July 2026), etc. Other data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ADI	Agricultural Development Index
WCI	Water Resource Condition Index
AACCD	annual average coupling coordination degree
CCD	coupling coordination degree
sCoV	spatial coefficient of variation
SDE	standard deviation ellipse

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