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Spatiotemporal Evolution and Driving Factors of Coupling Coordination in the Agricultural Eco-Economic System of the Yellow River Delta

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Abstract

The Yellow River Delta is a crucial ecological function zone in the Yellow River Basin and a nationally important demonstration area for high-efficiency ecological agriculture. Using data from six prefecture-level cities and 19 counties (county-level cities and districts) from 2015 to 2024, this study constructs an evaluation indicator system for the regional agricultural eco-economic system and applies the CRITIC weighting method, the coupling coordination degree model, and the Spatial Durbin Model with Fixed Effects (SDM-FE) to investigate its spatiotemporal patterns and driving factors. The main results are as follows: (1) The coupling coordination development of the agricultural eco-economic system exhibited dual characteristics in temporal evolution and spatial distribution. (2) Positive spatial dependence existed in the coupling coordination development of the agricultural eco-economic system, indicating regional spatial linkages. (3) Industrial structure upgrading and traditional agricultural modernization were negatively associated with coupling coordination, whereas agricultural scale operations and urbanization development were positively associated with coupling coordination, with spatial spillover associations varying across factors. The main findings were generally consistent across alternative indicator weighting schemes, spatial weight matrices, and leave-one-out and influence diagnostics, while the core direct effects remained stable under the two-way fixed-effects specifications. Policy recommendations include strengthening cross-county collaboration, promoting appropriate-scale agricultural operations and green agricultural modernization, improving infrastructure connectivity, and optimizing industrial upgrading and fiscal investment.

Keywords: spatiotemporal evolution; driving factors; coupling coordination; agricultural eco-economic system; Yellow River Delta

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1. Introduction

Agriculture is fundamental to human societies, providing essential food resources and playing a central role in global food security [1]. Beyond its production function, it provides ecological functions, such as supporting human welfare through food provision, soil fertility, climate regulation, and water regulation [2]. Agricultural systems should therefore not be seen solely as production systems but as complex socioecological systems [3] involving interactions among biological components, environmental conditions, and human management activities. Agricultural ecosystems (agroecosystems) are human-managed ecological systems in which biological, environmental, and socioeconomic components interact to achieve agricultural production goals while maintaining productivity, stability,

sustainability, and equity [3]. Historically, ecology and agricultural science developed from common roots in the study of biological interactions, but their relationship shifted from early integration to specialization before converging again through agroecology and sustainable agriculture approaches [4].

Agroecosystems deliver ecosystem services that support human well-being, including food production, soil fertility maintenance, water regulation, and biodiversity conservation [5,6]. In addition to supporting agricultural productivity, they generate broader ecological and social benefits, such as climate regulation, cultural services, and other non-market ecosystem services that are often undervalued in conventional agricultural decision-making [7]. Many of these ecosystem services, particularly supporting and regulating services, provide the ecological processes essential for maintaining agricultural productivity [8].

For instance, soil quality, water availability, nutrient cycling, and biodiversity contribute to crop yields. Biodiversity enhances ecosystem function and productivity through species complementarity and diverse ecological processes [9,10]. Conversely, intensive agricultural practices can impair ecosystem function by increasing resource consumption, driving biodiversity loss, and weakening the capacity of ecosystems to provide critical services [11]. Consequently, maintaining a balance between agricultural production and ecosystem sustainability has become a key concern in efforts to achieve sustainable agricultural development [12].

The reciprocal relationship between agricultural production and ecological processes further indicates that the ecological and economic dimensions of agriculture are inextricably linked. This dynamic forms agricultural eco-economic systems, which are characterized by the interaction, mutual reinforcement, and balance between the agricultural ecological environment and agricultural economic development [13]. From a systems perspective, the agricultural eco-economic system can therefore be considered a coupled system formed through interactions between the agricultural ecological and economic subsystems, involving material and energy flows, resource inputs, economic activities, and environmental interactions [13,14]. The ecological subsystem provides the resource and environmental foundations for agricultural economic development, while economic activities simultaneously exert feedback effects on ecological conditions. Maintaining coordination between the two subsystems is consequently essential for achieving long-term agricultural sustainability [15].

Located at the downstream end of the Yellow River, the Yellow River Delta (YRD) is a young estuarine delta that has developed largely since the river avulsion in 1855 and supports the youngest coastal wetland ecosystem in China [16]. Its formation and morphological evolution are strongly influenced by riverine water and sediment inputs and coastal hydrodynamic processes, which have shaped the extensive and continuously evolving dynamic wetland environments of the region [16,17]. The YRD is therefore an ecologically important but environmentally sensitive coastal zone, where changes in water and sediment regimes and land use can substantially affect wetland spatial patterns, ecological processes, and ecosystem functioning [18–20].

Agriculture is an important component of land use and socioeconomic development in the YRD, but agricultural production is closely constrained by the region's distinctive ecological conditions [21]. Extensive saline-alkali soils, freshwater limitations, and the fragile ecohydrological environment can restrict agricultural production and increase the difficulty of sustainable resource management [18,22,23]. At the same time, agricultural cultivation, irrigation, land reclamation, and other human activities have progressively altered regional land and water processes [18,24]. The coexistence of agricultural development demands

and ecological constraints consequently makes the YRD a particularly important region for examining the sustainable development of agricultural ecosystems.

Sustainable agricultural development in the YRD has gained increasing strategic significance since ecological protection and high-quality development of the Yellow River Basin was elevated to a major national strategy [25]. As a key region in the lower Yellow River, the YRD is situated at the intersection of ecological conservation, agricultural development [26], and regional socioeconomic development, making the coordination of ecological and economic objectives particularly important [27]. Given this context, investigating the coupling coordination of the agricultural eco-economic system and its driving factors can provide scientific evidence for the formulation of regionally differentiated agricultural development policies and the efficient use of agricultural resources [28], contributing to the coordinated advancement of agricultural development and ecological protection and supporting food and ecological security [29].

Against this background, this study makes two contributions. Geographically, it provides a county-level assessment of agricultural eco-economic coupling coordination across 19 county-level administrative units in the YRD, offering evidence from a region where agricultural production and ecological conservation face distinctive resource and environmental constraints. Methodologically, this study integrates the coupling coordination degree model with a spatial Durbin model to examine local associations and cross-county spatial relationships using panel data from 2015 to 2024. The decomposition of direct, indirect, and total effects further distinguishes local statistical associations from spatial associations involving neighboring counties. Together, these contributions extend regional evidence on agricultural eco-economic coordination and provide a basis for geographically differentiated policy recommendations.

Despite growing research on agricultural eco-economic coupling coordination and spatial spillovers in China, the county-level coordination of agricultural ecological and economic subsystems across the YRD and the spatial relationships between its driving factors and neighboring counties warrant further investigation. The YRD presents a distinctive geographical context where agricultural production, saline-alkali soils, freshwater constraints, and coastal wetlands interact. Geographically, this study examines 19 county-level administrative units across six prefecture-level cities, providing detailed evidence on the spatial heterogeneity of agricultural eco-economic coupling coordination in this ecologically sensitive delta. Methodologically, the research combines a coupling coordination degree model with a spatial Durbin model with fixed effects (SDM-FE), using county-level panel data from 2015 to 2024 to examine direct, indirect, and total spatial effects. Rather than claiming novelty in these established methods, the study contributes a region-specific empirical assessment of local and cross-county statistical associations, providing evidence to inform geographically differentiated agricultural and ecological policies.

2. Literature Review

2.1. Research on the Conceptualization of Agricultural Ecosystems

The conceptual scope of agroecology has expanded from an initial focus on crop production and protection to encompass a broader range of environmental, social, economic, and developmental dimensions. Its analytical scale has likewise extended from individual plots and fields to farms, agroecosystems, and ultimately food systems [30]. Within this broad systems perspective, agroecosystems are defined as ecosystems managed by humans to provide agricultural production [8], while their productivity remains dependent on supporting and regulating ecological processes and ecosystem services [7,8]. Unlike natural ecosystems, their structure, functions, and resource flows are influenced by management activities [8], including cultivation, irrigation, fertilization, pest management, and land-use

decisions [31,32]. However, their productivity and stability remain dependent on ecological processes such as soil formation, nutrient cycling, water regulation, and biodiversity maintenance [6].

Studies incorporating an ecosystem-services perspective have broadened the understanding of agroecosystems by emphasizing that they are not only sources of food, fiber, and fuel, but also systems that depend on and provide a range of supporting, regulating, cultural, and nonmarket ecosystem services [7]. Supporting and regulating processes, including soil fertility maintenance, pollination, biological pest regulation, nutrient cycling, and water regulation, contribute directly or indirectly to agricultural productivity [6]. While agricultural management and intensification may also generate environmental disservices, including habitat loss, nutrient runoff, pesticide impacts, and broader alterations to biotic interactions and resource availability [6,32], agricultural production and ecological processes are increasingly regarded as mutually dependent rather than isolated components [6,33].

This reciprocal relationship provides a conceptual basis for viewing agricultural development as a coupled eco-economic system rather than as separate ecological and economic processes [34]. The agricultural eco-economic system is conceptualized as an integrated system in which agricultural, ecological, and economic subsystems interact and exhibit coupling and coordination relationships [13]. Agricultural production relies on land, water, biological resources, and the ecological capacity that support farming activities [11,35]. Simultaneously, economic activities alter ecological conditions through technological inputs and production intensification, including fertilization, irrigation, pesticides, and land conversion [32], as well as through resource consumption and waste emissions [11,35]. These natural resource inputs, economic investments, agricultural production, and resulting environmental impacts constitute key pathways through which the ecological and economic subsystems remain interconnected [35].

Consequently, sustainable agricultural development is framed not simply in terms of improvements within the ecological or economic subsystem in isolation, but also in terms of their coupling interactions and coordinated development [36]. Agricultural intensification based on increased chemical and resource inputs and land conversion can enhance agricultural production but may simultaneously alter ecological processes and undermine the long-term capacity of ecosystems to sustain food production [11,32]. Conversely, ecological protection that does not adequately account for livelihood and economic considerations is also difficult to sustain [37]. The agricultural eco-economic system therefore provides a systems-based framework for examining how ecological conditions and agricultural economic activities interact, constrain, and respond to each other over time [38].

2.2. Research on the Evaluation and Coupling Coordination of Agricultural Eco-Economic Systems

Quantitative tools and indicator-based approaches have been developed to assess agricultural sustainability across environmental, economic, and social dimensions [39,40]. Agricultural system performance has been examined from multiple perspectives, including agricultural eco-economic development [38], green development [41], eco-efficiency [42], resilience [43], productivity and efficiency [44], and multidimensional sustainability performance [39,40]. Although these approaches differ in their analytical emphasis, they extend agricultural performance assessment beyond production and economic outcomes by incorporating ecological conditions, resource use, environmental pressures, technological and modernization capacity, and socioeconomic dimensions [39,41,42,45,46].

Multidimensional indicator systems are widely used to assess agricultural green and sustainable development [39,40,47]. These assessments incorporate indicators covering different aspects of agricultural-system performance, such as resource endowment, agricultural production, science and technology, ecological and economic performance, and

social well-being [48]. A range of weighting and multicriteria evaluation methods, including entropy weighting, TOPSIS, CRITIC, and principal component analysis, have been applied to aggregate multidimensional indicators into composite measures of agricultural sustainability and development [15,47–50]. For example, Fu et al. [48] developed a resource use-efficiency-based framework covering agricultural resource endowment, production, science and technology, and ecological, economic, and social benefits and applied an entropy-weighted TOPSIS approach to evaluate agricultural sustainable development in Zhejiang Province.

From an efficiency perspective, frontier-based methods, particularly data envelopment analysis (DEA), are widely applied to agricultural efficiency and productivity assessment [51–54]. Agricultural eco-efficiency focuses on the relationship between agricultural production efficiency and environmental performance, emphasizing the efficient use of production inputs while reducing associated environmental pressures [42,55]. Consequently, agricultural efficiency has been evaluated using various DEA models and their extensions, including conventional DEA, super-efficiency DEA, slack-based measure (SBM) models, models incorporating undesirable outputs, and Malmquist-type productivity approaches [52,54,56]. Compared with composite index approaches, efficiency models focus on the input-output transformation process, evaluating how effectively resource and environmental inputs are transformed into desirable agricultural outputs while incorporating undesirable environmental outputs in specific models [51,52,55,57].

Agricultural resilience represents another dimension of system evaluation [43,58]. Unlike conventional sustainability assessments that focus primarily on environmental, economic, and social performance, resilience research emphasizes how agricultural systems respond to shocks, stresses, uncertainty, and change through the capacities to absorb disturbance, maintain functions, adapt, and transform [58,59]. Resilience assessments therefore provide additional information on the capacity of agricultural systems to maintain and adjust their functions under external disturbances [43,58,60,61].

Existing studies have also analyzed the temporal evolution and spatial differentiation of agricultural performance [56]. Provincial-scale assessments in China have revealed spatial heterogeneity across multiple dimensions of agricultural performance, including agricultural green development, sustainability, and eco-efficiency [62–64]. Spatiotemporal analyses can therefore reveal changing development trajectories, persistent regional disparities, spatial clustering, and spatially differentiated drivers of agricultural system performance [64,65].

Contemporary agricultural-system evaluation extends beyond conventional production and economic performance measures to encompass ecological conditions, resource use, efficiency, resilience, and broader dimensions of sustainability [39,40]. These approaches provide complementary information on the ecological, economic, productive, and adaptive characteristics of agricultural systems. However, assessments of individual dimensions or composite development levels do not reveal the interactions, trade-offs, and feedback among different components of agricultural systems [39,40,66]. This limitation has motivated research examining the coordination, coupling, and dynamic relationships between agricultural ecological and economic subsystems [13,38,67].

Previous studies have investigated the degree of coupling and coordination between agricultural ecological and economic subsystems [13,67]. The coupling coordination degree (CCD) model has been widely applied to characterize the degree of coupling and coordinated development between these subsystems [13,67,68]. Comprehensive development indices are first calculated separately for the ecological and economic subsystems, after which coupling and coordination measures are used to assess their relative coordination and identify whether the development of one subsystem lags behind the other [13,67,68].

Empirical studies have applied this approach at different spatial scales, ranging from national and provincial assessments to river basin and county-level analyses [13,15,67]. At the county level, studies have shown that heterogeneity can occur even within the same agricultural region [67]. For instance, Zhang et al. [67] examined 16 major grain-producing counties in Jilin Province and found steady improvements in agricultural eco-economic coupling coordination alongside pronounced spatial heterogeneity. Similarly, Yao et al. [15] examined six counties in the Ebinur Lake Basin and found that strong coupling between the agricultural ecological and economic systems did not necessarily correspond to a high level of coordination. Recent county-level evidence has documented improvement and pronounced within-region heterogeneity. For example, Zhan et al. [68] identified regional disparities and structural barriers to coordinated agricultural and ecological development across China.

Studies of agricultural eco-economic systems have covered multiple regions, each with distinct ecological constraints and socio-economic characteristics. In karst ecologically vulnerable regions, studies have examined the coordination between ecological restoration and agricultural economic development under conditions of ecological fragility and resource constraints [69]. In the Loess Plateau, agricultural eco-economic coupling has been investigated in hilly-gully areas [70], where long-term land use change, vegetation restoration, and terrace construction have altered ecological processes such as soil erosion [71]. At finer spatial scales, township-level studies have assessed the development potential of agricultural eco-economic systems and examined the spatial distribution of agricultural industries [72]. In the YRD, recent research has examined overall agricultural productivity [29] and the effects of land-use change on ecosystem services and ecological security [27], reflecting the region's environmental constraints like saline-alkali, freshwater, and coastal wetlands.

2.3. Research on Spatial Econometric Approaches in Agricultural Systems

The STIRPAT framework has been widely used to investigate how population, affluence, technology, and other socioeconomic factors affect agricultural environmental outcomes [73–75]. For example, Xiong et al. [74] applied an extended STIRPAT model to examine the drivers of agricultural carbon emissions in Jiangsu Province. More recent studies have integrated STIRPAT with spatial econometric models to account for spatial dependence in agricultural environmental impacts. Guo et al. [76] applied a spatial STIRPAT framework to investigate the environmental effects of agricultural production and their spillovers across Chinese cities, while Sunge and Espoir [77] combined STIRPAT with spatial econometric analysis to distinguish local effects from cross-regional environmental spillovers.

Spatial econometric approaches have extended agricultural research beyond the identification of local determinants to the analysis of spatial dependence and interregional spillover effects [65,78,79]. Agricultural environmental and economic outcomes may exhibit spatial dependence because pollution, production factors, infrastructure, and market-related effects can extend beyond administrative boundaries [65,79]. For example, Cheng et al. [65] employed a spatial Durbin model across 30 Chinese provinces and identified significant spatial dependence in agricultural green development and spillover effects associated with regional development factors. Similarly, spatial econometric analyses of agricultural eco-efficiency have shown that regional performance may be associated with local conditions and spatial interactions among neighboring regions [79].

Compared with existing literature on agricultural eco-economic coupling coordination and spatial spillovers, two aspects warrant further investigation. Geographically, previous studies have examined coupling coordination at provincial and county levels in Chinese regions, including major grain-producing areas and ecologically vulnerable basins. However,

these findings may not fully reflect conditions in the YRD, where agricultural production, saline-alkali soils, freshwater constraints, and coastal wetlands interact. A county-level analysis covering 19 county-level administrative units across six prefecture-level cities provides more geographically detailed evidence on the spatial heterogeneity of agricultural eco-economic coordination and its relationships with neighboring areas.

Methodologically, cross-county spatial spillovers of agricultural eco-economic coupling are examined less often than local determinants, and coupling measurements are rarely integrated with spatial effect decomposition within a single framework. This approach provides evidence for understanding regional differences and informing geographically differentiated agricultural and ecological policies.

3. Theoretical Analysis

The agricultural eco-economic coupling coordination system is a complex open system. The agricultural economic and ecological subsystems do not evolve independently but form spatiotemporal interactions through factor flows, resource allocation, industrial linkages, and ecological interactions. The system exhibits spatial dependence and externality characteristics, providing the theoretical foundation for applying spatial econometric models. Based on regional coordinated development theory, spatial externality theory, and ecological-economic coordination theory, and taking the county-level development characteristics of the YRD into consideration, the effects of driving factors on agricultural eco-economic coupling coordination can be decomposed into local direct effects and cross-regional spatial spillover effects. These two mechanisms shape the evolutionary patterns of regional coordination.

Driving factors influence the balance between local agricultural economic outputs and ecological carrying capacity by reshaping regional industrial structures, factor input structures, and ecological loss patterns. Industrial restructuring may be associated with changes in coupling coordination through factor reallocation. The expansion of secondary and tertiary industries may compete for agricultural production factors, including land, water, and labor, while generating ecological pressures through industrial pollution and land-use expansion. This disrupts the balance between agricultural production and ecological conservation, potentially generating an ecological crowding-out effect. Traditional agricultural modernization, which relies on chemical inputs and mechanized expansion, can improve agricultural output efficiency in the short term. However, it may lead to ecological problems such as soil salinization, agricultural non-point source pollution, and excessive consumption of water and land resources in the long run. This results in an imbalanced development pattern characterized by "economic gains accompanied by ecological losses" and constrains improvements in system coupling coordination. In contrast, large-scale agricultural operations may improve resource use efficiency and help with the adoption of green technologies through more standardized production practices. These improvements can enhance agricultural efficiency and reduce environmental pressures, supporting the coordinated development of local agricultural eco-economic systems. Urbanization may also contribute to agricultural development and ecological governance by improving infrastructure and public services and attracting production factors, promoting local eco-economic coordination.

In terms of spatial spillover mechanisms, counties in the YRD are geographically adjacent, connected by river systems, and linked through agricultural production and related economic activities. Cross-county factor flows, ecological governance spillovers, industrial model diffusion, and resource competition ensure that development activities within an individual county extend beyond administrative boundaries and indirectly influence the coupling coordination level of neighboring counties. Agricultural scale management,

urbanization, and regional transportation infrastructure exhibit positive spatial spillover mechanisms. Advanced agricultural technologies, large-scale operation models, urban-rural infrastructure, and transportation networks achieve cross-regional sharing through regional cooperation, industrial linkages, technological diffusion, and factor mobility. Cross-county labor migration further aids the transfer of production skills, management practices, and labor endowments, while regional market integration, through unified markets for agricultural products and factors, allows local shocks to affect neighboring regions. These processes encourage neighboring counties to optimize agricultural development patterns, improve ecological governance capacity, and enhance factor allocation efficiency, contributing to a coordinated regional development pattern.

Economic development levels exhibit differentiated spatial interaction characteristics. Counties with higher economic development levels are more likely to generate factor agglomeration and siphon effects, attracting high-quality labor, capital, and industrial resources from surrounding counties. Such processes may constrain the coordinated development of agricultural, ecological, and economic systems in neighboring regions, creating negative spatial spillover pressures. Negative ecological impacts associated with extensive agricultural development patterns and disorderly industrial expansion also demonstrate spatial transmissibility. Environmental problems such as soil and water pollution and ecological degradation can spread to neighboring regions through river systems, atmospheric circulation, and land corridors, generating negative ecological spillover effects across counties.

The coupled coordination development of agricultural eco-economic systems across counties in the YRD involves local endogenous effects and cross-regional spatial interactions. Different driving factors show heterogeneity in their effect directions, transmission pathways, and spillover characteristics. Traditional panel models cannot capture spatial dependence among regions and may introduce model specification bias. By contrast, the spatial Durbin model accounts for the spatial lag term of the dependent variable and the spatial interaction terms of explanatory variables, enabling it to identify local direct effects, cross-regional spillover effects, and overall effects. This approach is consistent with the theoretical mechanisms discussed above and provides a theoretical foundation for the following empirical testing and interpretation of results.

Based on the mechanisms discussed above, the following hypotheses are proposed.

H1. *Industrial structure advancement (reflected in the expansion of secondary and tertiary industries) is negatively associated with local coupling coordination due to potential competition for agricultural resources and ecological space, with limited spillover effects on neighboring counties.*

H2. *Traditional chemical- and machinery-intensive agricultural modernization is negatively associated with coupling coordination both locally and in neighboring counties.*

H3. *Agricultural scale operations are positively associated with local and neighboring coupling coordination through technology diffusion and demonstration.*

H4. *Urbanization is positively associated with local and especially neighboring coupling coordination, with an indirect effect larger than the direct effect.*

H5. *Regional economic development has an ambiguous local effect but a negative indirect effect through factor agglomeration and siphoning effects.*

H6. *The effect of regional transportation infrastructure is directionally ambiguous (connectivity gains versus corridor-related land and ecological costs).*

H7. *Fiscal support for agriculture has a weak or statistically insignificant effect in the short term because of homogeneous investment and long ecological-governance lags.*

4. Research Design

4.1. Area of Study

The Yellow River Delta (YRD) is an ecological functional zone of the Yellow River Basin and a demonstration area for high-efficiency ecological agriculture. The region is subject to a warm temperate continental monsoon climate, with synchronous precipitation and temperature variations and distinct seasonal changes. Rainfall is concentrated in summer. The mainstream of the Yellow River flows into the sea within this region, where river networks and tidal channels are extensively developed. Shaped by river, sea, and land interactions, the physical environment is dominated by alluvial plains and includes diverse ecosystems such as estuarine wetlands, coastal tidal flats, and saline-alkali wastelands. Based on its saline-alkali land resources, this region has developed high-efficiency ecological agriculture and has become one of the major production areas in China for salt-tolerant grain and cotton crops, specialty livestock and poultry products, and coastal aquatic products.

To ensure representativeness and statistical consistency, this study defined the research scope according to the boundaries specified by the National Development and Reform Commission [80]. The study area includes all counties and county-level administrative units in Dongying and Binzhou cities, as well as Hanting District, Shouguang City, and Changyi City in Weifang, Laoling City and Qingyun County in Dezhou, Gaoqing County in Zibo, and Laizhou City in Yantai, covering 19 counties (cities and districts) across six prefecture-level cities, with a total area of approximately 26,500 km^2.

4.2. Research Methods

4.2.1. CRITIC Weighting Method

The CRITIC weighting method accounts for the effects of indicator correlations and variability in the weighting process. This study applied the CRITIC method to determine the weights of the selected indicators. Raw indicators were first normalized to a [0, 1] range to eliminate dimensional differences, with positive and negative indicators treated separately. The normalization formulas, indicator definitions, units, and directional assignments are provided in Appendix A. Before applying the CRITIC method, all indicators were normalized to eliminate dimensional effects and ensure comparability. To ensure comparability across 2015–2024, both the extrema used for normalization and the CRITIC weights were calculated on the pooled county–year panel (19 counties × 10 years) rather than year by year, and the same fixed transformation and weights were then applied to each year. This pooled treatment preserves the temporal dimension and avoids artificial trends induced by year-specific rescaling, following the composite-index framework of Greco et al. [81].

For positive indicators:

$$x'_{ij} = \frac{x_{ij} - min\left(x_j\right)}{max\left(x_j\right) - min\left(x_j\right)}$$

For negative indicators:

$$x'_{ij} = \frac{max\left(x_j\right) - x_{ij}}{max\left(x_j\right) - min\left(x_j\right)}$$

The specific formulas are as follows:

$$S_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x'_{ij} - \overline{x}'_j\right)^2}{m-1}} \quad (1)$$

$$R_{ij} = cov\left(x'_{ii}, \quad x'_j\right) / \left(S_i, \quad S_j\right) \quad (2)$$

$$E_j = S_j \times \sum_{i=1}^{n}\left(1 - R_{ij}\right) \quad (3)$$

$$W_i = E_j / \sum_{j=1}^{n} E_j \quad (4)$$

where m represents the number of indicators; S_j represents the standard deviation of the ith indicator; R_{ij} represents the correlation coefficient between the ith and jth indicators; E_j represents the information content of the indicator; and W_i represents the weight of the ith indicator.

4.2.2. Coupling Coordination Degree Model

To assess the coupling coordination degree between the agricultural ecological system and the agricultural economic system, this study introduced the coupling coordination degree model. Consider the n-dimensional system model previously applied by Chinese scholars to determine the coupling degree C:

$$C = \left[\frac{\prod_{i=1}^{n} U_i}{\left(\frac{1}{n}\sum_{i=1}^{n} U_i\right)^n}\right]^{1/n} \quad (5)$$

where n represents the number of subsystems, and U_i represents the value of each subsystem. With U_i ranging from 0 to 1, the coupling degree also ranges from 0 to 1. A higher value of C indicates a smaller degree of disparity among subsystems and stronger coupling between them, while a lower value indicates weaker coupling among subsystems. When n is equal to 2:

$$C = \frac{2\sqrt{(u_1 \times u_2)}}{u_1 + u_2} \quad (6)$$

where U_1 represents the agricultural ecological system and U_2 represents the agricultural economic system. The two subsystems were standardized before calculation. The coupling degree C ranges from 0 to 1. A value closer to 0 indicates weaker coupling between the two subsystems, while a value closer to 1 indicates stronger coupling.

The coupling degree model only reflects the intensity of interaction between subsystems and cannot adequately represent their coordination level. For example, when both the agricultural ecological and economic systems remain at low development levels, the coupling degree may still approach 1. To objectively evaluate the coordination between the two subsystems, this study introduced the coupling coordination degree model based on the coupling degree model:

$$T = aU_1 + bU_2 \quad (7)$$

$$D = \sqrt{C \times T} \quad (8)$$

where T is the comprehensive evaluation index, and D refers to the coupling coordination degree. a and b represent the contribution coefficients of the agricultural ecological system and agricultural economic system to the overall development level, respectively, with $a + b = 1$. Following previous studies [82], the two subsystems were assumed to have equal importance and were assigned a value of 0.5. The coupling coordination degree D ranges from 0 to 1. A value closer to 0 indicates a lower level of coupling coordination, while a value closer to 1 indicates a higher level of coupling coordination.

To better reflect the coupling coordination level of the agricultural ecological and economic systems, this study adopted the classification criteria proposed in previous studies [81] to categorize coupling coordination degrees, as shown in Table 1. These boundaries are conventional and used only for descriptive categorization. All quantitative analyses and conclusions are based on continuous D values and their changes, which are unaffected by the threshold. Marginal adjustments to the boundaries would not change the upward trend or spatial pattern.

Table 1. Classification criteria of coupling coordination degree.

Degree	Coordination Level	Degree	Coordination Level
$0 \leq D < 0.1$	Extreme disorder	$0.5 \leq D < 0.6$	Basic coordination
$0.1 \leq D < 0.2$	Severe disorder	$0.6 \leq D < 0.7$	Primary coordination
$0.2 \leq D < 0.3$	Moderate disorder	$0.7 \leq D < 0.8$	Intermediate coordination
$0.3 \leq D < 0.4$	Mild disorder	$0.8 \leq D < 0.9$	Good coordination
$0.4 \leq D < 0.5$	On the verge of disorder	$0.9 \leq D \leq 1$	Excellent coordination

4.2.3. Spatial Econometric Model

(1) Construction of spatial weight matrix

The spatial weight matrix represents a core component of spatial econometric models and is used to characterize the structure and intensity of spatial associations among regions. This study focused on 19 counties in the Yellow River Delta, including all counties in Dongying and Binzhou cities and related counties in surrounding areas as the research units, and employed an inverse distance spatial weight matrix. The underlying principle is that the closer two county-level areas are geographically, the greater their spatial association. Conversely, the greater the distance between them, the weaker the association.

Assuming that there are N regional units and the geographic distance between the ith and the jth counties is d_{ij}, the elements of the spatial weight matrix W are defined as follows:

$$w_{ij} = 1/d_{ij} \tag{9}$$

where $i \neq j$, $w_{ii} = 0$. Here, d_{ij} is calculated based on the longitude and latitude coordinates of the administrative locations of the two counties using the Haversine formula to measure spherical distance. To eliminate dimensional effects and improve the stability of model estimation, the spatial weight matrix was standardized by ensuring that the sum of each row was equal to 1. This row-standardized matrix allows the spatial lag terms to be interpreted as weighted averages of neighboring regional variables. The final spatial weight matrix W_{sp} is a 19 × 19 row-standardized matrix.

The selection of a geographic inverse distance spatial weight matrix rather than an economic distance weight matrix or an adjacency matrix is based on the following considerations. First, geographic distance is strictly exogenous to the economic system and is determined solely by locational conditions, which effectively avoids the endogeneity problem caused by reciprocal causality among economic variables in economic weight matrices. Second, the inverse distance function can capture continuous spatial associations among all regions and avoid the limitation of binary adjacency matrices, which may lose spatial spillover information from distant regions due to artificially defined distance thresholds. Third, counties in the YRD are interconnected through river systems and transportation networks, and the agricultural eco-economic system shows clear distance decay characteristics in its spatial interactions. The geographic inverse distance matrix is therefore suitable for representing these spatial dependence relationships. Given that the 19 county-level

administrative units form a compact and geographically contiguous study area, inverse distance weights place greater emphasis on nearby counties, making the matrix broadly comparable to a Queen contiguity matrix while retaining information on distance-decaying links between non-adjacent counties. This study acknowledges, however, that the results may be sensitive to the assumed distance-decay function (e.g., $1/d$ versus $1/d^2$). Testing alternative decay functions and spatial weight matrices, together with conducting spatial diagnostics on the residuals, are therefore identified as directions for further research [83].

(2) Specification of Spatial Econometric Models

Spatial panel data models are generally classified into three categories according to different sources of spatial dependence: the spatial autoregressive (SAR) model, the spatial error model (SEM), and the spatial Durbin model (SDM).

(a) Spatial Autoregressive Model

The SAR model assumes that spatial dependence originates from the spatial spillover effect of the dependent variable. Specifically, the coupling coordination degree of the agricultural eco-economic system in one region is influenced by both local driving factors and the coupling coordination degree of neighboring regions. The model is specified as follows:

$$D_{it} = \rho \sum_j w_{ij} D_{jt} + \beta' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (10)$$

where D_{it} represents the coupling coordination degree of the agricultural eco-economic system in the ith county in year t, ρ represents the spatial autoregressive coefficient, which measures the spatial spillover effect of coupling coordination degree from neighboring regions to the local region, w_{ij} represents the elements of the spatial weight matrix, X_{it} represents the vector of explanatory variables, β' represents the corresponding coefficient vector, μ_i represents individual fixed effects, λ_t represents time fixed effects, and ε_{it} represents the random disturbance term.

(b) Spatial Error Model

The SEM assumes that spatial dependence originates from the spatial correlation of error terms. Specifically, omitted variables or unobservable factors (e.g., regional ecological policies and climate variations) may exhibit spatial associations among regions. The model is specified as follows:

$$D_{it} = \beta' X_{it} + \mu_i + \gamma_t + \phi_{it} \quad \phi_{it} = \gamma \sum_j w_{ij} \phi_{jt} + \varepsilon_{it} \quad (11)$$

where γ represents the spatial error autocorrelation coefficient, and ϕ_{it} represents the spatially correlated error term.

(c) Spatial Durbin Model

The SDM builds on the SAR model by including spatially lagged terms of both the dependent variable and explanatory variables. It simultaneously captures the spatial spillover effects of the dependent variable and the driving factors, making it a more general spatial panel model. For the agricultural eco-economic system in the YRD, the cross-regional spillover effects of driving factors may be more important than the direct transmission effects of explanatory variables. Therefore, the SDM provides greater applicability for this study. The model is specified as follows:

$$D_{it} = \rho \sum_j w_{ij} D_{jt} + \beta' X_{it} + \theta' \sum_j w_{ij} X_{jt} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

where θ' represents the coefficient vector of the spatial lag terms of explanatory variables, which measures the influence of driving factors in neighboring regions on the coupling

coordination degree of the local agricultural eco-economic system. The definitions of other variables remain the same as above. The SDM has two important nesting properties: when $\theta' = 0$, the SDM reduces to the SAR model; when $\theta' + \rho\beta' = 0$, the SDM reduces to the SEM.

(3) Model Selection and Testing

The selection of spatial panel models requires a strict testing procedure. This study sequentially conducted the following tests:

First, the Hausman test evaluated the applicability of fixed versus random effects models. The null hypothesis assumes that the coefficient estimates from both models do not exhibit systematic differences. If the null hypothesis is rejected, the fixed effects model is selected. Considering the significant heterogeneity among counties in the YRD in terms of resource endowments, industrial foundations, and other characteristics, this study adopted the individual fixed effects spatial Durbin model (SDM-FE). Equation (12) is the general SDM form containing both individual (μ_i) and time (λ_t) effects. Given the short panel (N = 19, T = 10), the baseline specification controls for individual fixed effects only. The SDM already estimates 14 local and spatially lagged coefficients in addition to the spatial autoregressive coefficient (ρ), and including year dummies would consume scarce degrees of freedom. Furthermore, time fixed effects are collinear with the spatially lagged terms W × X and W × D, whose temporal variation identifies the indirect effects central to this study. As the counties form a geographically compact region and are exposed to shared annual shocks, individual fixed effects are used in the baseline model to account for time-invariant county-level heterogeneity, while the potential influence of common time-varying shocks is acknowledged as a limitation.

Second, likelihood ratio (LR) tests evaluated whether the SDM could be reduced to the SAR or SEM. The first test examined the relationship between the SDM and SAR models, with the null hypothesis θ = 0. Rejection of the null hypothesis indicates that the spatial lag terms of explanatory variables cannot be ignored and that the SDM cannot be reduced to the SAR model. The second test examined the relationship between the SDM and SEM models, with the null hypothesis $\theta' + \rho\beta' = 0$. Rejection of the null hypothesis indicates that the SDM cannot be reduced to the SEM model. If both tests reject the null hypotheses, the SDM is selected.

Third, the Wald test examined the overall significance of spatial interaction terms, including the spatial lag terms of the dependent variable and explanatory variables. If the Wald test rejects the null hypothesis, the spatial interaction terms are jointly significant, indicating that the model specification incorporating spatial effects is appropriate.

(4) Decomposition of Spatial Effects

In the SDM, regression coefficients ß cannot be directly interpreted as marginal effects due to the existence of spatial feedback effects. LeSage and Pace [84] suggested that spatial effects should be decomposed into direct and indirect effects using the partial differentiation method. Equation (12) can be rewritten in matrix form as follows:

$$Y_t = (I - \rho W)^{-1}(\beta' X_t + \theta' W X_t + \mu + \lambda_t + \varepsilon_t) \quad (13)$$

where Y_t represents the $N \times 1$ vector of the dependent variable, X_t represents the $N \times K$ matrix of explanatory variables, and I represents the N identity matrix. For the kth explanatory variable, the partial derivative matrix of the dependent variable with respect to this variable is expressed as follows:

$$\frac{\partial Y}{\partial X_k} = (I - \rho W)^{-1}(\beta_k I + \theta_k W) \quad (14)$$

The main value of the diagonal elements in this matrix represents the direct effect, which measures the average impact of changes in local driving factors on the coupling

coordination degree of the local agricultural eco-economic system. This effect also includes spatial feedback effects through the pathway from the local region to neighboring regions and back to the local region. The mean value of off-diagonal elements represents the indirect effect (spatial spillover effect), which measures the average impact of changes in driving factors in adjacent regions on the coupling coordination degree of the local agricultural eco-economic system. The sum of the direct and indirect effects represents the total effect.

For the agricultural eco-economic system in the YRD, identifying indirect effects is particularly important because the systemic characteristics of agricultural ecosystems and the externalities of transportation networks determine that cross-regional spillovers represent a crucial mechanism affecting coupling coordination. This study adopted the simulation approach proposed by LeSage and Pace [84] to estimate the standard errors and significance levels of the effects.

4.3. Indicator Selection

4.3.1. Evaluation Indicators of the Agricultural Eco-Economic System

Guided by the principles of systematicity, scientific validity, regional applicability, and data availability, this study referred to existing literature and constructed an evaluation indicator system for the agricultural eco-economic system from four dimensions: ecological pressure, ecological conditions, industrial development, and economic benefits. The CRITIC weighting method was used to determine the weights of the selected indicators. The detailed indicator system is presented in Table 2.

Table 2. Evaluation indicator system for the agricultural eco-economic system.

System Layer	First Level Indicators	Second-Level Indicators	Indicator Type	Weight	Indicator Description
Agricultural eco-economic system	Ecological pressure	Intensity of agricultural plastic film use (t/hm^2)	–	0.058	Reflects the risk of soil pollution caused by agricultural plastic film use and indicates the degree of pressure exerted by agricultural production inputs on the soil environment.
		Intensity of fertilizer application (t/hm^2)	–	0.061	Reflects the risk of soil nutrient imbalance and water eutrophication caused by fertilizer application, indicating the pressure of agricultural production on soil and water environments.
		Intensity of pesticide application (t/hm^2)	–	0.068	Reflects the risks of soil pollution and biodiversity degradation caused by pesticide application, indicating the negative impacts of agricultural production on ecological stability.

Table 2. *Cont.*

System Layer	First Level Indicators	Second-Level Indicators	Indicator Type	Weight	Indicator Description
Agricultural eco-economic system	Ecological pressure	Proportion of total agricultural water consumption (%)	−	0.090	Reflects the occupation of regional water resources by agricultural production and indicates the pressure of agricultural activities on water resource systems.
		Livestock breeding density (heads/hm^2)	−	0.075	Reflects the environmental pressure caused by intensive livestock production and indicates the impact of livestock activities on the ecological environment.
		Agricultural machinery diesel consumption (t/kW)	−	0.088	Reflects fossil energy consumption and carbon emissions associated with agricultural mechanization and indicates the environmental pressure from agricultural production.
		Proportion of aquaculture area (%)	−	0.079	Reflects the pressure of aquaculture activities on water ecological space and indicates their impacts on aquatic ecosystems.
	Ecological condition	Forest coverage rate (%)	+	0.094	Reflects the capacity of forest resources to maintain soil and water conservation and climate regulation functions, indicating ecological support capacity for agricultural production.
		Proportion of cultivated land area (%)	−	0.078	Reflects the intensity of land development and land use structure, indicating the degree of agricultural dependence on land resources.
		Proportion of wetland area (%)	+	0.089	Reflects the functions of wetlands in water purification and water resource regulation, indicating ecological support capacity.
		Proportion of water area (%)	+	0.079	Reflects regional water resource endowment and aquatic ecosystem regulation capacity, indicating support capacity of water ecosystems for agricultural production.

Table 2. *Cont.*

System Layer	First Level Indicators	Second-Level Indicators	Indicator Type	Weight	Indicator Description
Agricultural eco-economic system	Ecological condition	Proportion of effective irrigation area (%)	+	0.072	Reflects the irrigation guarantee capacity and the proportion of cultivated land with reliable water supply. A higher share indicates stronger agricultural production conditions and drought resilience, and is therefore a positive indicator in the ecological subsystem.
		Proportion of drought-resistant cultivated land (%)	+	0.070	Reflects drought resistance capacity of cultivated land and indicates the stability of agricultural resource production.
Agricultural economic system	Industrial development	Grain output per capita (t/person)	+	0.145	Reflects agricultural production capacity and indicates regional grain production efficiency.
		Aquatic product output per capita (t/person)	+	0.132	Reflects aquatic production efficiency and indicates regional aquatic product production capacity.
		Meat output per capita (t/person)	+	0.130	Reflects livestock production efficiency and indicates regional livestock production capacity.
	Economic benefits	Rural residents' disposable income per capita (yuan/person)	+	0.120	Reflects rural living standards and indicates the quality and benefits of agricultural economic development.
		Agricultural land output rate (yuan/hm^2)	+	0.093	Reflects the economic transformation efficiency of agricultural land units and indicates the economic benefits generated from land resources.
		Agricultural labor productivity (10,000 yuan/person)	+	0.091	Reflects economic output capacity per agricultural worker and indicates the level of agricultural modernization and production efficiency.
		Grain yield per unit area (t/hm^2)	+	0.148	Reflects grain production capacity per unit cultivated land area and indicates grain production efficiency and land resource utilization efficiency.

Table 2. *Cont.*

System Layer	First Level Indicators	Second-Level Indicators	Indicator Type	Weight	Indicator Description
Agricultural economic system	Economic benefits	Aquatic product yield per unit water area (t/hm^2)	+	0.140	Reflects aquatic product output capacity per unit water area and indicates aquatic production efficiency and resource utilization efficiency.

As an ecologically fragile coastal alluvial plain, the YRD is characterized by extensive saline-alkali land, coastal wetlands, and concentrated agricultural non-point source pollution, while serving as a base for modern and efficient agriculture. Accordingly, the ecological subsystem captures both the environmental pressures associated with intensive agricultural production, including agricultural film, fertilizer, pesticides, irrigation water, livestock, agricultural machinery diesel, and aquaculture, and the region's ecological conditions, reflected in forest resources, wetlands, water resources, cultivated land, effective irrigation, and drought-resistant land. The economic subsystem captures modern, scale, and characteristic agriculture and farmers' income, as reflected in per capita grain, aquatic, and meat output, disposable income, land output rate, labor productivity, and yields per unit area. This indicator structure reflects the dual goals of protecting the fragile coastal ecosystem and raising agricultural economic efficiency, which are central to high-quality development in the YRD.

4.3.2. Selection of Driving Factors

Based on existing studies, seven indicators were chosen from two dimensions (socioeconomic development and agricultural development support) to examine the driving factors of coupling coordination in the agricultural eco-economic system. These indicators are regional economic development level, industrial structure level, fiscal support for agriculture, urbanization development level, agricultural modernization level, agricultural scale operation level, and regional transportation infrastructure, as shown in Table 3.

Table 3. Selection of Driving Factor Indicators.

Dimension	Variable Symbol	Variable	Indicator Description
Socioeconomic development	*redl*	Regional economic development level	Regional GDP per capita (yuan/person)
	isl	Industrial structure level	Proportion of secondary and tertiary industry output in regional GDP (%)
	fsa	Fiscal support for agriculture	Share of local fiscal expenditure on agriculture, forestry, and water affairs in general public budget (%)
	udl	Urbanization development level	Proportion of urban permanent residents in total population (%)
Agricultural development support	*aml*	Agricultural modernization level	Total agricultural machinery power per unit sown area of major grain crops (kW/hm^2)
	asol	Agricultural scale operation level	Total sown area of crops per agricultural labor force (hm^2/person)
	rti	Regional transportation infrastructure	Year-end highway mileage per unit administrative area (km/km^2)

4.4. Data Source

County-level panel data from Dongying, Binzhou, Weifang, Dezhou, Zibo, and Yantai cities in Shandong Province were used in this study. The original statistical data were obtained mainly from the statistical yearbooks of national economic and social development, local statistical yearbooks, agricultural and rural statistical materials, fiscal statistical reports, and water resources bulletins of relevant prefecture-level cities and counties from 2015 to 2024. Land-use indicators were derived from the China Land Use/Cover Dataset (CNLUCC) of the Resource and Environmental Science and Data Center, Chinese Academy of Sciences (30 m spatial resolution, produced by human–computer interactive visual interpretation of Landsat imagery with field verification; reported overall accuracy above 90% for first-level classes). Rasters for each year were clipped to the 19 county boundaries, reclassified into cropland, forest, wetland, water, and other classes, and used to compute class shares per county, with cross-year consistency checks. Coastal wetlands, mudflats, saline-alkali land, and water have similar spectral signatures and may be mutually misclassified, introducing limited classification error. This error is stable across years, and the affected indicators carry only part of the CRITIC weight, so the main conclusions are unaffected.

Composite indicators, including fiscal support for agriculture, industrial structure level, agricultural modernization, and agricultural scale operation, as well as intensity indicators such as agricultural plastic film use, fertilizer application, pesticide application, livestock breeding density, and output efficiencies, were calculated from the original statistical data. Missing observations were sparse and confined to a few county–year cells. Interior gaps in continuous series were filled by linear interpolation within each county between adjacent observed years. For a small number of slow-moving, stock-like indicators, the nearest observed value was carried forward or back-filled. No model-based or trend-based extrapolation or forecasting was used. The resulting panel is balanced, and the imputed cells are few and lie within observed series, so they are unlikely to alter the main conclusions. After these procedures, all variables in the final estimation sample are complete with no missing values, so the estimations are based on a fully balanced panel and no observations need to be dropped. Observations for the latest year (2024) are official preliminary statistics published in the latest yearbooks and bulletins, not model estimates or forecasts. The small number of unavailable cells, including any in 2024, was handled by the procedures above rather than by forecasting. Finally, a comprehensive agricultural and socioeconomic dataset was established at the county level.

5. Empirical Analysis

5.1. Coupling Coordination Analysis

5.1.1. Temporal Characteristics

Figure 1 illustrates the temporal evolution of the coupling degree (C), comprehensive development index (T), and coupling coordination degree (D) of the agricultural eco-economic system in the study area from 2015 to 2024.

The results show that the coupling degree (C) remained between 0.986 and 0.993, indicating strong interactions between the agricultural ecological and economic subsystems. Factor flows and coordinated feedback mechanisms provided a stable foundation for these interactions. However, the annual improvement in the coupling degree was limited. In contrast, the comprehensive development index (T) and coupling coordination degree (D) exhibited a continuous upward trend. T increased from 0.320 in 2015 to 0.582 in 2024, while D increased from 0.561 in 2015 to 0.760 in 2024. The increasing trends of these indicators demonstrate that the overall development level of the agricultural eco-economic system in the study area has improved, driving enhanced coupling coordination. The parallel

improvement of the two subsystems is further supported by the relationship between T and C. Specifically, T is calculated as the equally weighted average of the ecological and economic subsystem indices (U1 and U2), while C remained high and stable as T increased. This pattern is consistent with concurrent improvements in both subsystems rather than a one-sided increase in one subsystem relative to the other. The individual trajectories of U1 and U2 provide direct evidence of their respective contributions to the observed improvement in coupling coordination.

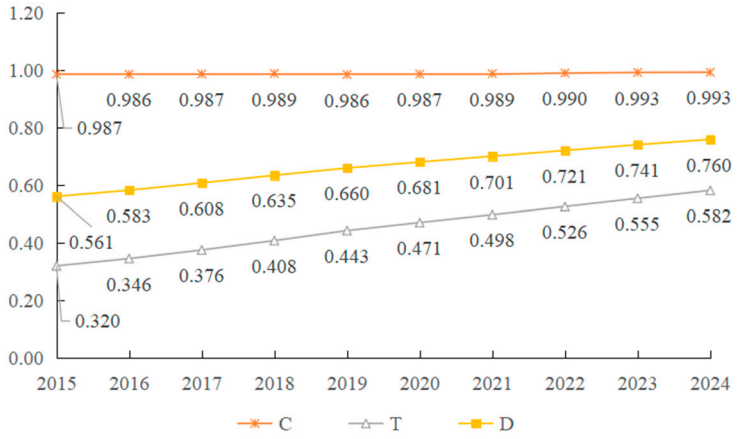


Figure 1. Temporal characteristics of coupling coordination in the agricultural eco-economic system.

This trend is attributable to regional ecological protection measures, agricultural non-point source pollution control, and wetland ecological restoration during the study period, which improved the carrying capacity of agricultural ecosystems. Simultaneously, agricultural modernization and large-scale operations advanced alongside rising rural incomes and improved agricultural economic development. The simultaneous improvement of both subsystems enhanced coupling coordination.

From 2015 to 2018, T and D grew slowly, and coupling coordination gradually improved. After 2018, growth rates increased, indicating an acceleration in improvement. Ecological protection policies continued to strengthen, and agricultural green transformation progressed. On the other hand, the modern agricultural industrial system gradually improved, and agricultural production efficiency continued to increase. These combined advantages accelerated improvements in the overall development level of the system.

The coupling degree (C) showed no significant increase, suggesting that the main constraint on improving coupling coordination in this region no longer lies in the interaction intensity between subsystems, but rather in the comprehensive development levels of the two subsystems (T). Therefore, future improvements in coupling coordination should focus on addressing ecological weaknesses, strengthening agricultural economic development, and further enhancing the overall development capacity of the system.

5.1.2. Spatial Characteristics

Regarding temporal evolution, the coupling coordination levels of all counties in the study area transitioned from lower to higher coordination levels. All counties achieved positive growth in coupling coordination degrees, with the improvement ranging from 0.166 to 0.225, indicating significant improvements in the coordinated development of the agricultural eco-economic system. The county-level D values, coordination grades, and changes for 2015 and 2024 are reported in detail in Table 4.

Table 4. Spatial characteristics of coupling coordination in the agricultural eco-economic system.

County	2015	Coordination Level	2024	Coordination Level	Change in Value
Dongying	0.487	Near disorder	0.703	Moderate coordination	0.216
Hekou	0.568	Basic coordination	0.773	Moderate coordination	0.206
Kenli	0.605	Primary coordination	0.827	Good coordination	0.222
Lijin	0.609	Primary coordination	0.814	Good coordination	0.205
Guangrao	0.543	Basic coordination	0.739	Moderate coordination	0.196
Bincheng	0.529	Basic coordination	0.709	Moderate coordination	0.180
Zhanhua	0.625	Primary coordination	0.813	Good coordination	0.188
Huimin	0.525	Basic coordination	0.730	Moderate coordination	0.205
Yangxin	0.549	Basic coordination	0.742	Moderate coordination	0.193
Wudi	0.559	Basic coordination	0.784	Moderate coordination	0.224
Boxing	0.544	Basic coordination	0.726	Moderate coordination	0.182
Zouping	0.569	Basic coordination	0.741	Moderate coordination	0.172
Hanting	0.570	Basic coordination	0.761	Moderate coordination	0.191
Shouguang	0.554	Basic coordination	0.778	Moderate coordination	0.225
Changyi	0.588	Basic coordination	0.802	Good coordination	0.214
Lelin	0.528	Basic coordination	0.730	Moderate coordination	0.202
Qingyun	0.489	Near disorder	0.686	Primary coordination	0.197
Gaoqing	0.563	Basic coordination	0.751	Moderate coordination	0.188
Laizhou	0.658	Primary coordination	0.823	Good coordination	0.166

In 2015, the coupling coordination levels were mainly concentrated in three categories: on the verge of disorder, basic coordination, and primary coordination. Specifically, Dongying District and Qingyun County were classified as being on the verge of disorder, with coupling coordination degrees of 0.487 and 0.489, respectively. Thirteen counties, namely Hekou District, Guangrao County, Bincheng District, Huimin County, Yangxin County, Wudi County, Boxing County, Zouping City, Hanting District, Shouguang City, Laoling City, Changyi City, and Gaoqing County, were classified as having basic coordination. Kenli District, Lijin County, Zhanhua County, and Laizhou City reached the primary coordination level, indicating that ecological conservation and agricultural economic development had begun to demonstrate positive interactions. No counties reached the levels of intermediate,

good, or excellent coordination, suggesting considerable potential for further improvement in overall coupling coordination.

By 2024, the coupling coordination levels across the region had improved, and counties classified as being on the verge of disorder had disappeared. Qingyun County improved from the verge of disorder to primary coordination. Thirteen counties, namely Hekou District, Guangrao County, Bincheng District, Huimin County, Yangxin County, Wudi County, Boxing County, Zouping City, Hanting District, Shouguang City, Laoling City, Gaoqing County, and Dongying District, advanced to intermediate coordination, indicating an effective balance between ecological conservation and agricultural economic development. Kenli District, Lijin County, Zhanhua County, Changyi City, and Laizhou City improved to good coordination, suggesting that a favorable interaction pattern among the systems had formed. However, no counties entered the excellent coordination category, indicating that highly balanced development still requires further improvement.

In terms of growth magnitude, Shouguang City (0.225), Wudi County (0.224), and Kenli District (0.222) achieved the largest improvements, exhibiting the strongest enhancement in system coordination. In contrast, Laizhou City (0.166) showed the smallest improvement, indicating that further efforts are needed to activate its potential for coordinated system development.

In terms of spatial patterns, in 2015, regions with high coupling coordination levels were predominantly concentrated in Laizhou City, Zhanhua County, Kenli District, and Lijin County. These areas possessed strong agricultural-industrial foundations and favorable ecological conditions, laying the groundwork for coordinated development. In contrast, low-coordination areas were concentrated in Dongying District and Qingyun County, where traditional development patterns remained dominant and constraints from industrial structure and development pathways limited the coordination between ecological and economic systems.

By 2024, the number of high-coordination units expanded. Kenli District, Lijin County, Zhanhua County, Changyi City, and Laizhou City jointly formed a high-coordination cluster, while intermediate coordination became widespread across most counties in the study area. Overall, the eastern coastal counties exhibited higher coupling coordination levels than the western inland counties. Coastal counties benefited from the advantages of marine resources and, driven by wetland ecological restoration, modern agricultural industry cultivation, and rural revitalization policies, achieved dual improvements in ecological protection and agricultural economic development, accelerating the enhancement of coupling coordination levels. Although western counties experienced improvements in coordination levels, many remained at the intermediate coordination stage. A high proportion of traditional grain and oil crop cultivation and insufficient development of specialized agricultural industries remained important factors constraining further improvements in coordination levels.

5.2. Analysis of Driving Factors

5.2.1. Descriptive Statistics

This study selected balanced panel data from 19 counties in the YRD from 2015 to 2024, comprising 190 observations. The dependent variable is the coupling coordination degree (D) of the agricultural eco-economic system in the YRD. The explanatory variables are the logarithmic transformations of seven driving factors: regional economic development level ($lnredl$), industrial structure level ($lnisl$), fiscal support for agriculture ($lnfsa$), urbanization development level ($lnudl$), agricultural modernization level ($lnaml$), agricultural scale operation level ($lnasol$), and regional transportation infrastructure ($lnrti$). Table 5 presents the descriptive statistics for each variable.

Table 5. Descriptive statistics of variables.

Variable	Observations	Mean	Median	Standard Deviation	Minimum	Maximum
D	190	0.6650	0.6608	0.0768	0.4874	0.8270
lnredl	190	11.2382	11.2072	0.4205	10.2834	12.1847
lnisl	190	4.4825	4.4903	0.0676	4.3014	4.5799
lnfsa	190	2.5846	2.6494	0.2740	1.5686	3.3755
lnudl	190	4.0049	4.0547	0.2543	3.3326	4.3927
lnaml	190	2.3999	2.4715	0.3236	1.4279	3.1454
lnasol	190	0.0189	0.0198	0.2156	−0.5447	0.4700
lnrti	190	0.4761	0.5625	0.3233	−0.4308	0.8796

Note: All explanatory variables are logarithmically transformed. D represents the coupling coordination degree of the agricultural eco-economic system, with values ranging from [0, 1].

As shown in Table 5, the mean coupling coordination degree of the agricultural eco-economic system in the YRD was 0.6650, with a standard deviation of 0.0768, a minimum of 0.4874, and a maximum of 0.8270. This indicates that the sample counties exhibited moderate to high levels of coordination, with considerable regional differences. Some counties reached good coordination (approaching 0.83), while others remained barely coordinated (below 0.5), reflecting uneven development. Among the explanatory variables, regional economic development level had the highest mean (11.2382), reflecting the effect of economic scale. The mean values for agricultural scale operations and regional transportation infrastructure were 0.0189 and 0.4761, respectively. Both variables contained negative values, indicating some counties remained underdeveloped in terms of land-scale management and transportation network construction. This is consistent with the characteristics of certain YRD counties, where extensive land distribution and insufficient transportation network density remain important constraints.

5.2.2. Multicollinearity Test

To ensure the reliability of regression estimation, the variance inflation factor (VIF) was applied to test the multicollinearity among explanatory variables. A VIF value greater than 10 indicates severe multicollinearity. Table 6 presents the test results.

Table 6. Multicollinearity test (VIF).

Variable	VIF	1/VIF	Variable	VIF	1/VIF
lnisl	3.42	0.2924	*lnrti*	1.91	0.5236
lnudl	2.79	0.3584	*lnasol*	1.59	0.6289
lnredl	2.55	0.3922	*lnaml*	1.22	0.8197
lnfsa	1.91	0.5236	MeanVIF	2.20	—

Note: Variables with excessively high VIF values have been removed. All variables have VIF values below 10, indicating no severe multicollinearity.

As shown in Table 6, the VIF values of the seven explanatory variables ranged from 1.22 to 3.42, with an average VIF value of 2.20, well below the threshold value of 10. This indicates that no severe multicollinearity exists in the model and that the regression results are reliable. Among the explanatory variables, the industrial structure level exhibited the highest VIF value (3.42), which is likely associated with the urbanization development level and regional economic development level. This value remained within an acceptable range.

These VIFs diagnose collinearity among the original explanatory variables and do not include the spatially lagged regressors (WX) introduced by the SDM. The stability of the spatially lagged coefficient estimates is supported by the robustness test, where the indirect

effects retain their signs, significance, and magnitudes after winsorization. While the low VIF values rule out conventional multicollinearity, the constructed nature of the dependent variable warrants an additional check for mechanical correlation arising from shared denominators. For example, agricultural labour productivity (in the economic subsystem of the coupling index) and the scale-operation driver (sown area per agricultural worker) share the agricultural labour force as a denominator. However, their numerators differ (output versus land area), so they measure distinct dimensions, and a shared denominator alone does not induce a spurious association. Moreover, agricultural labour productivity is only one CRITIC-weighted indicator within the composite index, so any shared-denominator influence is diluted in the aggregate index. A sensitivity analysis excluding individual indicators from the index is discussed as a future robustness check in Section 6.3.

5.2.3. Model Selection Test

Before determining the spatial econometric specification, LR tests were conducted to examine whether the SDM can be reduced to the SAR or SEM, and Wald tests were applied to verify the overall significance of spatial interaction terms. Table 7 presents the test results.

Table 7. Results of model selection tests.

Test Type	Null Hypothesis	Statistics	Degree of Freedom	*p* Value	Conclusion
LR test (SDM vs. SAR)	$\theta' = 0$, SDM can be reduced to SAR	LRchi2(7) = 20.35	7	0.0049	Reject the null hypothesis
LR test (SDM vs. SEM)	$\theta' + \rho\beta' = 0$, SDM can be reduced to SEM	LRchi2(7) = 63.65	7	0.0000	Reject the null hypothesis
Wald spatial test	Spatial interaction terms are jointly insignificant	chi2(8) = 408.03	8	0.0000	Reject the null hypothesis

Note: The LR tests are likelihood ratio tests. The Wald test examines the joint significance of all spatial interaction terms in the SDM.

As shown in Table 7, the LR test between SDM and SAR was significant at the 1% level ($p = 0.0049$), rejecting the null hypothesis that the SDM could be reduced to the SAR model. This indicates that the spatial lag terms of explanatory variables provide additional explanatory power and cannot be ignored. The LR test between SDM and SEM was also significant at the 1% level ($p = 0.0000$), rejecting the null hypothesis that the SDM could be reduced to the SEM. Both LR tests supported the selection of the SDM. In addition, the Wald spatial test was significant at the 1% level ($p = 0.0000$), indicating that the spatial interaction terms were jointly significant and that incorporating spatial effects into the model specification was necessary. This result is consistent with the characteristics of the agricultural eco-economic system in the YRD. The interconnected regional water systems, dense transportation networks, and close industrial linkages indicate that cross-regional spillovers of driving factors represent a mechanism influencing coupling coordination. Considering the limited temporal span of the research sample and the need to control for unobserved county-specific heterogeneity, the SDM-FE was applied for estimation.

An additional specification issue concerns the choice between individual and two-way fixed effects. The baseline controls for county-specific fixed effects but omits time fixed effects for three reasons. First, the panel is short (T = 10), and adding nine year dummies would consume degrees of freedom and reduce estimation efficiency with only 19 cross-sectional

units. Second, the SDM already accounts for common time-varying shocks through its spatial lag terms. A province-wide policy, climate, or macroeconomic shock in a given year propagates across counties via the spatially lagged dependent variable (ρWD) and the spatially lagged regressors (θWX). Year dummies would be redundant and collinear with the spatial terms. Third, the 19 counties form a compact, highly homogeneous delta exposed to the same regional institutions and environment, and the coupling coordination degree rises smoothly and monotonically (0.561–0.760) without abrupt year-specific structural breaks. The individual fixed effects, in contrast, absorb time-invariant heterogeneity across counties in resource endowments, geography, and long-standing institutions, which is the main source of spatial disparity. A two-way fixed-effects or spatial-HAC specification, which would be feasible with a longer panel, is therefore identified as a future robustness check in Section 6.3 rather than imposed on the current sample.

5.2.4. Baseline Regression Results of SDM

The SDM-FE was employed for baseline regression analysis. The model had a log-likelihood value of 699.1595 and a Pseudo-R^2 value of 0.5341, indicating that it provided a strong explanation of variations in the coupling coordination degree of the agricultural eco-economic system in the YRD. As presented in Table 8, the spatial autoregressive coefficient ρ was 0.4698 and positive at the 1% level, indicating that the coupling coordination degree among counties exhibited significant local spatial dependence.

Table 8. Baseline regression results of SDM-FE.

Variable	Coefficient	z Value	*p* Value	Variable	Coefficient	z Value	*p* Value
lnredl	0.0050	1.43	0.154	W × *lnredl*	−0.0254 **	−2.44	0.015
lnisl	−0.0791 ***	−3.10	0.002	W × *lnisl*	−0.0151	−0.16	0.871
lnfsa	−0.0067	−1.64	0.102	W × *lnfsa*	−0.0079	−0.33	0.744
lnudl	0.0059	0.60	0.551	W × *lnudl*	0.2701 ***	3.76	0.000
lnaml	−0.0162 ***	−4.54	0.000	W × *lnaml*	−0.0149	−1.29	0.197
lnasol	0.1021 ***	6.20	0.000	W × *lnasol*	0.0540	1.27	0.204
lnrti	−0.0277	−1.58	0.114	W × *lnrti*	−0.1528 *	−1.83	0.067
ρ (W × D)	0.4698 ***	3.85	0.000				
Individual fixed effects	Controlled			Time fixed effects	Not controlled		
Loglikelihood	699.1595			sigma2	0.0000 ***	9.65	0.000
Wald spatial test	chi2(8) = 408.03 ***			Observations	190		

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. *p* represents the spatial autoregressive coefficient.

In terms of main effects, the industrial structure level (*lnisl*) and agricultural modernization level (*lnaml*) showed negative effects at the 1% significance level, indicating that both factors exerted inhibitory effects on the coupling coordination development of the local agricultural eco-economic system. In contrast, the agricultural scale operation level (*lnasol*) had a positive effect at the 1% significance level, suggesting that it promoted local system coupling coordination. The main effects of the remaining variables did not pass the significance test.

Regarding spatial lag effects, the regional economic development level (W × *lnredl*) exhibited a negative effect at the 5% significance level, showing that the economic development level of neighboring counties may inhibit local coupling coordination. The urbanization development level (W × *lnudl*) showed a positive effect at the 1% significance level, suggesting that urbanization development in adjacent counties could generate positive spatial spillovers. The regional transportation infrastructure (W × *lnrti*) presented a negative effect at the 10% significance level, indicating weak negative spatial spillovers. While the spatial lag terms of other variables were statistically insignificant, they were retained considering model completeness and the requirements of LR tests.

The SDM simultaneously accounts for the spatial lag term of the dependent variable and the spatial lag terms of all explanatory variables. Therefore, the original regression coefficients cannot be directly interpreted as marginal effects or spillover effects but only reflect the basic association characteristics of variables. Accordingly, the partial differentiation decomposition approach proposed by LeSage and Pace [84] was followed to decompose the long-term direct effects, indirect effects, and total effects, providing more precise economic interpretations.

5.2.5. Decomposition of Spatial Effects

The estimated direct effects, indirect effects, and total effects of each driving factor are as seen in Table 9.

Table 9. Decomposition Results of Spatial Effects.

Variable	Direct Effect	*p* Value	Indirect Effect	*p* Value	Total Effect	*p* Value
lnredl	0.0036	0.331	−0.0439 **	0.034	−0.0403 *	0.066
lnisl	−0.0825 ***	0.002	−0.0752	0.676	−0.1577	0.413
lnfsa	−0.0070	0.145	−0.0197	0.700	−0.0266	0.623
lnudl	0.0230 *	0.073	0.5182 ***	0.001	0.5412 ***	0.001
lnaml	−0.0176 ***	0.000	−0.0419 *	0.055	−0.0595 ***	0.009
lnasol	0.1089 ***	0.000	0.1847 ***	0.000	0.2936 ***	0.000
lnrti	−0.0388 *	0.099	−0.3266	0.133	−0.3653	0.123

Note: Standard-error-based *p*-values are reported for each direct, indirect, and total effect to indicate estimation uncertainty; $p < 0.05$ corresponds to a 95% confidence interval that excludes zero. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

The direct effect of the industrial structure level was −0.0825 (significant at the 1% level), indicating that the advancement of local industrial structure was negatively associated with coupling coordination of the local agricultural eco-economic system. As a traditional agricultural region, the industrial upgrading of the YRD is primarily characterized by the expansion of secondary and tertiary industries, which occupy essential agricultural resources such as cultivated land and water resources, weaken agricultural ecological functions, and disrupt the balance between the agricultural economic subsystem and ecological subsystem. This process may generate an "agricultural ecological crowding-out effect" associated with industrial upgrading. The indirect and total effects did not pass the significance test, suggesting that the negative impact of industrial structure advancement was confined to the local region, with limited cross-regional spillover effects.

The direct effect of the agricultural modernization level was −0.0176 (significant at the 1% level), while its indirect effect was −0.0419 (significant at the 10% level). The total effect was negative and significant at the 1% level. As agricultural modernization is measured by agricultural machinery power per unit sown area, it captures mechanization intensity rather than fertilizer or pesticide use. In the ecologically fragile YRD, it may be associated with, but does not directly measure, ecological problems such as soil degradation and

agricultural non-point source pollution, a mechanism that warrants direct testing. Such a pathway may involve ecological costs that offset some gains from improved production efficiency. The negative direct and indirect estimates are consistent with a negative association between agricultural modernization and coupling coordination, although the underlying mechanisms are not directly tested in this study.

In comparison, the direct effect, indirect effect, and total effect of the agricultural scale operation level were all positive at the 1% level, with a total effect of 0.2936, representing the largest positive value among all explanatory variables. Since the explanatory variables are in logarithms while D is a level, the estimates are semi-elasticities: a 10% increase in the scale-operation level is associated with a rise of roughly 0.010 in local D and 0.018 in neighboring counties' D, or about 0.028 in total (the coefficients multiplied by $\ln(1.10) \approx 0.095$). Because the scale-operation indicator measures land-operating scale (sown area per agricultural worker) rather than enterprise size, the following mechanism should be read as a plausible association rather than a direct measurement. Larger operating scale may aid the adoption of ecological agricultural technologies, such as water-saving irrigation and integrated pest management, which in turn improve local agricultural production efficiency while reducing ecological pressures. Through industrial demonstration, technological diffusion, and cross-regional cooperation, scale operations were associated with positive spatial spillover estimates and higher coupling coordination among neighboring counties. Therefore, agricultural scale operations represent a driving force supporting the evolution of agricultural eco-economic coupling coordination in the YRD.

For the urbanization development level, the direct effect was positive at the 10% level, while both the indirect effect and total effect were positive at the 1% level. Moreover, the indirect effect was larger than the direct effect. Urbanization development can improve regional infrastructure, optimize factor allocation, and promote local coordinated development. Meanwhile, through transportation network connectivity, factor mobility, and public service sharing, urbanization was positively associated with cross-regional coupling coordination, serving as a carrier for promoting overall regional coordinated upgrading.

The regional economic development level did not exhibit a significant direct effect but presented a significant negative indirect effect and a marginally significant negative total effect. The economic development of neighboring counties may inhibit local coordinated development through factor competition and resource attraction. Because the explanatory variables are in logarithms, the estimate is a semi-elasticity. A 10% increase in neighbors' per capita GDP is associated with a decline of roughly 0.0042 in local D. The absence of a significant direct effect combined with a significant negative indirect effect is consistent with a siphon mechanism, where more developed counties attract high-quality labor, capital, and industrial resources from surrounding counties, rather than local economic scale itself being strongly associated with local coordination. Regional transportation infrastructure exhibited a significant negative direct effect at the 10% level, while its overall spatial spillover effect and total effect were not statistically significant, suggesting that its constraint on agricultural eco-economic coupling coordination is limited. Road density also measures road length rather than network quality or actual connectivity between farms and markets, which may further limit its explanatory power.

Finally, the direct, indirect, and total effects of the agricultural fiscal support level did not pass the significance test. This may be attributed to several factors. Specifically, agricultural fiscal funds often suffer from homogeneous investment structures, insufficient utilization efficiency, and long-term lags in ecological governance returns. Consequently, their contribution to improving agricultural eco-economic coupling coordination may not be fully reflected in the short term. Moreover, because the fiscal indicator is an aggregate measure of expenditure scale, it cannot capture the targeting, allocation, or efficiency of

funds. An insignificant estimate may therefore partly reflect this measurement limitation rather than an absence of effect.

The magnitudes of the spillovers are plausible given intercounty integration in the YRD. The 19 counties form a compact, contiguous delta with shared river systems, integrated transport, and similar industrial structures, so cross-county effects are expected. The largest indirect effects (urbanization 0.5182, scale operation 0.1847) are consistent with the region-wide sharing of infrastructure and the diffusion of large-scale farming models, whereas the smaller negative indirect effect of economic development (−0.0439) indicates that intercounty competition is weaker than these synergistic effects. In scale, a 10% increase in neighbors' urbanization (scale operation) corresponds to a rise of about 0.049 (0.018) in local D, comparable to the observed annual change (roughly 0.022 per year). These spillovers may operate through technology diffusion, labor migration, and pollution transfer, although the reduced-form SDM identifies only the spatial association and does not establish these mechanisms, which would require mediation analysis and micro-level data in future work.

Overall, the results are consistent with the hypotheses in Section 3. The negative local effect of industrial structure with no significant spillover supports H1; the negative local and indirect effects of traditional agricultural modernization support H2; the positive local and indirect effects of scale operation, the largest positive driver, support H3. The positive, indirectly dominant urbanization effects support H4. The insignificant direct but negative indirect effect of regional economic development is consistent with the siphon-based expectation in H5. Evidence for transportation infrastructure (H6) is mixed, showing only a marginally negative local effect and no significant spillover, while fiscal support for agriculture (H7) shows no significant effect, consistent with its expected short-term weakness.

5.2.6. Robustness Tests

(1) Extreme-value treatment

To verify the robustness of the baseline regression results, two-sided 1% winsorization was applied to the dependent variable to eliminate the potential influence of extreme values on the estimation results. Table 10 presents the decomposition results of spatial effects from the robustness test.

Table 10. Robustness Test: Decomposition Results of Spatial Effects after Two-sided 1% Winsorization of the Dependent Variable.

Variable	Direct Effect	*p* Value	Indirect Effect	*p* Value	Total Effect	*p* Value
lnredl	0.0037	0.319	−0.0432 **	0.038	−0.0394 *	0.073
lnisl	−0.0831 ***	0.002	−0.0792	0.661	−0.1624	0.402
lnfsa	−0.0068	0.158	−0.0116	0.819	−0.0184	0.734
lnudl	0.0230 *	0.074	0.5169 ***	0.001	0.5399 ***	0.001
lnaml	−0.0175 ***	0.000	−0.0426 *	0.053	−0.0600 ***	0.009
lnasol	0.1079 ***	0.000	0.1852 ***	0.000	0.2931 ***	0.000
lnrti	−0.0377	0.110	−0.3252	0.136	−0.3629	0.127
Wald spatial term test	chi2(8) = 408.94 ***					

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

The robustness test results show that the signs and significance of the core variables remained consistent with the baseline. The only exception is the marginal direct effect of regional transportation infrastructure, which is significant at the 10% level in the baseline ($p = 0.099$) but becomes insignificant after winsorization ($p = 0.110$), consistent with its insignificant total effect. This variable therefore does not support a strong conclusion.

Because the negative effects of industrial structure and agricultural modernization remain significant and of similar magnitude after trimming, they are not driven by extreme or outlying county–year observations but reflect a systematic pattern across the sample.

The main conclusions remain unchanged: industrial structure advancement and traditional agricultural modernization had significant negative effects on coupling coordination, whereas agricultural scale operations and urbanization development generated significant positive direct effects and spatial spillover effects. Regional economic development exhibited negative spatial spillovers, while agricultural fiscal support and regional transportation infrastructure were statistically insignificant in terms of their overall effects. Additionally, the Wald test for spatial terms remained significant at the 1% level, and the spatial autoregressive coefficient ρ remained positive. These results demonstrate that the core conclusions are not driven by extreme values, although the marginal direct effect of transportation infrastructure is sensitive to the treatment of extreme values.

(2) Spatial weight matrices and spatial dependence diagnostics

To verify that the findings are not driven by a particular weighting scheme, we re-estimated the SDM using k-nearest-neighbor (kNN) matrices and a distance threshold contiguity matrix constructed solely from the geographic coordinates of the counties. Under a kNN matrix, each county is connected to its k nearest neighbors, and each connection receives a weight of 1/k. The main check uses k = 4 and a supplementary check uses k = 3. The contiguity matrix connects two counties when the distance between their administrative centres is within 60 km. All matrices are row-standardized. Table 11 compares the main coefficient estimates, the spatial autoregressive coefficient rho, and the total effect of scale operations under the baseline inverse-distance matrix and the three alternative matrices. Across all four weighting schemes, the signs and significance of the core coefficients remain unchanged, the scale-operation total effect is highly similar (0.2936, 0.2984, and 0.3346), and rho remains positive and statistically significant. The results therefore are not sensitive to the choice of spatial weight matrix.

Table 11. Robustness under alternative spatial weight matrices (main coefficients, rho and scale-operation total effect).

Variable	Inverse-Distance (Baseline)	kNN (k = 3)	kNN (k = 4)	Contiguity (60 km)
ln_red	0.0050	0.0006	−0.0010	0.0005
ln_iss	−0.0791 ***	−0.0897 ***	−0.0818 ***	−0.0890 ***
ln_fas	−0.0067	−0.0018	−0.0034	−0.0045
ln_udl	0.0059	0.0050	0.0070	0.0201 *
ln_aml	−0.0162 ***	−0.0151 ***	−0.0150 ***	−0.0171 ***
ln_also	0.1021 ***	0.1177 ***	0.1189 ***	0.1055 ***
ln_rti	−0.0277	0.0222	0.0222	0.0112
rho	0.4698 ***	0.6759 ***	0.6789 ***	0.6350 ***
Total:	0.2936 ***	0.2893 ***	0.2984 ***	0.3346 ***

Note: *** and * indicate significance at the 1% and 10% levels. Entries are main coefficient estimates; rho is the spatial autoregressive coefficient; the last row reports the scale-operation total effect.

We further computed the Lagrange multiplier tests on the non-spatial LSDV residuals. Table 12 shows that under the inverse-distance matrix, LM-error and LM-lag are 51.78 and 8.38, and under the kNN matrix they are 50.74 and 15.63, all statistically significant, rejecting

the null of no spatial dependence and supporting a model with spatial lag terms. The spatial-dependence findings are therefore independently confirmed by the LM diagnostics.

Table 12. Lagrange multiplier diagnostics on non-spatial LSDV residuals.

Weight Matrix	LM-Error	LM-Lag
Inverse-distance (Wid)	51.775 ***	8.378 ***
kNN (Wk)	50.739 ***	15.632 ***

Note: Both tests have one degree of freedom; *** indicates significance at the 1% level. The null hypothesis is the absence of spatial error dependence (LM-error) or spatial lag dependence (LM-lag).

To provide a formal clustering diagnostic, we computed the global Moran I for each year over 2015–2024 using the kNN-4 matrix. Table 13 shows that the Moran I is positive in all ten years, ranging from 0.097 to 0.224, and rises markedly after 2022, indicating persistent positive spatial clustering that strengthens over time. This finding is consistent with the significant LM test results reported in Table 13 and the significant rho in the SDM. Given only 19 cross-sectional units, local indicators of spatial association have limited power; constructing reliable LISA cluster maps would require more detailed geographic data. Therefore, this study relies on the global Moran I and the LM tests to assess spatial dependence.

Table 13. Global Moran I of the coupling coordination degree by year (kNN-4).

Year	Global Moran I
2015	0.1712
2016	0.1532
2017	0.0972
2018	0.1236
2019	0.1780
2020	0.1871
2021	0.1831
2022	0.2239
2023	0.2244
2024	0.2102

Note: All values are positive; Moran I increases in the later years, indicating strengthening positive spatial clustering.

(3) Two-way fixed effects

As an additional robustness check, year dummies were added to the baseline SDM to construct a two-way fixed-effects specification that controls for both individual and time effects. Table 14 compares the direct effect estimates and rho between the baseline and the two-way fixed-effects models. After controlling for time fixed effects, the signs and significance of the core direct effects remain consistent with the baseline results. Industrial structure advancement and agricultural modernization remained negative and significant, while agricultural scale operations remained positive and significant. The year dummies are monotonically significant and capture the common upward trend of the coupling coordination degree over the sample period. Once this common trend is absorbed, the residual spatial autoregressive coefficient rho is no longer significant, consistent with the collinearity between the year effects and the spatial lag terms in this short panel (N = 19,

T = 10). We therefore retain the individual fixed-effects model as the baseline and report the two-way fixed-effects specification as a supplementary check. The core conclusions remain unchanged. The two-way fixed-effects model also addresses the shared annual shocks over 2015–2024, including policy changes, climatic variability, and market fluctuations. The year dummies are monotonically significant, while the core direct effects remain stable (see Table 14).

Table 14. Direct effects under the baseline and two-way fixed-effects specifications.

Variable	Baseline Direct Effect	Two-Way FE Direct Effect
ln_red	0.0036	0.0082 **
ln_iss	−0.0825 ***	−0.0978 ***
ln_fas	−0.0070	−0.0072 *
ln_udl	0.0230 *	−0.0035
ln_aml	−0.0176 ***	−0.0234 ***
ln_also	0.1089 ***	0.0897 ***
ln_rti	−0.0388 *	−0.0232
rho	0.4698 ***	−0.1762 (n.s.)

Note: The two-way FE model includes nine year dummies (2016–2024), *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively, n.s. denotes not significant.

(4) Overlap between the explanatory variables and index components

We assessed the potential overlap from both conceptual and empirical perspectives. Conceptually, the coupling coordination degree D is calculated using indicators from the ecological and economic subsystems, with weights determined by the CRITIC weighting method and the coupling coordination formula. In contrast, the seven driving variables were independently selected as external variables. The raw variables used to construct D are distinct from the seven driving variables, indicating that there is no direct mathematical overlap by construction. Where indicators share a denominator, their numerators represent distinct dimensions and the influence is diluted by the CRITIC weight (see Section 5.2.2). Empirically, Table 15 presents the correlation matrix for D and the driving variables: the highest correlation between D and a driving variable was 0.627, while the highest correlation among the drivers is 0.64, with no perfect collinearity. These results indicate that the variables are not perfectly correlated, although the correlation matrix alone cannot rule out all potential forms of conceptual or construction-related overlap.

(5) Alternative indicator weighting schemes

To verify that the findings do not depend on the CRITIC weights, we reconstructed the index under two alternative schemes. Using the same 21 raw indicators, we applied (i) the entropy weighting method, in which the weight of each indicator is derived from its proportion and the corresponding information entropy (one minus the entropy term), and (ii) equal weighting, in which indicators within the same subsystem receive equal weights. Weights were normalized within the ecological and economic subsystems separately, and the same coupling coordination formula was then applied to obtain two new dependent variables, D_entr and D_equal, without altering the original index. Table 16 reports the descriptive statistics and correlations across the three weighting schemes: the equal-weight D correlates with the baseline D at 0.9982 and the entropy-weight D at 0.8324. Table 17 compares the corresponding SDM estimates. Under all three schemes, industrial structure advancement and agricultural modernization remain negative, agricultural scale operations remain positive with the largest total effect, and rho remains positive and significant.

These results indicate that the main findings are generally consistent across alternative weighting schemes.

Table 15. Correlation matrix of the coupling coordination degree and the driving variables.

	D	ln_red	ln_iss	ln_fas	ln_udl	ln_aml	ln_also	ln_rti
D	1.0000	0.2761 ***	−0.2509 ***	0.0924	0.1100	0.0091	0.6268 ***	−0.2264 ***
ln_red	0.2761 ***	1.0000	0.5848 ***	−0.2593 ***	0.5810 ***	0.3280 ***	0.0826	−0.3355 ***
ln_iss	−0.2509 ***	0.5848 ***	1.0000	−0.5810 ***	0.6396 ***	0.2278 ***	−0.2404 ***	0.0719
ln_fas	0.0924	−0.2593 ***	−0.5810 ***	1.0000	−0.5527 ***	−0.1880 ***	0.2874 ***	−0.0564
ln_udl	0.1100	0.5810 ***	0.6396 ***	−0.5527 ***	1.0000	0.1970 ***	−0.0406	−0.3024 ***
ln_aml	0.0091	0.3280 ***	0.2278 ***	−0.1880 ***	0.1970 ***	1.0000	−0.2148 ***	−0.2208 ***
ln_also	0.6268 ***	0.0826	−0.2404 ***	0.2874 ***	−0.0406	−0.2148 ***	1.0000	0.1686 **
ln_rti	−0.2264 ***	−0.3355 ***	0.0719	−0.0564	−0.3024 ***	−0.2208 ***	0.1686 **	1.0000

Note: *** and ** indicate significance at the 1% and 5% levels respectively. Coefficients without asterisks are not statistically significant.

Table 16. Descriptive statistics and correlations of the coupling coordination degree under three weighting schemes.

Variable	Mean	Std. Dev.	Min	Max	Corr. with Baseline
D_couple (CRITIC, baseline)	0.6650	0.0768	0.4874	0.8270	1.0000
D_entr (entropy)	0.5953	0.1152	0.3473	0.8463	0.8324
D_equal (equal)	0.6690	0.0818	0.4775	0.8444	0.9982

Note: All pairwise correlations are significant at the 1% level. The correlation between D_entr and D_equal is 0.8382.

Table 17. SDM estimates under three weighting schemes (core coefficients and total effects).

Estimate/Variable	CRITIC (Baseline)	Entropy (D_entr)	Equal (D_equal)
rho	0.4698 ***	0.7088 ***	0.7155 ***
Main: ln_iss	−0.0791 ***	−0.0407 *	−0.0615 **
Main: ln_aml	−0.0162 ***	−0.0070 **	−0.0125 ***
Main: ln_also	0.1021 ***	0.0879 ***	0.1036 ***
Total effect: ln_iss	n.s.	−0.4783 **	n.s.
Total effect: ln_also	0.2936 ***	0.2285 ***	0.3176 ***

Note: Baseline uses the inverse-distance matrix; entropy and equal-weight checks use the kNN matrix, *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively, n.s. denotes not significant; the signs of the core coefficients are consistent across all three schemes.

(6) Leave-one-out and influence diagnostics

To check whether the results are driven by a single county, we performed a leave-one-county-out analysis. Each of the 19 counties was removed in turn, the spatial weight matrix was rebuilt for the remaining 18 counties, and the model was re-estimated. Table 18 reports the spatial autoregressive coefficient rho and the coefficients of four core variables from each run. Across all 19 runs, rho remains positive and significant, staying within the range 0.60–0.69, and the signs of the four core coefficients never change. Laizhou County has the

largest influence on the estimates. When it was excluded, the coefficient for agricultural scale operations decreased to 0.063, compared with approximately 0.12 in the baseline sample, and it remains positive. These results suggest that the main findings are not driven by the exclusion of any single county.

Table 18. Leave-one-county diagnostics (rho and four core coefficients).

Excluded County	rho	ln_also	ln_aml	ln_udl	ln_iss
Dongying	0.6589	0.1168	−0.0180	0.0067	−0.1102
Hekou	0.6530	0.1350	−0.0152	0.0035	−0.1061
Kenli	0.6725	0.1349	−0.0184	0.0085	−0.1018
Lijin	0.6855	0.1317	−0.0168	0.0041	−0.0961
Guangrao	0.6889	0.1076	−0.0135	−0.0020	−0.0807
Bincheng	0.6579	0.1238	−0.0146	−0.0036	−0.0830
Zhanhua	0.6581	0.1179	−0.0182	0.0111	−0.0857
Huimin	0.6835	0.1172	−0.0136	0.0061	−0.0734
Yangxin	0.6824	0.1119	−0.0142	−0.0042	−0.0964
Wudi	0.6532	0.1122	−0.0124	0.0009	−0.0724
Boxing	0.6875	0.1194	−0.0149	−0.0051	−0.0766
Zouping	0.6445	0.1086	−0.0177	0.0069	−0.0564
Hanting	0.6811	0.1332	−0.0132	0.0041	−0.0780
Shouguang	0.6826	0.1289	−0.0115	0.0064	−0.0702
Changyi	0.6529	0.1090	−0.0153	0.0030	−0.0723
Laoling	0.6003	0.1167	−0.0134	0.0233	−0.0533
Qingyun	0.6469	0.1163	−0.0152	0.0072	−0.0759
Gaoqing	0.6042	0.1230	−0.0150	0.0093	−0.1186
Laizhou	0.6660	0.0628	−0.0130	0.0061	−0.0980

Note: Each row corresponds to one county being left out, with the SDM re-estimated on the other 18 counties using a rebuilt kNN matrix. All rho values are positive and significant.

We then removed each year from 2015 to 2024 in turn and re-estimated the model. Table 19 shows that across all ten specifications rho remains positive and statistically significant (0.603–0.701), and the signs of the four core coefficients never change. Scale operations and urbanization stay positive, while industrial structure and agricultural modernization stay negative. The leave-one-county results are as seen in Table 14 and are equally robust. Table 20 reports Cook's distances and DFBETA statistics. The mean Cook's distance was 0.0065, and the maximum was 0.103, well below the strong-influence threshold of 1, so there are no extreme influential observations. A few DFBETA values exceed the rule-of-thumb threshold $2/\mathrm{sqrt}(N) = 0.145$, but these observations do not alter the leave-one-county and leave-one-year conclusions. The negative associations of industrial structure and agricultural modernization are therefore not driven by particular counties or years.

Table 19. Leave-one-year-out diagnostics (rho and four core coefficients).

Excluded Year	rho	ln_also	ln_aml	ln_udl	ln_iss
2015	0.6666	0.1248	−0.0148	0.0109	−0.0865
2016	0.6697	0.1247	−0.0146	0.0109	−0.0865
2017	0.6746	0.1235	−0.0149	0.0108	−0.0858
2018	0.6779	0.1223	−0.0150	0.0109	−0.0857
2019	0.6843	0.1198	−0.0150	0.0109	−0.0853
2020	0.6875	0.1190	−0.0150	0.0108	−0.0848
2021	0.6922	0.1172	−0.0151	0.0107	−0.0841
2022	0.6960	0.1154	−0.0152	0.0106	−0.0833
2023	0.7014	0.1100	−0.0153	0.0105	−0.0825
2024	0.6033	0.1301	−0.0122	0.0030	−0.0567

Note: Each row corresponds to one year being left out; all rho values are positive and significant, and the core coefficient signs never change.

Table 20. Cook's distance and DFBETA influence diagnostics (summary).

Diagnostic	Summary
Cook's distance (mean)	0.0065
Cook's distance (max; Lijin 2020)	0.1027
Strong-influence threshold (1)	No observation exceeds it
DFBETA threshold 2/sqrt(N)	0.145
DFBETA largest range (ln_udl)	−1.202 to 0.577
DFBETA other variables	Mostly within ± 0.63; a few exceed 0.145

Note: The largest Cook's distances are Lijin 2020 (0.103) and Laizhou 2015 (0.100). DFBETA exceedances do not change the conclusions when combined with Tables 14 and 19.

(7) Functional-form sensitivity of the road proxy

We examined the fiscal and road proxies without introducing variables outside the manuscript. The fiscal variable correlates with the coupling coordination degree at only 0.0924 (not significant), and the low VIFs (1.22–3.42) rule out multicollinearity. Its insignificant estimate therefore reflects a genuinely weak aggregate-scale effect rather than measurement error or collinearity. For the road proxy, we replaced the logarithm of road density with its level and re-estimated the model to test functional-form sensitivity. Table 21 shows that under the level specification, the direct and total effects of road density are weakly positive and significant (total effect 0.168), whereas under the baseline log specification they are not significant, indicating some functional-form sensitivity. In either specification, the total effect is much smaller than that of agricultural scale operations (about 0.304). These results are consistent with the directionally ambiguous hypothesis H6. Therefore, the transportation effect is interpreted as mixed, and no strong conclusion is drawn regarding its impact on coupling coordination. This functional-form sensitivity is also explicitly acknowledged.

Table 21. Functional-form sensitivity of the road density proxy.

Road Specification/Variable	rho	Road Main	Road Direct	Road Total	ln_also Total
Log road density (baseline, ln_rti)	0.4698 ***	−0.0277 (n.s.)	−0.0388 *	n.s.	0.2936 ***
Level road density (rti)	0.6684 ***	0.0138 *	0.0274 **	0.1683 **	0.3044 ***

Note: The level specification uses the same controls and the kNN matrix; *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively, n.s. denotes not significant. The road total effect is far smaller than the scale-operation effect in both specifications.

6. Conclusions, Policy Implications, and Discussion

6.1. Conclusions

Using balanced panel data from 19 counties in the YRD from 2015 to 2024, this study constructed a geographical inverse distance spatial weight matrix and employed an individual fixed effects spatial Durbin model to empirically examine the impacts of regional economic development, industrial structure, agricultural fiscal support, urbanization, agricultural modernization, agricultural scale operations, and regional transportation infrastructure on the coupling coordination of the agricultural eco-economic system, including their spatial spillover effects. The following conclusions emerged through LR tests, Wald tests, and effect decomposition analysis:

(1) Coupling coordination development exhibited dual characteristics in temporal and spatial dimensions from 2015 to 2024. Temporally, the coupling degree of the regional system remained consistently high, suggesting that the interaction between the two subsystems approached saturation. Meanwhile, the comprehensive development index and coupling coordination degree exhibited continuous upward trends, accelerating after 2018. This suggests that the primary constraint on further enhancing coupling coordination shifted from the intensity of subsystem interactions to the comprehensive development capacity of the subsystems themselves. Spatially, all counties achieved positive transitions in coupling coordination levels, but no county reached the high-quality coordination stage. Overall, the YRD exhibits a spatial pattern where coastal counties demonstrate higher coordination levels than inland counties. Several coastal counties entered the stage of good coordination, while most western counties remain at the stage of intermediate coordination. The insufficient cultivation of characteristic agricultural industries became a major constraint on coordinated development in western counties, indicating potential for further improving regional internal coordination.

(2) Agricultural eco-economic coupling coordination development in the YRD exhibited positive spatial dependence with regional spatial linkages. The spatial autoregressive coefficient ρ is significantly positive, indicating direct positive spatial associations in coupling coordination levels among counties. Meanwhile, the joint significance of all spatial lag terms of explanatory variables confirms that regional coupling coordination results from the combined effects of spatial dependence of the dependent variable and cross-regional spillovers of driving factors. This finding refines the conventional understanding that emphasizes only factor-driven mechanisms without considering spatial linkages, and it is consistent with the interconnected regional development characteristics of counties in the YRD.

(3) Industrial structure upgrading and traditional agricultural modernization were negatively associated with the coupling coordination of the agricultural eco-economic system. Industrial structure advancement may occupy agricultural ecological resources and generate local agricultural ecological crowding-out effects. Traditional input-

intensive agricultural modernization involves ecological costs, producing negative local effects and negative cross-regional spillovers. In ecologically fragile saline-alkali regions, promoting industrial upgrading and agricultural modernization may further worsen the imbalance between ecological and economic systems.

(4) Agricultural-scale operations and urbanization were positively associated with regional coupling coordination. Agricultural-scale operations generate local improvement effects and positive spatial spillover effects, representing an optimal development pathway that integrates agricultural production efficiency with ecological protection. The spatial spillover effect of urbanization is greater than its direct effect. Through transportation network connectivity, factor mobility, and public service sharing, urbanization can reduce county-level market segmentation and promote regional coordinated upgrading.

(5) Regional economic development exhibited negative spatial spillover effects, while its local direct effect was insignificant. The direct effects of regional transportation infrastructure and agricultural fiscal support did not show statistically significant overall effects. Economic development in neighboring counties may inhibit local coordinated development through factor competition. The estimated direct, indirect, and total effects of agricultural fiscal support were statistically insignificant in the current sample and period. The aggregate fiscal indicator may not fully capture the targeting, allocation, or efficiency of funds. In addition, the effects of fiscal support may involve longer ecological governance lags. Therefore, the insignificant estimates do not necessarily indicate that fiscal support has no effect on coupling coordination.

(6) The model setting was stable. After conducting the two-sided 1% winsorization test, the direction of effects, significance levels, and spillover mechanisms of core variables remained unchanged. These results confirm the stability of the empirical findings and provide empirical support for coordinated governance of the agricultural eco-economic system in the YRD.

6.2. Recommendations

Based on these findings and the regional characteristics of the YRD, the following policy implications are proposed:

(1) Establish a cross-county collaborative governance system to activate positive spatial spillovers. Because coupling coordination in the YRD exhibits positive spatial autocorrelation driven by urbanization and agricultural scale operations, provincial and city-county coordination must overcome administrative barriers. At the provincial level, integrated planning should align industrial layouts, ecological standards, and infrastructure. Cross-county platforms for land transfers, product circulation, and ecological compensation will promote the sharing of water-saving technologies and large-scale operation experience. Meanwhile, county-level evaluations must incorporate coordinated development metrics to reduce factor competition and fragmented governance.

(2) Optimize industrial upgrading to avoid ecological crowding-out. Excessive expansion of secondary and tertiary industries negatively affects local eco-economic coordination by occupying agricultural resources and disrupting system balance. The YRD must pursue coordinated industrial development upgrading that prioritizes the environment. Red lines for ecological protection, cultivated land protection, and wetlands must be strictly enforced to regulate urban and industrial expansion. Integrated development should focus on agriculture-related industries, such as deep processing and eco-tourism, enhancing rather than replacing agricultural functions. Furthermore,

an ecological assessment and access mechanism for industrial relocation will prevent high-pollution and high-energy industries from entering major agricultural areas.

(3) Deepen appropriate-scale agricultural operations. Scale of operations was the only driving factor that exhibited significant positive direct, indirect, and total effects, making it the greatest contributor to system coordination. Given the advantages of contiguous land resources in the YRD, ecologically oriented appropriate-scale operations should serve as a core pathway for modern agricultural development. Relying on counties such as Dongying, which possess abundant land resources and agricultural foundations, the YRD should develop large-scale agriculture demonstration zones on saline-alkali land. The focus must be on cultivating family farms, cooperatives, and leading enterprises, while promoting the integration of fragmented farmland and unified management. Supporting services, such as integrated pest management, soil-testing-based fertilization, and water-saving irrigation, will merge large-scale operations with conservation. A "leading enterprises + cooperatives + farmers" model will enhance technology transfer, industrial linkages, and model replication region-wide.

(4) Improve infrastructure connectivity to facilitate factor mobility and interaction. The strong indirect spillover effect of urbanization highlights infrastructure as a key driver of regional coordination. To address incomplete logistics systems and high circulation costs, the YRD must prioritize upgrading intercity and rural roads into an integrated one-hour transportation network. Regional cold-chain logistics hubs and wholesale markets will reduce cross-regional circulation costs. Moreover, integrating digital e-commerce and intelligent logistics will optimize the flow of resources and market information. A joint infrastructure construction mechanism will coordinate planning, investment, and benefit distribution, maximizing the positive spatial spillover effects of infrastructure development.

(5) Transform agricultural modernization toward green development. Traditional modernization, heavily reliant on chemical and mechanical inputs, produces negative local effects and is incompatible with YRD's fragile ecology. The region should adopt agricultural technologies, including saline-alkali restoration, organic fertilizers, green pest and disease control, and integrated crop-livestock systems, to reduce soil degradation and agricultural non-point source pollution. Given regional water shortages, dry farming and water-saving agriculture should be encouraged. Targeted subsidies and policy support should incentivize green cultivation, ecological breeding, and circular practices, supported by regular ecological monitoring to keep modernization within carrying capacity limits.

(6) Optimize agricultural fiscal support and enhance funding efficiency. Because fiscal support for agriculture did not show a significant association within the current sample and period, these measures should be regarded as exploratory, practice-based directions rather than evidence-based causal recommendations. Fiscal support could be shifted from expanding investment scale to optimizing structure, with resources channeled toward areas such as saline-alkali governance, ecological technologies, scale operations, and rural infrastructure. A county-level coordination mechanism could consolidate fragmented investments into collaborative projects, and incorporating ecological improvement and coordinated development metrics into performance evaluations may improve targeting and multiplier effects. These measures should be evaluated in future research with longer panels, since the ecological returns of agricultural fiscal investment may involve long lags.

6.3. Discussions

Although this study investigated the driving factors and spatial spillover effects of coupling coordination evolution in the agricultural eco-economic system of the YRD, several limitations remain and require further investigation.

(1) This study focused on 19 counties in the YRD and conducted empirical analysis at the county level. This limited spatial coverage constrains the external applicability of the estimation results. In addition, this study conducted an overall effect analysis based on county-level panel data but did not distinguish the heterogeneous characteristics of counties with different resource endowments and development levels. Consequently, the differentiated driving mechanisms among regions with high and low coupling coordination levels remain insufficiently explored. Future studies could expand the sample boundary by incorporating counties in the lower reaches of the Yellow River Basin for comparative analysis, examining the universality and stability of the findings. Furthermore, approaches such as quantile regression and heterogeneity tests could identify the differentiated effects of driving factors under different coupling coordination levels, providing empirical evidence for differentiated policy implementation.

(2) This study identified the overall direct and spatial spillover effects of different variables but did not examine the transmission pathways and underlying mechanisms through which these variables influence agricultural eco-economic coupling coordination. Therefore, the mechanism underlying spatial spillovers remains insufficiently revealed. For example, the negative ecological crowding-out effect of industrial structure upgrading, the positive spillover effect of agricultural scale operations, and the negative spatial competition effect of regional economic development may involve complex pathways related to factor flows, resource allocation, and ecological responses, which have not been fully clarified. Future research could introduce mediation and moderation effect models to examine how different driving factors influence system coupling coordination through factor mobility, technological diffusion, ecological governance, and industrial specialization. This would help identify key transmission pathways and provide a comprehensive understanding of the internal mechanisms underlying spatial spillovers.

Finally, these measures should be implemented with region-specific priorities and explicit attention to trade-offs. In line with the coastal–inland disparity found in the results, the counties that have reached good coordination (e.g., Kenli, Lijin, Zhanhua, Changyi, Laizhou) should focus on consolidating ecological advantages, developing high-value characteristic and eco-tourism agriculture, and preventing high-pollution industries from encroaching on wetlands. The counties that remain at intermediate coordination should prioritize cultivating characteristic agriculture, expanding appropriate-scale operations, and improving connectivity. Because green transformation, saline-alkali rehabilitation, and scale operations require upfront investment and land-transfer coordination and may entail short-term output costs, these measures should be phased in by pairing near-term subsidies and efficient technology transfer with long-term ecological benefits instead of being pursued through industrial expansion at the expense of agriculture. This differentiated, staged approach improves feasibility and balances development with conservation.

(3) Several additional limitations should be acknowledged. First, the conventional coupling degree approaches unity when two subsystems develop in tandem, which compresses its discriminating power. Because C remains within 0.986–0.993 and D is driven mainly by T, C is interpreted as interaction strength rather than coordination quality, and a re-estimation using the modified coupling formula of Wang et al. [85] is warranted. Second, the spatial analysis originally relied on the inverse-distance weight matrix.

The model has now been re-estimated using k-nearest-neighbor (k = 3 and k = 4) and distance-threshold contiguity matrices, with the core results remaining stable across these specifications. Global Moran I computed for each year was positive throughout the study period and increased over time. Lagrange multiplier (LM) tests on the non-spatial residuals reject the null hypothesis of no spatial dependence. Given the limited number of cross-sectional units (19), local LISA inference may have limited statistical power and reliable LISA cluster maps would require additional geographic data. An economic-distance weight matrix and alternative distance-decay functions remain directions for future work [85].

Third, the baseline model included individual fixed effects but not time fixed effects, owing to the short panel and the collinearity between year effects and the spatially lagged terms. A two-way fixed-effects specification has now been estimated as a robustness check: the core direct effects retain their signs and significance, while the year dummies absorb the common upward trend and the residual rho is no longer significant in this short panel. A spatial-HAC specification with a longer panel remains a direction for future work. Fourth, although the VIFs (1.22–3.42) and the CRITIC aggregation indicate no severe multicollinearity, additional robustness checks have now been completed. The index has been reconstructed using entropy and equal weighting, and the core findings remain consistent across the three weighting schemes. In addition, leave-one-county and leave-one-year analyses together with Cook's distance and DFBETA diagnostics confirm that no single county or year drives the results. Reconstructing the index after excluding specific indicators, condition-number diagnostics for the spatially lagged terms, bootstrap confidence intervals for the decomposed effects, and theoretically justified nonlinear specifications remain directions for future work.

Fifth, missing data were imputed for only a few county–year cells, and the fiscal-support and road-density variables are coarse proxies. The final estimation sample is complete with no missing values, so no observations need to be dropped. The functional form sensitivity of the road proxy has been examined using its level rather than its logarithm, showing a weak positive effect that is much smaller than that of scale operations and is consistent with the directionally ambiguous hypothesis H6. Finer measures, such as fiscal expenditure targeting, road quality and connectivity, and high-standard farmland coverage, remain directions for future work. Finally, ecological and economic processes cross administrative boundaries and county aggregates conceal within-county heterogeneity. Because the individual fixed effects control only time-invariant factors, they cannot address contemporaneous reverse causality. Higher-D counties may themselves be better placed to promote urbanization, scale operations, and modernization or to attract fiscal support, nor can they remove time-varying institutional and socioeconomic confounders that remain in the error term. These issues mean the SDM-FE estimates should be read as statistical associations rather than causal effects, and the underlying mechanisms (technology diffusion, labor migration, market integration, and pollution transfer) should be tested through dynamic or quasi-experimental designs. These extensions are priorities for future research.

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Abbreviations

The following abbreviations are used in this manuscript:

CCD	Coupling Coordination Degree
CRITIC	Criteria Importance Through Intercriteria Correlation
DEA	Data Envelopment Analysis
FE	Fixed Effects
GDP	Gross Domestic Product
LR	Likelihood Ratio
OECD	Organization for Economic Co-operation and Development
SAR	Spatial Autoregressive Model
SBM	Slacks-Based Measure
SDM	Spatial Durbin Model
SDM-FE	Spatial Durbin Model with Fixed Effects
SEM	Spatial Error Model
STIRPAT	Stochastic Impacts by Regression on Population, Affluence, and Technology
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIF	Variance Inflation Factor
YRD	Yellow River Delta

Appendix A. Indicator Definitions, Normalization, and Formulas

Appendix A.1. Range Normalization

All raw indicators are normalized to the interval $[0, 1]$ using pooled range normalization across the full sample, with the extrema computed on the pooled county–year panel (19 counties × 10 years) and the same fixed transformation applied to each year. For a positive indicator (a larger value is better), where x_{ij} is the raw value, the normalized value is:

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}$$

For a negative indicator (a larger value is worse), the normalized value is:

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)}$$

Appendix A.2. CRITIC Weighting

Consistent with the CRITIC weighting method in Section 4.2.1, the standard deviation of each normalized indicator is:

$$S_j = \sqrt{\frac{\sum_{i=1}^{m}\left(x'_{ij} - \overline{x}'_j\right)^2}{m-1}}$$

the correlation coefficient between indicators i and j is:

$$R_{ij} = \frac{cov\left(x'_i, x'_j\right)}{S_i S_j}$$

the information content of indicator j is:

$$E_j = S_j \sum_{i=1}^{n} \left(1 - R_{ij}\right)$$

and the CRITIC weight, normalized within the ecological and economic subsystems separately, is:

$$W_i = \frac{E_j}{\sum_{j=1}^{n} E_j}$$

Appendix A.3. Entropy Weighting (Alternative Scheme)

For normalized indicator j, let p_{ij} be the proportion of observations i:

$$p_{ij} = \frac{x'_{ij}}{\sum_i x'_{ij}}$$

The information entropy is:

$$e_j = -\frac{1}{lnn} \sum_i p_{ij} ln\left(p_{ij}\right)$$

where $p_{ij} ln(p_{ij})$ is treated as zero when $p_{ij} = 0$. The difference coefficient is:

$$d_j = 1 - e_j$$

and the entropy weight, normalized within each subsystem, is:

$$w_j = \frac{d_j}{\sum_{\mathrm{j}} d_{\mathrm{j}}}$$

Appendix A.4. Coupling Coordination Degree

Let U_1 and U_2 be the ecological and economic subsystem scores. The coupling degree is:

$$C = \frac{2\sqrt{U_1 \times U_2}}{U_1 + U_2}$$

the comprehensive development index is:

$$T = aU_1 + bU_2, \qquad a = b = 0.5$$

and the coupling coordination degree is:

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

Appendix A.5. Indicator Units and Directional Assignments

Symbol	Indicator	Unit	Direction
apf	Intensity of agricultural plastic film use	t/hm^2	Negative
cfa	Intensity of fertilizer application	t/hm^2	Negative
pai	Intensity of pesticide application	t/hm^2	Negative

Symbol	Indicator	Unit	Direction
awp	Proportion of total agricultural water consumption	%	Negative
lpd	Livestock breeding density	heads/hm^2	Negative
amf	Agricultural machinery diesel consumption	t/kW	Negative
aap	Proportion of aquaculture area	%	Negative
fcr	Forest coverage rate	%	Positive
csp	Proportion of cultivated land area	%	Negative
map	Proportion of wetland area	%	Positive
wba	Proportion of water area	%	Positive
eip	Proportion of effective irrigation area	%	Positive
dfs	Proportion of drought-resistant cultivated land	%	Positive
pgo	Grain output per capita	t/person	Positive
pao	Aquatic product output per capita	t/person	Positive
pmo	Meat output per capita	t/person	Positive
rpd	Rural residents' disposable income per capita	yuan/person	Positive
alor	Agricultural land output rate	yuan/hm^2	Positive
alp	Agricultural labor productivity	10,000 yuan/person	Positive
gyp	Grain yield per unit area	t/hm^2	Positive
ayp	Aquatic product yield per unit water area	t/hm^2	Positive

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