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Unveiling the Dynamics of Rural Revitalization: From Disorder to Harmony in China's Production-Life-Ecology Space

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Abstract: This study utilizes provincial panel data from China spanning the period from 2011 to 2020 to assess the coupled and coordinated development of spatial functions related to production, life, and ecology (PLE) in rural areas. The assessment is based on quantifying the spatial function indices for PLE in China's rural regions. Additionally, it examines the characteristics of their spatial and temporal evolution, spatial correlation, and driving factors. The findings indicate a modest upward trend in the spatial coupling and coordination levels of these functions across rural China, although a significant proportion of provinces still exhibit a near-disordered decline. Exploratory spatial data analysis reveals a geographical disparity, with higher levels of coupled and coordinated development observed in the eastern regions, lower levels in the west, and noticeable spatial clustering. By employing the spatial Durbin model to investigate the determinants of coupling degrees, we discovered that factors such as regional economic development, urbanization, the urban–rural income gap, financial support for agriculture, science and technology investment level, and agricultural structural adjustments significantly influence the spatial coupling of rural PLE functions. Furthermore, using the geographic detector model, the analysis identifies science and technology investment level, economic development, and financial support for agriculture as key drivers influencing the spatial coupling and coordination of these functions. These findings provide valuable reference points for policies and strategies related to rural management.

Keywords: rural management; production-life-ecology space; coupling coordination; spatial and temporal evolution; spatial Durbin model; geographical detector model

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1. Introduction

Rural spaces constitute the economic and ecological territories upon which rural inhabitants rely, serving as the primary arena for fostering synergies between villages and towns. The impetus of rapid urbanization has led to urban encroachment on extensive rural areas, altering agricultural landscapes. This encroachment not only exacerbates rural ecological degradation, but also hinders the progress of rural livelihoods and productive capacities [1,2]. In reshaping rural socio-economic structures, rural spatial development faces challenges such as diminished agricultural efficiency, countryside depopulation, and ecological deterioration. These challenges necessitate an expedited transformation of rural areas to reconfigure rural spaces. Drawing from China's experience in rural development, addressing the economic, social, and environmental issues stemming from these changes is achievable through land consolidation and redefining rural spatial patterns.

Rural spatial reconstruction involves the optimization and adjustment of production–life–ecology (PLE) spaces in rural areas [3]. The "sansheng" space concept (production–life–ecology space, PLES) introduced by China delineates PLES as the three primary rural components, categorized based on land's functional attributes [4]. The evolution of PLES is influenced by factors such as ecological environment, natural disasters, and biodiversity [5,6]. As the concept of sustainable development shifts from a global idea to local action, how to adjust the scientific layout of PLES to adapt to complex ecological environment changes and meet the increasing material needs of local residents has become a focus for global researchers [7–10].

Currently, China is in the midst of rapid urbanization, and the rural development strategy has gone through four stages: rural reconstruction, rural construction, rural reform, and rural revitalization [11–13]. Despite remarkable achievements, this process has also brought about a series of problems [14]. These include, for example, shrinking space for rural development, escalating conflicts among production, living, and ecological spaces, rural environmental pollution and ecological degradation, and extensive utilization of natural resources [15–19]. These issues pose significant challenges to the realization of the rural revitalization strategy, demanding urgent solutions from the perspective of PLES.

However, the scientific connotation of PLES has been vague for a long time, especially during the process of spatial planning transformation, leading to controversies in PLES practices [20]. With the influx of interdisciplinary thinking, comprehensive research on territorial spatial planning has been promoted, bringing new scientific perspectives and practical approaches to PLES. The earliest involvement of the PLE concept was in spatial planning research [21,22]. In spatial planning, the development scale of urban areas and land expansion should not exceed certain limits and boundaries [8]. It is essential to ensure that rural agricultural land meets the needs of local residents, as safeguarding agricultural land is crucial for agricultural economic development [23,24]. Due to the demand for rational urban spatial planning, the development and research of PLES have been effectively promoted [25,26].

Traditional spatial planning has long been guided by socio-economic development and population growth, proposing ideal planning blueprints for spatial layout, structure, and form [27,28]. These spaces are interdependent, interactive, and mutually influential [25]. The intrinsic relationship of PLES manifests as an interlocking pattern of interaction among production, living, and ecological spaces, with production and living spaces embedded in ecological space through coverage, inclusion, and intersection [29,30]. Changes in ecological and living spaces correspond to the development of productivity. Living space, as the main venue for residents' activities, is the space for residents to achieve their own goals, with production and ecological spaces serving it [31]. Ecological space is the foundation of production and living spaces, playing an important role in carrying and constraining. Only with orderly development within certain resource and environmental carrying capacities can PLES be sustainable [32,33].

Achieving sustainable PLES necessitates harmonizing the involved functions, as a singular focus on one aspect neglects the inherent interconnectedness and reciprocal dynamics within the system [34]. Thus, a holistic and systemic approach is crucial for the coordinated and integrated development of these spaces, emphasizing the need for regional spatial function alignment.

Contemporary scholarly discourse on the interplay between spatial functions and their coordination encompasses a range of aspects, including the identification of spatial functions, spatial classification and evaluation, as well as the analysis of spatial and temporal evolution and spatial optimization and reconstruction [35–37]. These studies predominantly adopt a macro-level perspective, focusing on entities such as entire countries [38], provinces [39], cities [40], urban agglomerations [41], and ecologically sensitive areas [42]. With the growing recognition of the need to harmonize PLES, researchers from diverse fields are increasingly applying multidisciplinary approaches. This has led to the development of a spatial function evaluation index system, employing methods like the entropy weight method and the analytic hierarchy process to assess PLES [43], and utilizing the coupling coordination degree (CCD) model to investigate the interplay among these spatial functions [44]. Furthermore, classification of functional spatial types is based on their coupling coordination levels (CCL) [45]. To analyze spatial–temporal evolution in PLES, techniques like land use transfer matrices [46], gravity center models [42], and landscape indices [36] are employed. Spatial correlation analyses [47] and the Theil index [48] help in understanding regional geospatial correlations and disparities. Additionally, the geographical detector model [49], geographically weighted regression [50], and grey correlation analysis [4] have been instrumental in identifying drivers of spatial differentiation and developing optimization strategies.

In examining the impact of various quantitative methods on the sustainable and harmonious development of rural areas, numerous studies have focused on factors such as regional urbanization levels, the urban–rural income disparity, financial expenditure intensity, and agricultural structural adjustments [51–54]. The interplay between urban and rural dynamics significantly influences agricultural production scale and rural living conditions. During urbanization, an escalating urban–rural income divide impedes agricultural productivity improvements [55]. A pronounced income gap prompts rural population migration to urban areas, offering greater development prospects and higher wages. This migration results in an agricultural labor shortfall, adversely affecting rural sustainability and diminishing development incentives [56]. Conversely, directing financial resources towards rural areas facilitates the inflow of capital and technology, supporting a balanced resource allocation between urban and rural zones. This enhances overall agricultural productivity, boosts rural incomes, improves infrastructure, and fosters rural social programs. Specifically, government financial aid for agriculture and rural regions, along with local scientific and technological support, involves regional financial resource distribution. Transferring these resources to rural areas incentivizes agri-environmental regulation and bolsters the agricultural sector financially [57]. Moreover, regional financial backing promotes a green agricultural development model, encouraging learning and exchanges with neighboring areas, thereby offering policy and technical insights [58]. This approach creates a spatial spillover effect. Beyond financial and technological aid, the reconfiguration of regional agricultural industries significantly impacts rural sustainability. Optimizing agricultural industry structures benefits regional agriculture by fully leveraging local resources and strengths, thereby overcoming regional limitations, to achieve sustainable development [59].

This study elucidates the interplay between PLE spatial functions, offering insights for the quantitative assessment of these functions in rural areas and identifying their driving factors. Despite advances, existing research lacks comprehensive understanding of rural spatial function correlations, their dynamic evolution, and geographical differentiation. To address these gaps, our study employs CCD analysis, exploratory spatial data analysis, spatial panel metrology, and geographical detection. These methods aim to deepen our understanding of rural spatial function coordination and its role in sustainable rural development. It is crucial to examine the interconnections and mutual constraints among PLE spatial functions to fully grasp their relationships, coordination, spatial–temporal variability, and geographical correlations. This research constructs an indicator system for rural PLE spatial functions to measure and evaluate their CCD. It also analyzes their spatial evolution, correlations, and driving factors. Focusing on regional spatial integrity, the study encompasses 30 provinces in China, spanning from 2011 to 2020. The findings will contribute to optimizing the spatial arrangement of PLE functions in rural areas, thereby fostering sustainable agricultural and rural development.

2. Materials and Methods

2.1. Study Area

This research selected 30 provinces (excluding Tibet, Hong Kong, Macau, and Taiwan), because they collectively reflect the main economic, social, cultural, and ecological characteristics of China. The data from these provinces had good coherence and comparability. These provinces feature diverse geographical environments, ranging from the plains along the eastern coast to the plateaus and mountainous areas in the west. For example, the North China Plain is a major grain-producing area in China, while the middle and lower reaches of the Yangtze River region are the most economically active areas. This diversity in terrain directly influences land use patterns, which in turn shapes different production spatial structures. Additionally, these provinces have a variety of climate types, from the temperate monsoon climate in the north to the subtropical and tropical monsoon climates in the south. This diversity fosters varied agricultural practices and ecosystems, making it significant for studying production and ecological spaces.

Furthermore, as shown in Figure 1, the village density in eastern and central China is high, especially in places like Hunan, Hubei, and Anhui, where the map shows deep yellow and red colors, indicating high village density. In contrast, western areas like Xinjiang, Qinghai, and Gansu have a lower density, depicted in light green. The level of village density is often closely related to agricultural activities. High-density areas may reflect concentrated agricultural production or diversified rural economic activities, which helps us understand the layout of agricultural production spaces. Village density is also an important indicator of residential patterns and the condition of social services facilities. Areas with relatively lower density might possess more natural geographical features and ecological value, which is crucial for comparing production, living, and ecological spaces, assessing the condition of the ecological environment, and understanding the pressures an area faces. Thus, studying these 30 provinces effectively reveals the regional relationships and conflicts between resource utilization and ecological balance.

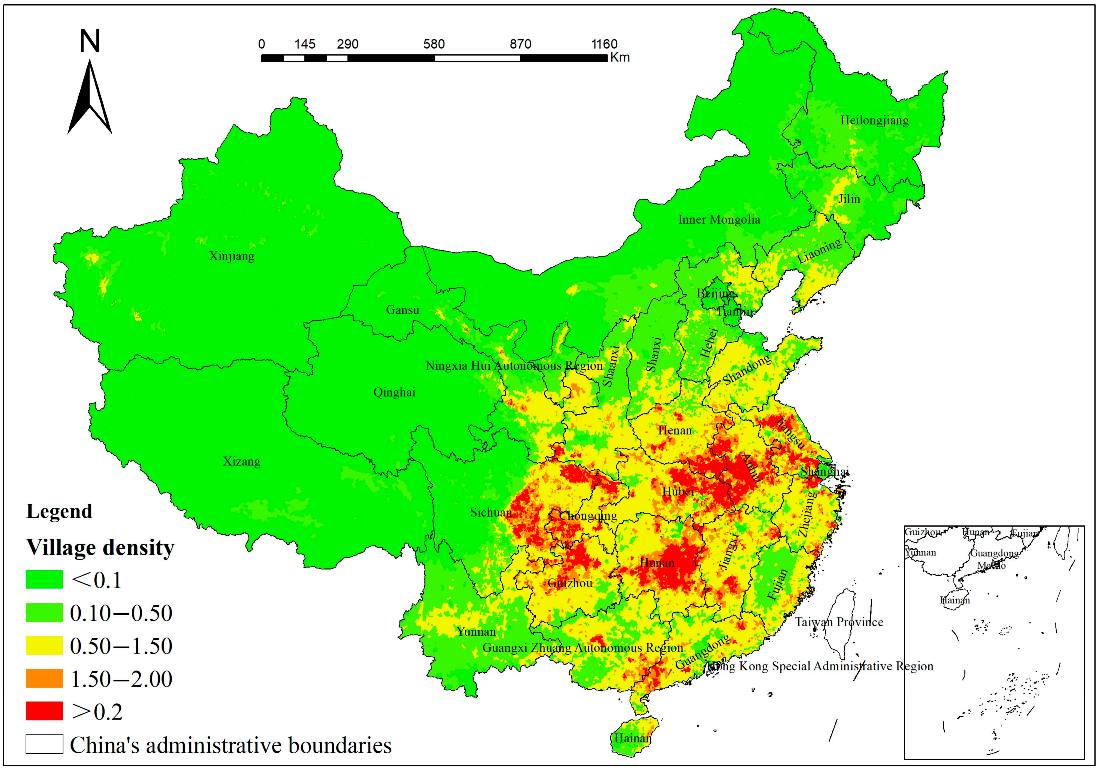


Figure 1. Study area and basic characteristics of the countryside.

2.2. Data Source

This paper focused on 30 provinces in mainland China, excluding Tibet, Hong Kong, Macao, and Taiwan due to substantial data gaps in these regions. Covering the period from 2011 to 2020, this research predominantly sourced its data from editions of the China Statistical Yearbook, China Rural Statistical Yearbook, China Social Statistical Yearbook, China Urban-Rural Construction Statistical Yearbook, and China Population and Employment Statistical Yearbook spanning from 2012 to 2021. Additionally, wetland area information was obtained from the First and Second National Wetland Resource Surveys, while forest coverage rates were derived from the Ninth National Forest Inventory. These data were obtained from the official website of the National Bureau of Statistics of China "https://www.stats.gov.cn/english/ (accessed on 1 October 2023)". To maintain consistency and accuracy, revisions have been made to some data points, with historical data aligned to the standards of the most recent yearbooks.

2.3. Relevant Theories

2.3.1. Urban–Rural Integration Theory

Urban–rural integration theory underscores the interconnectedness and interdependence between urban and rural areas [60]. Its goal is to harmonize their development, bridging the urban–rural gap and fostering regional balance. This theory emphasizes the synergy of resources, industries, and policies to achieve overall and sustainable development. Amidst economic progress, urban–rural integration theory has emerged as a pivotal framework for managing urban–rural relations and guiding integrated development [61]. Its objective is to overcome disparities between economically developed cities and underdeveloped rural regions, fostering close integration and the harmonious development of their economic and social fabric [62]. Integrated urban–rural development aims to reconfigure production factors geographically to enhance farmers' income and wealth, fostering a mutually beneficial social structure. Rather than eradicating urban–rural disparities, it seeks to rationalize the division of regional ecological communities [63]. Rooted in sustainable development principles and spatial concepts, integrated urban–rural development strives for economic progress, societal and cultural harmony, and functional integration through rational geographical linkages [64].

2.3.2. Coupling Coordination Theory

The concept of "coupling" originates from physics, denoting the interaction degree among elements within a system, while "coordination" emphasizes cooperative synergy between independent systems [65]. Coupling coordination theory asserts that components within a system are interdependent and mutually influential [66,67]. Amidst rural spatial reconstruction, this theory stresses the need to harmonize production, living, and ecological spaces, ensuring balanced development and the mitigation of conflicts. Synergetic development, rooted in diversity and unity, aims for holistic and stable progress by balancing and uniting systems or elements [68]. Amidst China's economic and social transition, synergetic development theory is invaluable for promoting social harmony and productivity [69]. It leverages mutual influences and constraints among economic, population, and ecological elements to achieve parallel, cooperative, and mutually beneficial development goals [70].

2.3.3. Sustainable Development Theory

Sustainable development theory advocates for meeting present needs without compromising future generations' ability to meet their own needs [71]. Amidst rural spatial reconstruction, it underscores the importance of balancing economic development, social equity, and environmental preservation. Emphasizing long-term sustainability and resilience, it advocates for strategies that safeguard rural areas [72]. Globally, nations and organizations, including the United Nations, prioritize ecological and environmental concerns, highlighting the significance of sustainable development in urban planning [73]. Sustainable development theory is a cornerstone ideology pursued by China and many nations worldwide. Amidst profound international and domestic changes, achieving sustainable development is a key challenge [74]. It represents a holistic development perspective grounded in nature conservation and adaptation, showcasing China's leadership in global sustainable development concepts [75].

2.4. Research Methods

Figure 2 illustrates the key steps in assessing the coupling coordination degree and understanding the impact mechanisms. Firstly, a system of indicators for the production, living, and ecological spaces is established, and the data for these indicators are standardized. Then, using the entropy weight method, weights are assigned to each indicator, and a weighted comprehensive calculation is conducted to determine the scores of each subsystem. Secondly, the coupling coordination model is applied to calculate the level of coupling coordination among the subsystems. From a temporal and spatial evolution perspective, this model visually displays the differences in the coupling coordination levels across provinces and utilizes a spatial autocorrelation model to assess the spatial clustering of the coupling coordination levels within the study area. Thirdly, the spatial Durbin model, a Geodetector model, and correlation models are employed to explore the influence and correlation strength of dynamic factors on the coupling coordination levels of provinces in a spatial context.

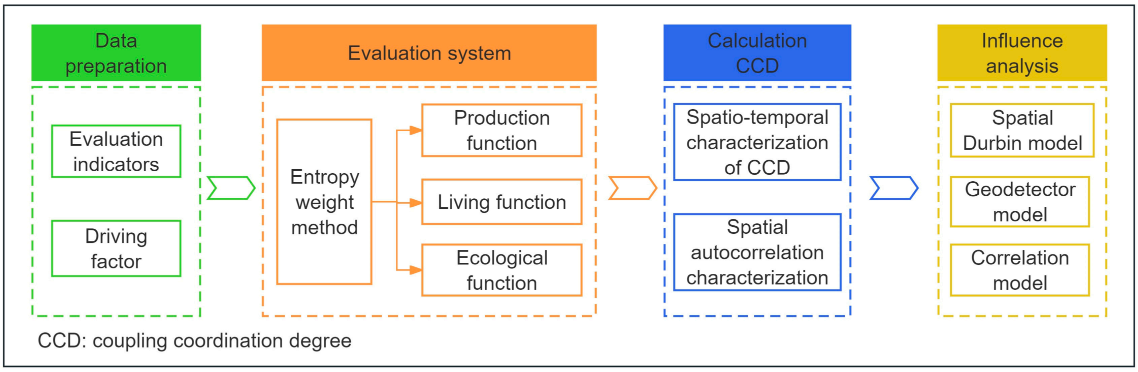


Figure 2. The process of applying methodologies.

2.4.1. Construction of Evaluation Index System

This paper, drawing on existing research and the spatial theory of territorial spatial planning, categorizes rural spatial functions into PLE functions [76,77]. It constructs a rural PLE spatial function evaluation index system based on scientific principles, representativeness, operability, continuity, and data availability. Building on prior work and the previous literature [43,47,78,79], the rural production space function is assessed through two dimensions, agricultural and non-agricultural production, encompassing eight sub-indicators [44]. The rural living space function is evaluated through two dimensions, livelihood and welfare security, incorporating five sub-indicators. Lastly, the rural ecological space function is measured in terms of ecological purification and conservation, comprising seven sub-indicators. The detailed structure of this index system is presented in Table 1.

Table 1. Rural PLES function evaluation index system.

Criteria	First Level Indicators	Basic Level Indicator	Calculation Method	Weight	Direction
Production function Index(P)	Agricultural production function	Per capita area sown with crops	Crop sown area/total rural population (hm^2/person)	0.139	+
		Per capita grain output	Total grain production/total rural population (tons/person)	0.220	+
		Average land grain yield	Total grain output/area sown with crops (tons/hm^2)	0.104	+
		Per capita agricultural output	Total agricultural output/total rural population (yuan/person)	0.104	+
		Per capita meat supply	Meat production/rural population (tons/person)	0.059	+
		Level of agricultural modernization	Total power of agricultural machinery/area sown with crops (kW/hm^2)	0.101	+
		Land reclamation rate	Crop sown area/total regional land area (%)	0.136	+
	Non-agricultural production function	Per capita total output value of agriculture, forestry, animal husbandry, and fishing services	Gross output value of agriculture, forestry, animal husbandry and fishery services/total rural population (yuan/person)	0.136	+

Table 1. *Cont.*

Criteria	First Level Indicators	Basic Level Indicator	Calculation Method	Weight	Direction
Living function index(L)	Basic living security function	Per capita rural disposable income	(Yuan)	0.274	+
		Rural Engel's coefficient	Rural residents' expenditure on food consumption/total household expenditure (%)	0.108	−
		Per capita housing area of rural residents	Total rural housing area/total rural population (square meters/person)	0.279	+
	Social welfare guarantee function	Proportion of rural school-age population receiving education	Rural educated population (number of students enrolled in primary and middle schools)/number of rural population (%)	0.257	+
		Proportion of rural population covered by the minimum subsistence allowance	Rural minimum subsistence guarantee population/number of rural population (10,000/million people)	0.082	−
Ecological function index I	Ecological purification function	The use intensity of diesel fuel	Diesel use/area sown under crops (tons/hectare)	0.022	−
		Fertilizer input intensity	Agricultural fertilizer application/area sown with crops (tons/hectare)	0.042	−
		Intensity of pesticide application	Total pesticide applications/area sown to crops (tons/hectare)	0.018	−
		Amount of agricultural plastic film used per unit area	Agricultural plastic film use/area sown with crops(tons/hectare)	0.021	−
	Ecological protection function	Forest coverage	(%)	0.137	+
		Area ratio of wetlands	Wetland area/total area of the region (%)	0.410	+
		Water Resources per capita	Cubic meters/person	0.350	+

2.4.2. Driving Factor Variable Setting

The literature review identified six variables as key drivers of the coupling and coordinated development of rural PLE spatial functions in China: economic development, urbanization degree, urban–rural income gap, financial support for agriculture, science and technology investment level, and agricultural structural restructuring [80–83]. The indicators representing these variables are detailed in Table 2. To mitigate heteroskedasticity, these variables were logarithmically transformed during the empirical analysis of this study.

Table 2. CCD power factor variable setting.

	Variable Name	Variable Operation
Explained variable	Coupling coordination degree (CCD)	Calculated based on the coupled coordination model
Explanatory variables	Economic development (ED)	GDP per capita (yuan)
	Urbanization degree (UD)	Share of urban population in total regional population (%)
	Urban-rural income gap (UIG)	Comparison of urban and rural residents' income levels (rural = 1)
	Financial support for agriculture (FSA)	Investment in agriculture, forestry and water affairs/total local fiscal expenditure (%)
	Science and technology investment level (STIL)	Science and technology expenditure/total fiscal expenditure (%)
	Agricultural structural restructuring (AR)	Area sown with food crops/area sown with crops (%)

2.4.3. Entropy Weight Method

Entropy weighting is a method of assigning weights based on the impact of each indicator's value changes on the overall system, calculated by the entropy value of the indicators, thus determining their weights [84]. According to the previous literature [85], this study calculates the index weights using the entropy method, which incorporates time-year variables, to leverage the applicability of panel data.

(1) Standardizing the raw data

Due to the dimensional discrepancies among various indices, standardization of the original data is essential prior to calculating the composite index. This paper employs the extremum method for the standardization of the original data.

$$\text{Positive indicators}: \ Y_{ijt} = \frac{x_{ijt} - min(x_j)}{max(x_j) - min(x_j)} + L \tag{1}$$

$$\text{Negative indicators}: \ Y_{ijt} = \frac{max(x_j) - x_{ijt}}{max(x_j) - min(x_j)} + L \tag{2}$$

In Equations (1) and (2), Y_{ijt} represents the standardized indicator data, while X_{ijt} denotes the unstandardized original data of the jth indicator for the ith province in the tth year. Furthermore, $\min(x_j)$ and $\max(x_j)$, respectively, signify the minimum and maximum values of the original data for the jth indicator across all provinces during the study period.

In order to prevent the existence of zero values in the standardized indicator data, which cannot be processed by the subsequent logarithmic processing, the calculated matrix is processed by translating L units, and to reduce the impact caused by the translation, this paper takes the value of L as 10^{-5}.

(2) Calculating the entropy value of the jth metric E_j.

$$E_j = -k\sum_{i=1}^{n}\sum_{i=1}^{r} P_{ijt} \ln(P_{ijt}) \tag{3}$$

$$P_{ijt} = \frac{Y_{ijt}}{\sum\limits_{i=1}^{n}\sum\limits_{t=i}^{r} Y_{ijt}} \tag{4}$$

The constant k is associated with the sample size of the system, at this time $k = \frac{1}{llnrn}$, when $P_{ijt} = 0$, so that $P_{ijt} \ln P_{ijt} = 0$, then $0 \leq E_j \leq 1$.

(3) Calculating the coefficient of variation in the jth indicator D_j.

$$D_j = -1 - E_j \tag{5}$$

(4) Calculating the weights w_j.

$$w_j = \frac{D_j}{\sum\limits_{j=1}^{m} D_j} \tag{6}$$

(5) The comprehensive index is calculated by sequentially weighting and summing the standardized data and the corresponding indicator weights to obtain the composite index for the rural PLE spatial functions of each province, city, and autonomous region.

$$Q_{itk} = \sum_{i=1}^{r} (Y_{ijt} W_j) \tag{7}$$

where Q_{itk} is the functional assessment value of subsystem k in the i province in year t.

2.4.4. Coupling Coordination Model

Referring to the previous literature [86–91], this paper employs classical and widely used coupled coordination models to calculate the CCD of rural PLE spatial functions across various regions, thereby illustrating the status of their interrelationships. To ensure that the coupling degree falls within the range of [0, 1], facilitating a scientific and effective analysis of the coordinated development of rural PLE spatial functions among Chinese provinces, a revised formula from [92] is utilized. The formula system for CCD is as follows:

$$C = \sqrt{\left[1 - \frac{\sqrt{(Q_3 - Q_1)^2} + \sqrt{(Q_2 - Q_1)^2} + \sqrt{(Q_3 - Q_2)^2}}{3}\right] \times \sqrt{\frac{Q_1}{Q_3} \times \frac{Q_2}{Q_3}}} \tag{8}$$

$$\begin{gathered} Q_1 = min\ \{Q_p,\ Q_l,\ Q_e\},\ Q_3 = max\{Q_p,\ Q_l,\ Q_e\} \\ T = \alpha Q_p + \beta\, Q_l + \gamma Q_e,\ \alpha + \beta + \gamma = 1 \end{gathered} \tag{9}$$

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

In this framework, Q_p, Q_l, and Q_e represent the comprehensive indices of regional rural production function, rural life function, and rural ecological function, respectively. C denotes the coupling degree, while T symbolizes the overall level of rural PLE spatial function. The weights of these indices, represented by α, β, and γ, are presumed to be of equal importance, with each assigned a value of 1/3, reflecting the balanced significance of rural PLE aspects [43]. D represents the CCD, which is categorized into ten distinct types based on its value (Table 3) [92,93].

Table 3. CCD classification criteria.

Interval of Coupling Degree	Interval of CCD	Level of Coordination
[0, 0.1)	[0, 0.1)	Extreme disorder decline
[0.1, 0.2)	[0.1, 0.2)	Severe disorder decline
[0.2, 0.3)	[0.2, 0.3)	Moderate disorder decline
[0.3, 0.4)	[0.3, 0.4)	Mild disorder decline
[0.4, 0.5)	[0.4, 0.5)	Near disorder decline
[0.5, 0.6)	[0.5, 0.6)	Barely coordinated development
[0.6, 0.7)	[0.6, 0.7)	Primary coordinated development
[0.7, 0.8)	[0.7, 0.8)	Intermediate coordinated development
[0.8, 0.9)	[0.8, 0.9)	Good coordinated development
[0.9, 1]	[0.9, 1]	High-quality coordinated development

2.4.5. Exploratory Spatial Data Analysis

(1) Global spatial autocorrelation

Spatial autocorrelation analysis is a technique that investigates the clustering and dispersion patterns of observations based on their spatial relationships [94]. This method can be broadly categorized into two types: global spatial autocorrelation, which assesses the spatial attributes of an entire study area, and local spatial autocorrelation, which focuses on identifying spatial clustering within specific localized regions [95–97].

Prior to conducting spatial autocorrelation analysis, it is essential to establish a spatial weight matrix. In this study, the matrix was constructed using Rook proximity, defined as follows:

$$w_{ij} = \begin{cases} 1,\ l_{ij} > 0 \\ 0,\ l_{ij} < 0 \end{cases} \tag{11}$$

where $i, j = 1, 2, \ldots 30$ is the space unit, l_{ij} is the boundary length, and w_{ij} is the positional relationship between space unit i and space unit j in space. When the boundary length is greater than 0, then it is considered that there is a common boundary between spatial unit i

and spatial unit *j*; at this time w_{ij}, takes the value of 1. When the boundary length is equal to 0, it is considered that there is no common boundary between spatial unit *i* and spatial unit *j*; at this time w_{ij}, takes the value of 0.

The global Moran′s I can be calculated as:

$$Moran's\ I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} z_i z_j}{\sum_{i=1}^{n} {z_i}^2} \tag{12}$$

where z_i represents the deviation of the observed value of variable Z in the spatial cell i from its mean value, w_{ij} refers to an element within the spatial weight matrix, n denotes the total number of spatial cells, and s_0 is the sum of all spatial weights. The $Moran's\ I$ statistic, which ranges between -1 and 1, serves as an indicator of spatial autocorrelation. A positive $Moran's\ I$ statistic signifies the presence of positive spatial autocorrelation, implying spatial aggregation, whereas a negative $Moran's\ I$ statistic indicates negative spatial autocorrelation, suggesting spatial dispersion [98].

(2) Local spatial autocorrelation

Local Morans I_i can be calculated as:

$$Local\ Moran's\ I_i = \frac{(-x_i - \overline{x})}{{S_i}^2} \sum_{j=1, i \neq j}^{n} \left(x_j - \overline{x}\right) \tag{13}$$

where x_i and x_j are the observations of the variable, $\overline{x}$ is the mean of the observations of the variable x, n denotes the total number of spatial cells, and s_0 is the sum of all spatial weights.

2.4.6. Spatial Durbin Model

The Spatial Durbin model effectively incorporates both the spatial lag of the dependent variable and the influence of the spatially lagged independent variables on the dependent variable [99,100]. Consequently, among prevalent spatial panel models, the Spatial Durbin model demonstrates enhanced stability and reliability [101]. The specific Spatial Durbin model formulated in this study is as follows:

$$\begin{aligned} D_{it} = \alpha + \rho w_{ij} D_{it} &+ \beta_1 lnED_{it} + \beta_2 lnUD_{it} + \beta_3 lnUIG_{it} + \beta_4 lnFSA_{it} \\ &+ \beta_5 lnSTIL_{it} + \beta_6 lnAR_{it} + \delta_1 w_{ij} lnED_{it} + \delta_2 w_{ij} lnUD_{it} \\ &+ \delta_3 w_{ij} lnUIG_{it} + \delta_4 w_{ij} lnFSA_{it} + \delta_5 w_{ij} lnSTIL_{it} \\ &+ \delta_6 w_{ij} lnAR_{it} + \mu_i + V_t + \varepsilon_{it} \end{aligned} \tag{14}$$

where D_{it} is the CCD of the spatial functions of rural PLE of the explained variables, ρ is the spatial autocorrelation coefficient, β is the regression coefficient, δ is the coefficient of the spatial lag term, μ_i denotes the spatial effect, V_t denotes the temporal effect, and ε_{it} is the random perturbation term.

2.4.7. Geodetector Model

Spatial heterogeneity is ubiquitous across various geographical phenomena, and Geodetector models are spatial analysis methods used extensively to detect spatial differentiation and reveal the driving forces behind it. They are widely employed for conducting driving force analysis and factor analysis [101–103]. Geodetector contains four detectors: divergence and factor detection, interaction detection, ecological detection, and risk detection. Factor detection aims to detect the spatial variability of Y and how much a factor X explains the spatial variability of attribute Y, measured by the q-value. Interaction detection can identify the strength of the effect on the dependent variable when different factors interact with each other [93,104]. The model is as follows:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h-1}^{L} N_h \sigma_h^2 \quad (15)$$

In this context, q symbolizes the effect that a particular factor has on the coupling and coordination of rural spatial functions. The variable h denotes the level of stratification for factor x, and N_h and N correspond to the count of units in stratum h and across the entire region, respectively. Meanwhile, σ_h^2 and σ^2 signify the variance in y-value for both stratum h and the region as a whole. The value of q falls within the [0, 1] range, where a higher q value suggests a stronger explanatory capacity of factor x regarding the y attribute, and a lower value implies a weaker explanatory strength.

3. Results and Discussion

3.1. Evolutionary Characteristics of Rural PLE Spatial Functions

This study employed the entropy method to weight and calculate the spatial function indices for rural PLE. We analyzed the composite index of these spatial functions in rural China from 2011 to 2020, with the findings illustrated in Figure 3. Regarding rural production, the average spatial functionality index across China increased from 0.214 in 2011 to 0.318 in 2020, marking a 48.60% rise. For rural living, the composite index for the spatial function of rural living areas escalated from 0.329 in 2011 to 0.425 in 2020, a growth of 29.18%. Overall, both the rural living and production spatial function indices exhibited a consistent upward trend during this period. In contrast, the rural ecological spatial function index showed more stable development, ranging from 0.214 to 0.245 over the decade, and remained lower compared to the indices for rural production and living spatial functions.

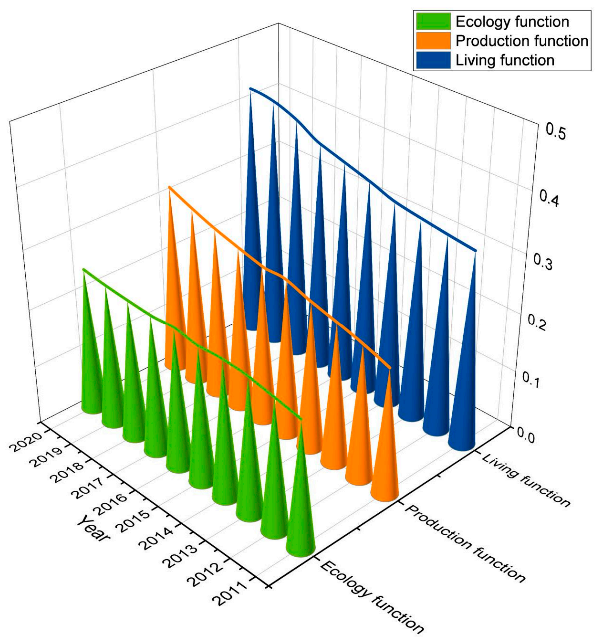


Figure 3. Changes in China's rural PLE spatial function index, 2011–2020.

Figure 4 presents the indices for rural PLE spatial functions across 30 Chinese provinces (including municipalities and autonomous regions) in 2011 and 2020. An analysis of these indices for 2011 and 2020 reveals a general upward trend in rural PLE spatial functions across the eastern, central, and western regions of China. Notably, the indices for rural living in the eastern region and rural production in the central region exhibited more substantial increases. This comparative evaluation of the rural PLE spatial function indices enables the categorization of the study area into three distinct types: production-priority, living-priority, and ecological-priority areas. Based on the degree of the three spatial function indices for each region, as seen in Figure 2, it is clear that the study area has the highest proportion of regions that prioritize living functions. The production-prioritized regions are Liaoning, Shandong, and Jilin in the eastern region, and Heilongjiang and the Inner Mongolia Autonomous Region in the central region. Among the production-prioritized regions, Jilin Province and Heilongjiang Province show significant rural production function advantages.

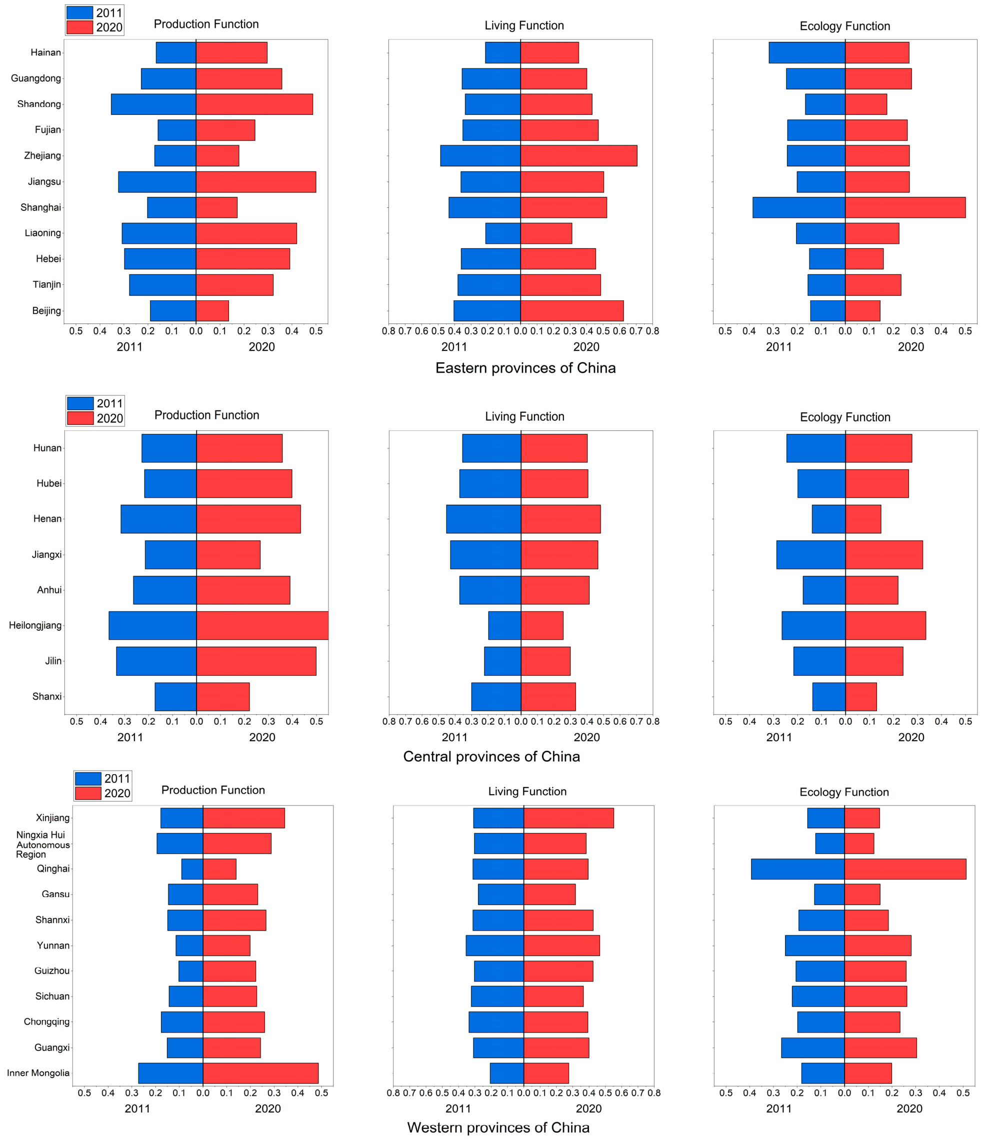


Figure 4. Rural PLE spatial function index of each province in 2011 and 2020.

3.2. Evolutionary Characteristics of the CCD

This paper employs a coupled coordination model to calculate the CCD of rural PLE spatial functions in 30 Chinese provinces (including municipalities and autonomous regions), with the results presented in Table 4 and Figure 5. We used the mean value of each province's CCD to analyze the temporal development trend in China from 2011 to 2020. During this period, the CCD of rural PLE in China exhibited an overall upward trend. Regionally, the eastern and central regions consistently outperformed the western region in terms of coupled coordination, with a noticeable lead. Specifically, in 2011, the average values of coupled coordination in the eastern, central, and western regions were 0.438, 0.437, and 0.391, respectively, and in 2020, these values were 0.444, 0.493, and 0.450. Despite this upward trajectory, the average CCD across China remained within the 0.40–0.50 range, indicating a state of near disorder decline. Spatially, provinces where the coupling of rural PLE functions has achieved a level of minimal coordinated development are predominantly in the eastern and central regions, while the western region is generally characterized by disorderly decline. There are certain spatial clustering features in the regions that have initially reached the coordination level, such as in the Shanghai and Jiangsu provinces in the east, and the Anhui, Jiangxi, and Hunan and Hubei provinces in the central region, all with spatial proximity features (Figure 6). This spatial agglomeration feature demonstrates the spatial aggregation of high CCL and low CCL. On the time scale, the spatial CCD of rural PLE functions in the eastern, central, and western regions of China has changed relatively little. From 2011 to 2020, the CCL of Beijing, Tianjin, Hebei, Liaoning, Zhejiang, Fujian, and Shandong in the eastern region, Henan, Heilongjiang, Jilin, and Shanxi in the central region, and Chongqing, Guangxi, and Inner Mongolia in the western region did not change. Of these areas, Beijing and Shanxi have always been at the level of mild disorder decline, and the other regions have always been at a level of near disorder decline. After 2013, the eastern regions of Shanghai, Jiangsu, and Guangdong and the central regions of Hubei, Hunan, Jiangxi, and Anhui gradually developed into a barely coordinated development class, thus reducing the proportion of provinces in the two regions in the dislocated recession category. In 2020, all western provinces were in the near disorder decline class.

Table 4. Functional CCD of rural PLES in China's provinces.

Place	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Beijing	0.378	0.373	0.368	0.364	0.367	0.355	0.350	0.347	0.363	0.343
Tianjin	0.430	0.432	0.467	0.471	0.473	0.473	0.472	0.470	0.477	0.487
Hebei	0.437	0.444	0.446	0.453	0.457	0.449	0.449	0.454	0.460	0.471
Liaoning	0.437	0.446	0.451	0.466	0.467	0.478	0.475	0.489	0.490	0.486
Shanghai	0.500	0.499	0.527	0.530	0.520	0.511	0.510	0.506	0.508	0.511
Jiangsu	0.484	0.486	0.528	0.536	0.548	0.552	0.555	0.557	0.561	0.575
Zhejiang	0.416	0.431	0.426	0.431	0.431	0.425	0.417	0.417	0.424	0.415
Fujian	0.417	0.440	0.445	0.454	0.460	0.478	0.455	0.456	0.474	0.469
Shandong	0.467	0.467	0.463	0.478	0.485	0.488	0.486	0.491	0.495	0.494
Guangdong	0.415	0.427	0.432	0.431	0.436	0.438	0.432	0.436	0.415	0.427
Hainan	0.412	0.431	0.442	0.454	0.470	0.489	0.512	0.523	0.507	0.514
Average value	0.438	0.444	0.455	0.461	0.464	0.465	0.460	0.462	0.438	0.444
Shanxi	0.371	0.378	0.379	0.388	0.387	0.373	0.370	0.374	0.377	0.389
Jilin	0.448	0.453	0.460	0.457	0.458	0.467	0.466	0.480	0.480	0.480
Heilongjiang	0.453	0.460	0.468	0.476	0.475	0.475	0.481	0.486	0.499	0.482
Anhui	0.438	0.450	0.462	0.479	0.489	0.498	0.488	0.494	0.493	0.517
Jiangxi	0.467	0.498	0.461	0.474	0.487	0.494	0.490	0.483	0.505	0.509
Henan	0.427	0.430	0.439	0.449	0.455	0.452	0.456	0.461	0.466	0.476
Hubei	0.430	0.443	0.461	0.476	0.488	0.502	0.513	0.510	0.510	0.550
Hunan	0.464	0.488	0.481	0.496	0.504	0.512	0.512	0.508	0.528	0.541
Average value	0.437	0.450	0.451	0.462	0.468	0.472	0.472	0.475	0.482	0.493
Inner Mongolia	0.424	0.424	0.450	0.430	0.438	0.436	0.436	0.445	0.447	0.447
Guangxi	0.429	0.452	0.458	0.468	0.480	0.475	0.483	0.476	0.486	0.496
Chongqing	0.408	0.409	0.419	0.435	0.435	0.449	0.451	0.452	0.454	0.471
Sichuan	0.399	0.415	0.420	0.430	0.432	0.437	0.446	0.457	0.457	0.471
Guizhou	0.362	0.390	0.388	0.422	0.432	0.434	0.443	0.441	0.452	0.461
Yunnan	0.389	0.403	0.414	0.424	0.431	0.439	0.446	0.443	0.433	0.452
Shaanxi	0.389	0.395	0.403	0.411	0.416	0.413	0.421	0.426	0.441	0.440
Gansu	0.350	0.362	0.376	0.383	0.389	0.370	0.379	0.391	0.395	0.410
Qinghai	0.393	0.393	0.405	0.398	0.412	0.406	0.416	0.433	0.452	0.453
Ningxia	0.372	0.378	0.383	0.390	0.397	0.388	0.393	0.405	0.404	0.412
Xinjiang	0.386	0.397	0.418	0.409	0.430	0.436	0.435	0.430	0.434	0.437
Average value	0.391	0.402	0.412	0.418	0.426	0.426	0.432	0.436	0.441	0.450

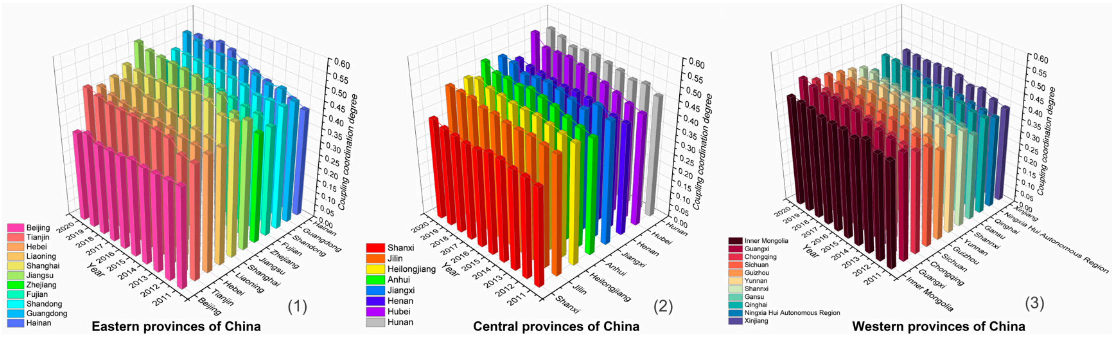


Figure 5. Comparison of the functional CCD of rural PLES by province in China, 2011–2020.

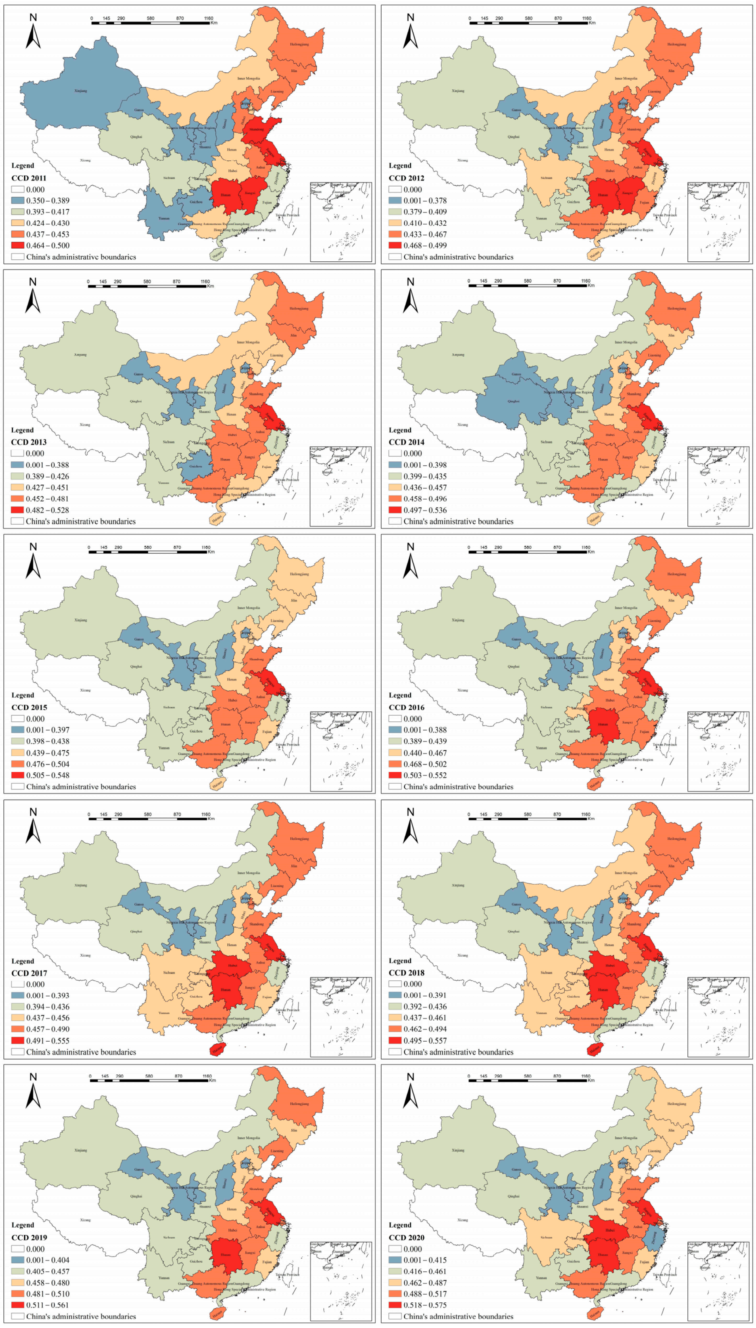


Figure 6. Comparison of spatial characteristics of PLES functional CCD in rural China by province, 2011–2020.

3.3. Exploratory Spatial Data Analysis

3.3.1. Analysis of the Moran's I of Coupled Coordination

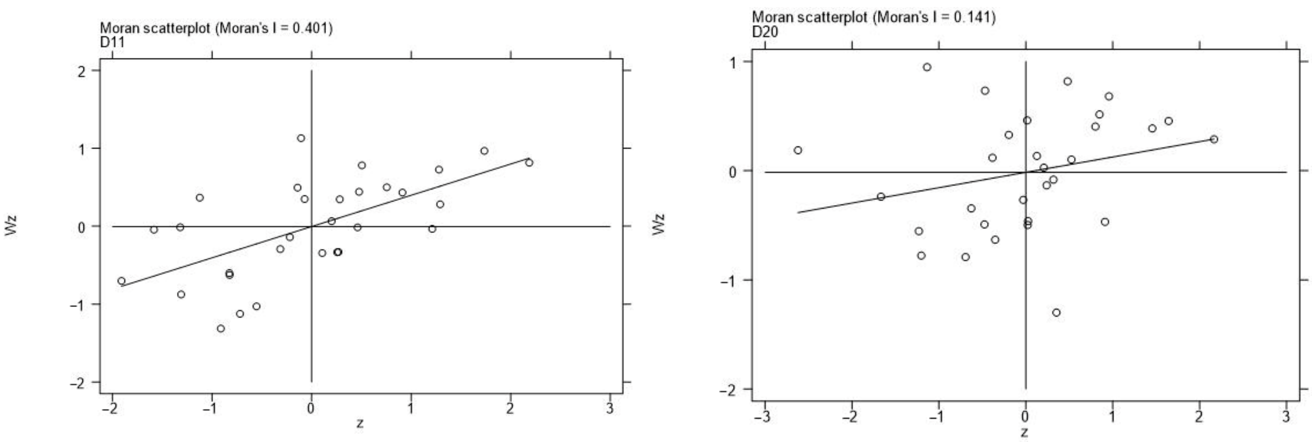
In examining the spatial characteristics of the CCL across eastern, central, and western China, we discovered a pronounced spatial aggregation of these levels. Utilizing the Moran index, we delved into the spatial aggregation traits of the rural PLE CCL. The global autocorrelation results, presented in Table 5, reveal significant spatial functional CCD within rural PLE at the 1% level from 2011 to 2016, and at the 5% level from 2016 to 2020. This suggests a marked positive spatial correlation in the coordination of rural PLE spatial functions. Notably, the global Moran index and its significance level exhibited a downward trend from 2011 to 2020. Despite the declining trend in spatial correlation significance, the positive spatial relationship in the coordination of rural PLE coupling underscores the necessity of employing spatial measurement analytical methods to investigate the factors influencing its development.

Table 5. Moran's I of the functional CCD of PLES in rural China, 2011–2020.

Year	Moran's I	Z	*p*-Value
2011	0.358	3.519	0.000
2012	0.382	3.722	0.000
2013	0.264	2.700	0.007
2014	0.320	3.200	0.001
2015	0.310	3.111	0.002
2016	0.314	3.139	0.002
2017	0.234	2.430	0.015
2018	0.185	1.997	0.046
2019	0.197	2.092	0.036
2020	0.181	1.968	0.049

3.3.2. Local Spatial Autocorrelation Analysis of CCD

We have analyzed the general spatial correlation characteristics of the study area above, and in this section, we describe the spatial aggregation in localized areas. We drew a local Moran's I scatter plot to analyze the local spatial aggregation characteristics of the spatial functional coupling and coordinated development of rural PLE. Figure 7 shows that the coupled coordination of rural PLE in China has obvious spatial aggregation, and the 30 provinces (municipalities and autonomous regions) studied are mainly concentrated in the first and third quadrants. This indicates that the coupled and coordinated development of regional rural spatial functions in China shows obvious H–H aggregation and L–L aggregation phenomena, and there is obvious heterogeneity among the provinces.



(**a**) Moran scatterplot for 2011 (**b**) Moran scatterplot for 2020

Figure 7. Moran scatter plot of the CCD of rural PLE spatial functions.

To further explore local spatial clustering in the coordination levels of PLE in rural China between 2011 and 2020, a z-value test at the LISA significance level was applied. The findings, detailed in Table 6, reveal a notable geographical disparity: high–high (H–H) clustering is predominantly found in the eastern and central regions, while low–low (L–L) clustering is prevalent in the west. This indicates a marked imbalance in the coordination of PLE spatial functions across rural China. In conclusion, the development of PLE in rural China exhibits significant spatial correlations, with clear patterns of spatial aggregation.

Table 6. Results of LISA significance z-value test.

Year	H–H	L–H	L–L	H–L
2011	Shanghai ***, Jiangsu ***, Shandong **	not present	Sichuan **, Shaanxi **, Gansu ***, Qinghai *, Ningxia **, Xinjiang **	not present
2012	Shanghai **, Jiangsu ***, Anhui *, Jiangxi ***, Shandong *	not present	Shaanxi **, Gansu ***, Qinghai **, Ningxia ***, Xinjiang **	not present
2013	Shanghai ***, Jiangsu ***	not present	Sichuan *, Shaanxi **, Gansu ***, Qinghai *, Ningxia **	not present
2014	Shanghai ***, Jiangsu ***, Anhui **, Shandong *	not present	Shaanxi **, Gansu ***, Qinghai **, Ningxia ***, Xinjiang **	not present
2015	Shanghai ***, Jiangsu ***, Anhui **, Shandong **	Zhejiang *	Shaanxi **, Gansu ***, Qinghai **, Ningxia **	not present
2016	Shanghai *, Jiangsu ***, Anhui **, Jiangxi *	Zhejiang **	Shanxi *, Shaanxi **, Gansu ***, Qinghai **, Ningxia ***	not present
2017	Shanghai *, Jiangsu **, Anhui *	Zhejiang **	Shaanxi *, Gansu ***, Ningxia	not present
2018	Jiangsu **, Anhui *, Shandong *	Zhejiang **	Gansu ***, Ningxia **	not present
2019	Jiangsu **, Anhui *	Zhejiang **	Gansu ***, Ningxia **	not present
2020	Jiangsu *, Anhui ***, Hubie **, Hunan **	Zhejiang ***	Gansu **, Ningxia **	not present

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

3.4. Analysis of the Driving Mechanism of the CCD

3.4.1. Spatial Econometric Model Identification and Testing

Spatial correlation analysis indicated significant correlation in the integrated development of PLE spatial functions in rural China, necessitating the selection of an appropriate spatial panel model for further investigation. Initially, the Lagrange multiplier (LM) test for spatial model selection was utilized to ascertain the suitability of either a spatial error or lag model, with results presented in Table 7. Both the LM test and robustness checks for the spatial error model and spatial lag model were significant at the 1% level, refuting the null hypothesis of no spatial lag or error term.

Table 7. Results of spatial econometric model tests.

Test Item	Statistical Value	*p*-Value
Moran's I	3.283	0.001
LM-spatial error	9.072	0.003
Robust LM-spatial error	9.067	0.003
LM-spatial lag	24.094	0.000
Robust LM-spatial lag	24.089	0.000
LR-Spatial-lag	49.41	0.000
LR-Spatial-error	43.98	0.000
Wald-spatial-lag	34.79	0.000
Wald-Spatial-error	34.26	0.000

Subsequently, the LR likelihood ratio test and Wald test were employed to evaluate if the spatial Durbin model (SDM) could be simplified to a spatial error model (SEM) or spatial lag model (SLM). The LR tests for spatial lag and error in the rural PLE function coordination registered values of 49.41 and 43.98, respectively, significant at the 1% level. Similarly, Wald test results yielded spatial lag and error values of 34.79 and 34.26, respectively, also significant at this level. These outcomes collectively dismiss the initial assumption that the SDM can be reduced to either SLM or SEM, underscoring the need for employing the SDM in analyzing influencing factors.

Lastly, the choice between random effects and fixed effects models was guided by the Hausman test results, which favored the fixed effects model with a confidence level of 1% (23.24, $p = 0.0007$). Subsequent analysis entailed comparing empirical results from spatial fixed effect, time fixed effect, and dual fixed effect models to ascertain the most representative model for the actual situation.

Table 8 shows the results of model estimation for spatial fixed, time fixed, and double fixed models based on the adjacency matrix, respectively. We compared the R2 values and log-likelihood estimating function values of the estimation results of each model, and found that the spatial fixed-effects model had the highest goodness-of-fit, while the LR test results for judging which fixed-effects model to use also showed that choosing the spatial fixed-effects Durbin model would be appropriate. Since the use of spatial lag terms to describe the spatial interaction effects may lead to erroneous conclusions, we further decomposed the direct, spillover, and total effects of each variable on the CCD of rural PLE in order to analyze the interaction information contained in the model.

Table 8. Analysis of spatial econometric models.

Variable	Spatial Fixed Effects	Time Fixed Effects	Double Fixed Effects
lnED	0.077 ***	−0.016	0.072 ***
	(0.016)	(0.013)	(0.017)
lnUD	0.100 ***	0.020	0.121 ***
	(0.025)	(0.029)	(0.025)
lnUIG	−0.012	−0.168 ***	0.003
	(0.018)	(0.017)	(0.019)
lnFSA	−0.010	0.009	−0.016 **
	(0.007)	(0.010)	(0.008)
lnAR	0.055 ***	0.043 ***	0.047 ***
	(0.016)	(0.013)	(0.016)
lnSTIL	−0.008 **	−0.007	−0.008 **
	(0.004)	(0.005)	(0.004)
lnED*W	−0.020	−0.071 **	−0.030
	(0.020)	(0.029)	(0.035)
lnUD*W	−0.198 ***	−0.007	−0.155 ***
	(0.047)	(0.050)	(0.051)
lnUIG*W	−0.082 ***	−0.007	−0.034
	(0.029)	(0.039)	(0.040)
lnFSA*W	0.044 ***	0.090 ***	0.023 *
	(0.012)	(0.018)	(0.014)
lnAR*W	−0.126 ***	−0.080 ***	−0.154 ***
	(0.031)	(0.023)	(0.035)
lnSTIL*W	0.019 ***	0.087 ***	0.015 **
	(0.006)	(0.012)	(0.007)
rho	0.144 *	0.188 **	0.093
	(0.080)	(0.082)	(0.087)
Sigma2	0.000 ***	0.001 ***	0.000 ***
	(0.000)	(0.000)	(0.000)
R2	0.722	0.101	0.699
Log-L	960.468	651.884	967.703

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

3.4.2. Analysis of Impact Effects

Table 9 displays the estimation outcomes of the spatial Durbin decomposition model, elucidating the driving factors behind the coordinated development of rural PLE spatial function coupling. The direct and total effects of regional ED on PLE spatial function coupling were significantly positive, whereas the indirect effects were not significant. This implies that an increase in per capita GDP positively influences PLE coupling and coordination. The direct, indirect, and total effects of UD on PLE spatial function coupling all showed statistical significance. Specifically, the direct effect was positively significant, whereas both the indirect and total effects were negatively significant. This suggests that UD positively influences the development of rural PLE spatial function coupling, yet it has a negative impact on neighboring regions. The indirect and total effects of the UIG on PLE spatial function coupling were significantly negative, indicating that an increasing gap hinders the coordinated and sustainable development of rural areas, with discernible spatial spillover effects. Finally, while the direct effect of FSA on PLE spatial function coupling was not significant, the indirect and total effects were positively significant, suggesting that local FSA fosters the coordinated and sustainable development of rural areas in neighboring regions, rather than locally.

Table 9. Utility decomposition of the Spatial Durbin Model (SDM).

Variable	Direct Effect	Indirect Effect	Total Effect
Economic Development (lnED)	0.077 *** (0.016)	−0.010 (0.024)	0.067 *** (0.017)
Urbanization degree (lnUD)	0.091 *** (0.020)	−0.213 *** (0.056)	−0.121 ** (0.055)
Urban-rural income gap (lnUIG)	−0.014 (0.019)	−0.099 *** (0.031)	−0.113 *** (0.027)
Financial support for agriculture (lnFSA)	−0.007 (0.008)	0.050 *** (0.015)	0.043 ** (0.018)
Agricultural structural restructuring (lnAR)	0.049 *** (0.017)	−0.134 *** (0.039)	−0.085 ** (0.038)
Science and technology investment level (lnSTIL)	−0.007 ** (0.003)	0.020 *** (0.007)	0.013 * (0.008)

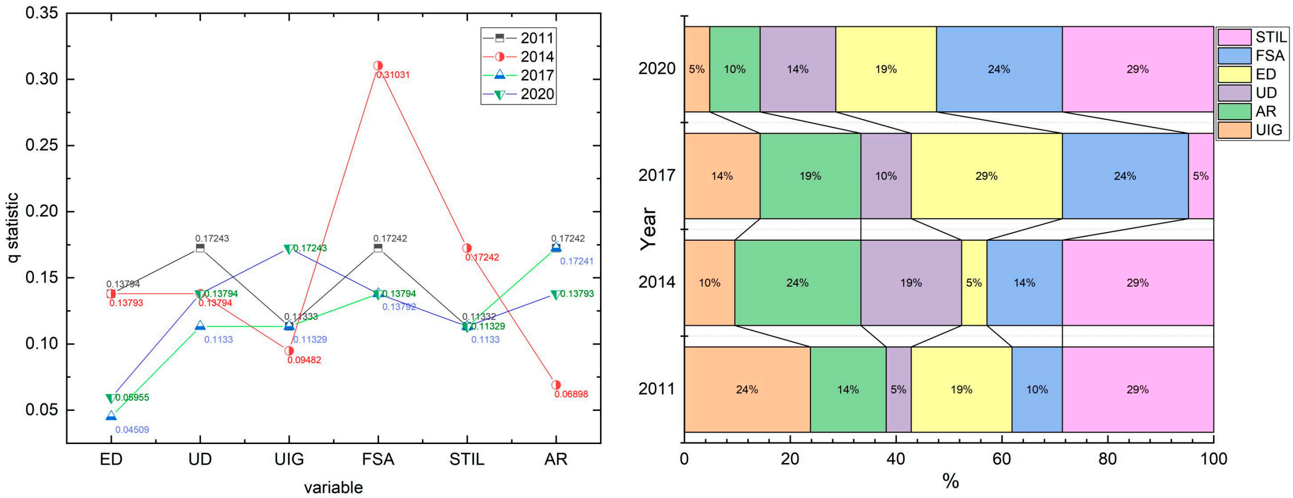
Note: ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.

The direct, indirect, and total effects of AR on the coordination and coupling of rural PLE spatial functions were all statistically significant. Specifically, the direct effect was positively significant, whereas the indirect and total effects were negatively significant. This implies that AR in the region positively influences the development of rural PLE spatial function coupling and coordination.

The direct effect of the STIL on the coupling and coordinated development of rural PLE spatial functions within the region was significantly negative at the 5% level. In contrast, its indirect effect was significantly positive at the 1% level, and the total effect was also significantly positive at the 10% level. This suggests that STIL exerts a mixed influence on the region's rural PLE function coordination.

3.4.3. Factorial and Interaction Detection of Perturbing Factors

The factor detection analysis, utilizing a geographical detector (as illustrated in Figure 8a,b), revealed that six perturbation factors, ED, UD, UIG, FSA, STIL, and AR, significantly influenced the spatial coupling coordination of PLE in China's rural areas. The impact magnitude of these factors varied across different years of the study. Notably, STIL emerged as the most influential, underscoring the critical role of science and technology inputs in rural development. Modern scientific and technological advancements enhance agricultural efficiency, minimize resource waste, and improve product quality, thereby elevating the living standards of rural residents. This has been corroborated by the literature, such as in Ma et al. (2022a) [105], which highlighted the Chinese government's efforts to foster scientific and technological innovation in rural areas, enhancing rural economy sustainability. Consequently, the level of STIL is vital for the coordinated development of rural PLE functions. ED and FSA followed in importance, indicating the ongoing significance of economic development and agricultural financial support. ED enhances rural economic opportunities and resident income levels, affecting the coordination of PLE functions. Agricultural financial support policies contribute to infrastructure development and improved social security systems in rural areas, offering increased support and security for residents, as evidenced by research [106,107]. In contrast, UD exhibited the lowest disturbance capacity, potentially due to urbanization-related issues like resource loss and labor outflow in rural areas. Urbanization alters the socio-economic structure of rural areas, potentially negatively impacting the coordination of rural PLE functions. Some studies, like Jiang et al. (2022) and Zhang et al. (2019), have suggested that the impact of urbanization's on rural areas is not universally positive, accounting for its relatively low impact [108,109].



(**a**) Factor detection results for each influencing factor during the study period. (**b**) Weighting of factor detection results for each influencing factor during the study period.

Figure 8. Results for each influencing factor.

In addition, the six perturbation factors were subjected to interaction detection, and the results are shown in Figure 9. Overall, most of the interactions between the factors showed nonlinear enhancement, and some of the interactions between the factors showed bifactorial enhancement, such as the highest influence of the interactions between FSA and STIL, and between AR and UIG, which were both 0.5; second were UD and UIG, FSA and UIG, and STIL and FSA, all with an influence of 0.333; third were UD and FSA, UD and STIL, and ED and AR, all with an influence of 0.25; and lastly, the interaction between UD and FSA had the lowest influence, at 0.2.

3.4.4. Relevance Analysis

Correlation analysis was conducted to assess the relationship between various impact factors and the CCD for the years 2011, 2014, 2017, and 2020, utilizing Origin 2021, as depicted in Figure 10. The findings revealed that the CCD had a significant negative correlation with UIG and FSA, and a significant positive correlation with UD and STIL.

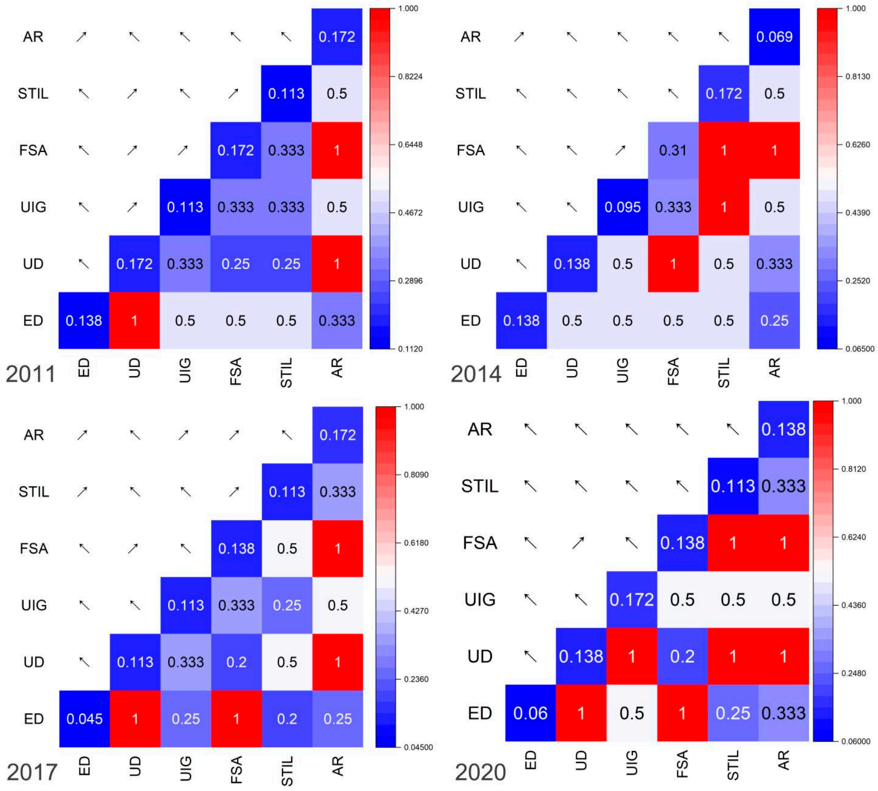


Figure 9. Interaction detection results during the study period (↖ denotes a nonlinear enhancement relationship, while ↗ represents a two-factor enhancement relationship).

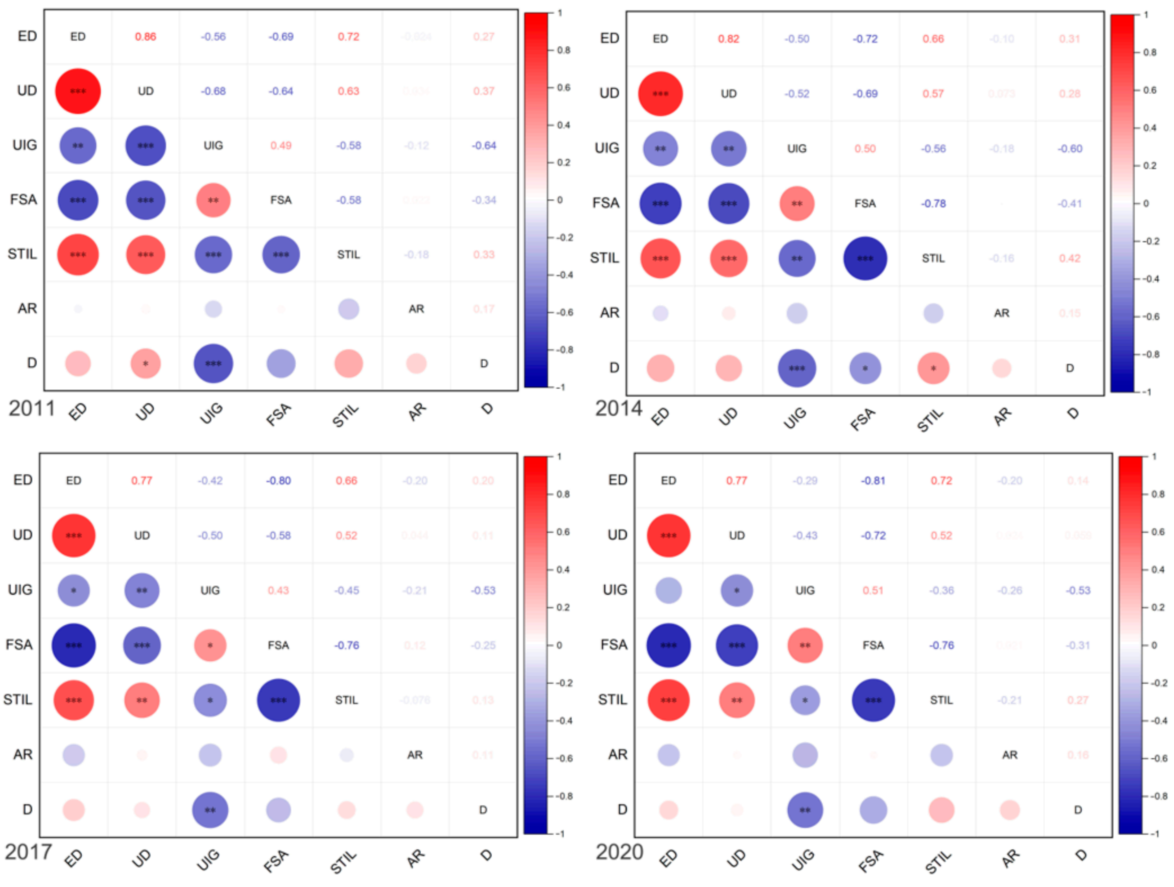


Figure 10. Correlation results. Note: * $p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$.

Among them, UIG had significant correlation with the CCD in all four study years, and the correlation was the highest, with absolute values of correlation coefficients of 0.64, 0.60, 0.53, and 0.53, respectively. This may be due to the unequal distribution of resources caused by the large income gap, and the relatively low level of infrastructure construction and social security in rural areas, which may have a negative impact on the coordination of the spatial functions of PLE in rural areas. This is similar to existing studies that have shown that income inequality may lead to poverty in rural areas, limiting economic development and resource flows [110,111].

The level of science and technology inputs had a significant positive correlation with coupling coordination only in 2014, with an absolute correlation coefficient of 0.42. The reason for this may be that science and technology inputs can improve the efficiency of agricultural production and the vitality of the rural economy, which in turn improves the spatial functioning of rural PLE. Some studies have shown that science and technology innovation and inputs can improve agricultural production in rural areas and promote economic development and sustainable rural development [112–114].

FSA had a significant negative correlation with coupling coordination only in 2014, with an absolute correlation coefficient of 0.41. This may be due to the fact that certain rural support policies are not sufficiently refined, leading to wasteful or irrational allocation of resources, which is not conducive to the coordination of rural PLE spatial functions. Some studies have pointed out that irrational rural policy implementation may lead to resource waste and inefficiency [111].

In 2011, UD exhibited a significant positive correlation with the spatial coordination of PLE functions in rural China, reflected by an absolute value of 0.37. This correlation can be attributed to the potential improvements in infrastructure and social services in rural areas brought about by UD, which in turn may enhance the coordination of PLE spatial functions. Supporting this notion, research (e.g., Liu et al. (2010)) has indicated that the urbanization process may lead to enhanced infrastructure and social services in rural areas, thereby improving the quality of life for rural residents [115].

4. Discussion

4.1. Discussion of the Findings

This study first demonstrates the situation of the coordinated development of rural spatial functions in China, based on objective data. Overall, the degree of coordination of PLE spatial function coupling in China is generally on an upward trend. However, the PLE spatial function coupling coordination degree shows a spatial differentiation in which coordination is higher in the East than in the West. This regional difference may be related to the fact that the eastern region has excellent agricultural resource endowment, while the western region has poor agricultural resource endowment, insufficient natural conditions, and a fragile ecological environment [57]. However, in addition to natural and ecological conditions, it is still worth exploring which factors influence the coordinated development of rural spatial functions, which is the key to identifying factors that promote coordinated and sustainable rural development.

The coupled coordination of production–life–ecological spatial functional relationships in rural China has an aggregation effect. Therefore, spatial effects need to be considered when analyzing the influencing factors affecting the coordinated development of rural spatial functions. This study used a spatial fixed-effects Durbin model and a Geodetector model to explore the direct and spatial spillover effects of the influencing factors on the coupled coordination of rural production-life-ecology spatial functions. It was found that the degree of spatial coordination of rural production–life–ecology functions in China is influenced by regional economic development, urban–rural income disparity, the level of scientific and technological inputs, and agricultural structural adjustment, among other factors. Regional expenditure on financial support for agriculture and science and technology inputs has a positive spillover effect on the development of the coupled spatial coordination of rural production–life–ecology functions. Financial support for agriculture and scientific and technological inputs involves the distribution of regional financial resources, and the transfer of financial resources to rural areas provides financial support for the agricultural sector, and at the same time, regulates the agro-environment in an incentive manner [57]. The flow of financial resources to rural areas can guide the flow of capital and technological factors to rural areas, which provides factor support for the achievement of a balanced allocation of resources between urban and rural areas, the enhancement of comprehensive agricultural productivity, an increase in the incomes of rural inhabitants, improvements in rural infrastructure, and the development of social services in rural areas. The spatial spillover effect of financial support for agriculture lies in the fact that financial support in the region is conducive to the creation of a regional green agricultural development model, attracting learning and exchanges from neighboring regions, which provides policy references as well as technical guidance for neighboring regions [58]. Agricultural structural adjustment has promoted the coordinated development of the spatial coupling of production, living, and ecological functions in rural areas in the region. Optimizing the structure of the agricultural industry is conducive to the development of the region's agriculture, making full use of the region's resources and advantages, and thus breaking through regional constraints to achieve sustainable development [59]. Regional economic development and agricultural restructuring have a negative spatial spillover effect on the coupled and coordinated development of rural production–life–ecological spatial functions. This phenomenon may be explained by the fact that local development attracts population inflows from neighboring regions, and human capital is a key factor in the socio-economic development of rural areas and the development of agricultural functions [116,117]. As a result, possible population movements reduce the ability of neighboring areas to develop in a coordinated manner. The urban–rural income gap has a negative impact on the coupled coordination of regional rural production–living–ecological spatial functions. The urban–rural income gap inhibits agricultural productivity gains. The wider income gap between urban and rural areas results in rural populations moving to urban areas, where development opportunities and labor remuneration are higher, and the resulting shortage of agricultural labor factors is detrimental to the sustainable development of rural areas, leading to a lack of incentives for rural development [105].

Globally, rural areas often face socio-economic vulnerabilities [118], regional poverty [119], inadequate infrastructure [120], land degradation [121], destruction of rural landscapes [122], and food insecurity resulting from the conversion of agricultural land [123]. Uneven rural development has become a global problem [124], and how to promote rural sustainability has become a hot topic of multidisciplinary concern. In China, rural production–living–ecological space is the carrier of rural land resource planning and management [125], and the coordinated development of rural space and rural spatial reconstruction constitute an important means through which to promote China's rural revitalization strategy [126]. China is currently adopting a series of policy measures to promote rural spatial structuring and sustainable development, such as the pilot project of "linking the increase of urban construction land to the decrease of rural construction land", which is aimed at restructuring the economic, spatial, and social structures of the pilot areas, thereby accelerating the restructuring of the countryside [127], and improving the economic development of rural areas by means of a policy for precise poverty alleviation [128]. As the largest developing country in the world, China has the largest rural population. Therefore, China's experience in promoting sustainable rural development based on a rural spatial perspective is of great relevance to countries with similar rural development characteristics and problems.

4.2. Study Contribution

This study, while focused on China's rural PLE spatial functions, provides insights that are valuable on a global scale. The entropy method applied here, coupled with spatial Durbin and geographic detector models, can serve as a methodological framework for other nations with similar rural challenges. Such tools are crucial for assessing the spatial coordination of environmental, production, and living functions in rural areas globally. The identification of high–high and low–low clusters in rural functional coupling and coordination offers a template for regional planning in diverse geopolitical contexts. These findings resonate with international efforts to enhance rural sustainability and echo priorities set by global entities such as the United Nations Sustainable Development Goals, particularly those related to sustainable cities and communities (Goal 11) and life on land (Goal 15).

The results of this study are of immense benefit to multiple stakeholders, including policymakers, regional planners, and environmental agencies. By understanding the drivers of rural PLE function coordination, these stakeholders can tailor their strategies to maximize ecological protection and sustainable rural development. The insights can also aid international development organizations in formulating aid strategies that prioritize ecological balance and sustainable rural infrastructure. In addition, this research facilitates informed decision-making by providing a clear picture of the spatial distribution of rural functions and their interdependencies. For instance, understanding the negative impacts of uncoordinated urbanization (UD) and unequal intergovernmental arrangements (UIG) on rural development can help policymakers formulate corrective measures. Similarly, the positive spillover effects of farm size adjustments (FSA) and technological innovation in local industries (STIL) highlight leverage points for enhancing rural productivity and sustainability.

4.3. Limitations and Future Research

The study offers significant insights into the spatial coordination of rural PLE functions in China. However, its singular focus on one nation restricts the direct global applicability of its findings. Future research should aim to broaden the scope by applying this framework to diverse national contexts to assess its universal relevance. Moreover, exploring the nonlinear interactions among the factors influencing rural development is crucial to achieve a comprehensive understanding of their intricate dynamics. Comparative analyses spanning various countries could then elucidate fundamental principles of rural development and functional coordination, building upon the findings of this study. Additionally, deeper exploration into the roles of technological innovation and policy frameworks in bolstering rural sustainability is warranted. Future studies can also enhance the assessment by expanding the scope of indicators to encompass a broader range of factors, such as natural reserves, rural settlements, and rural infrastructure.

5. Conclusions

The findings of this study indicate that: (1) China's rural areas have experienced modest growth in spatial production and living functions, alongside a slightly fluctuating increase in ecological functions, with noticeable disparities in their development; (2) The overall trend in the coupled coordination of PLE spatial functions between 2011 and 2020 has been upward, reflecting gradual improvements. However, the proportion of provinces achieving balanced development in PLE functions remains low, and a spatial divide exists, with higher coordination in the East compared to the West; (3) There are pronounced high–high and low–low clusters in the regional rural spatial functional coupling and coordination, along with significant inter-provincial heterogeneity; (4) Factors such as ED, UD, UIG, FSA, STIL, and AR influence the coordination of rural PLE spatial function coupling. UD, UIG, and AR negatively impact this coordination, whereas FSA and STIL have positive spillover effects; (5) The influence of these factors on the coordination of rural PLE functions varies significantly, with STIL having the strongest impact and UD the lowest. Furthermore, most factors exhibit nonlinear interactions, enhancing their collective effects.

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Abbreviations

CCD: coupling and coordination degree; CCL: coupling and coordination level; PLE: production, life, and ecology; PLES: production, life, and ecology space.

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