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EDITED BY
Tingting Bai,
Yangzhou University, China

REVIEWED BY
Xinqiang Chen,
Shanghai Maritime University, China
Cai Chaoyue,
Nankai University, China

*CORRESPONDENCE
Guoping Tian
✉ 20230065@huat.edu.cn
Xilin Zhang
✉ 18905442878@163.com

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# Coupling coordination between agricultural circular economy development and rural tourism development in China

Guangmin Yu[1], Yueling Yang[2], Suhao Fu[3], Yan Zhang[4], Huahua Chen[5], Guoping Tian[5]* and Xilin Zhang[1]*

[1]Shandong Huayu University of Technology, Dezhou, China, [2]University of Liège, Gembloux, Belgium, [3]South China Agricultural University, Guangzhou, China, [4]Guangzhou College of Technology and Business, Guangzhou, China, [5]Hubei University of Automotive Technology, Shiyan, China

The coordinated development of the agricultural circular economy and rural tourism provides an important pathway for transforming rural ecological advantages, strengthening industrial resilience, and advancing rural revitalization. The agricultural circular economy improves resource-use efficiency and environmental quality, whereas rural tourism expands the channels through which rural ecology, culture, and agricultural products can realize economic value. Based on balanced panel data for 30 Chinese provinces, autonomous regions, and municipalities from 2011 to 2022, this study constructs two composite indicator systems and applies the entropy weight method and the coupling coordination model to examine their coordinated evolution. Province-level spatial visualizations, Global Moran's I, Getis-Ord Gi* hot-spot analysis, convergence diagnostics, and obstacle-factor diagnostics are used as supporting empirical tests. The results show that: (1) the agricultural circular economy index increased steadily, and the regional pattern gradually shifted from eastern leadership to catch-up in the central and western regions; (2) rural tourism development followed a phased path of growth, short-term shock, and recovery, indicating both market vitality and external vulnerability; (3) the two systems maintained a high coupling degree, but the coupling coordination value provided clearer discrimination of development quality, increasing significantly over time (annual trend coefficient = 0.0139, $p < 0.001$) and showing beta convergence across provinces (coefficient = −0.368, $p < 0.001$); (4) global Moran's I remained positive and significant under 999 permutation tests, and the Getis-Ord Gi* statistics further identified stable eastern hot spots and northwestern cold spots, suggesting weak global association but meaningful local clustering; and (5) output per unit of land, fertilizer output efficiency, agricultural value added, machinery output efficiency, and domestic tourist arrivals were the main obstacle factors. These findings indicate that policy should treat agricultural circular transformation and rural tourism as interdependent rural subsystems, prioritizing ecological value conversion, efficiency upgrading, tourism recovery, eastern spillovers, and targeted support for northwestern cold-spot regions.

KEYWORDS

**agricultural circular economy, China, convergence, coupling coordination, entropy weight method, Getis-Ord Gi*, hot-spot analysis, obstacle diagnosis**

# 1 Introduction

The agricultural circular economy refers to an agricultural development model that reduces resource inputs, reuses production factors and waste resources, and recycles biomass and environmental capacity within agricultural production and rural ecological systems. Its core objective is to transform agricultural production from a linear input-output-pollution pattern into a closed-loop, efficiency-oriented system. In China, this transformation is particularly important because agricultural production still faces pressures from chemical input intensity, resource consumption, non-point source pollution, and carbon emissions. Improving circularity in agriculture can therefore strengthen ecological security while providing a more stable foundation for rural industrial upgrading (Mihai, 2023; Cahyadi et al., 2024; Peng et al., 2025b).

Rural tourism increasingly depends on the overall quality of rural space. Rural landscapes, ecological environments, local culture, public services, rural lifestyles, and agricultural experiences together shape the attractiveness of rural destinations. Agricultural tourism is one product form within this broader tourism system, whereas rural tourism also includes cultural, ecological, leisure, and service-oriented activities rooted in rural places. In this study, the agricultural circular economy represents the production-side green transformation of agriculture, while rural tourism captures the demand-side and service-side development of rural space. Their relationship is important because ecological improvement in agriculture can enhance destination attractiveness and product quality, while tourism demand can create market incentives for greener agricultural products and circular production practices (Ma et al., 2024; Turtureanu et al., 2025; Liu et al., 2023).

The key issue is therefore not only whether agricultural circular transformation and rural tourism are connected, but also whether their development levels and rhythms become mutually supportive. Strong interaction may coexist with uneven subsystem development. Coupling degree captures association intensity, whereas coupling coordination evaluates matched development and structural compatibility. This framework helps identify whether ecological improvement, tourism demand, and rural industrial upgrading form a coordinated trajectory (Liu et al., 2025a; Yang et al., 2025; Wang et al., 2024c; Liu et al., 2024a).

The mechanisms driving agriculture-tourism integration have also attracted increasing attention. On the one hand, cross-sector coordination between agriculture and tourism can create value through resource sharing, joint branding, and industrial-chain extension (Paunić et al., 2025). On the other hand, the integration of ecological farms and rural tourism can strengthen green development and support the accumulation of rural social capital (Xiao et al., 2025). More broadly, the integrated development of agriculture, culture, and tourism shows clear spatial differentiation, suggesting that regional resource endowments and policy environments strongly affect coupling coordination levels.

Against this background, this study examines how the agricultural circular economy and rural tourism evolved in China during 2011–2022, how their coordination changed over time, and which spatial patterns and structural constraints shaped that process. Compared with studies that examine circular agriculture or rural tourism separately, this study places the two subsystems within the same rural transformation process. Its contribution is to show how ecological improvement, tourism demand, public services, and production efficiency jointly shape the coordinated development of rural systems. More specifically, existing studies have not sufficiently distinguished the intensity of interaction between agricultural circular transformation and rural tourism from the quality of their coordinated development, nor have they jointly examined spatial association, convergence, and obstacle factors within a single empirical framework.

# 2 Literature review and theoretical foundations

## 2.1 Agricultural circular economy and agricultural circular transformation

As the global green transition advances and carbon-neutrality targets are gradually incorporated into national development strategies, the circular economy has moved from a policy idea to institutional practice. It has become an important response to resource and environmental constraints. In light of rising resource consumption and tightening ecological capacity, scholars generally argue that the circular economy can improve resource-use efficiency and reduce environmental burdens by restructuring material flows and extending product value chains (Geissdoerfer et al., 2017). Once this concept enters policy implementation and industrial operation, however, a more fundamental question emerges: does the circular economy merely improve the efficiency of existing production systems, or can it drive substantive changes in economic structure and development patterns?

Some studies analyze this issue mainly at the firm and industry levels. They emphasize the performance gains generated by resource recycling, technological upgrading, and lower emission intensity, and they suggest that circular transformation progresses as resource productivity improves. Other scholars take a broader view. They argue that without institutional change and cross-sector coordination, technical optimization alone cannot break the logic of linear growth (Kirchherr et al., 2017). In other words, the debate is not whether circular measures are effective, but how far their effects reach and at what level they operate. Do they improve a single system, or do they reconstruct relationships among subsystems? When circularity is examined at a broader scale, evaluation criteria cannot remain limited to internal sectoral efficiency.

This disagreement is also reflected in methodology. Material flow analysis (MFA), life-cycle assessment (LCA), and eco-efficiency indicator systems are widely used to measure circular economy performance (Korhonen et al., 2018; Haas et al., 2015; Niero and Kalbar, 2019). These tools can describe resource inputs and environmental emission pathways in detail, providing a basis for quantitative analysis at the industrial or regional level. In practice, however, system-boundary choices are often selective. Which links are included and which external effects are excluded can change the final results. Studies comparing alternative boundary settings show that the same case may lead to different conclusions under different evaluation frameworks (Bringezu, 2015). This suggests that local performance improvement does not necessarily imply overall structural optimization. When analysis is confined to a single sector, cross-sector linkages are easily overlooked, and the actual state of system coordination becomes difficult to identify.

Agriculture provides a concrete setting for this issue. As a resource-intensive sector, agricultural circular practices focus mainly on waste valorization, biomass recycling, and integrated agriculture-energy-fertilizer systems (Zhang et al., 2021). Related reviews show that research often centers on business-model innovation, supply-chain loss control, and policy-tool design (Moraga et al., 2019; Velenturf and Purnell, 2021). In evaluation methods, multi-indicator composite systems are widely used to measure regional agricultural circular development (Saidani et al., 2019). Empirical studies in China further show that technological progress and institutional supply significantly affect agricultural circular performance (Li et al., 2021), while also revealing the practical cost-benefit constraints of waste valorization (Peng et al., 2025a). These studies deepen our understanding of the internal operation of agricultural systems. Yet most remain concentrated on the production side and pay insufficient attention to the spatial restructuring and industrial linkage effects that agricultural circularity may generate. Whether improved agricultural efficiency can reshape broader rural development patterns remains insufficiently examined.

## 2.2 Rural tourism development and sustainability

By contrast, rural tourism research more often starts from the demand side. It emphasizes the importance of rural landscapes, ecological environments, cultural experiences, and visitor motivations for tourism behavior (Lane and Kastenholz, 2015; Sharpley, 2020; Park and Yoon, 2009; Su, 2011), and it treats sustainability as an outcome of balance across economic, social, and ecological dimensions (Sharpley, 2020). As agricultural functions change and rural industries diversify, rural tourism is increasingly viewed as an important pathway for rural revitalization and integrated rural development (Saxena et al., 2007; Moscardo, 2014; Zhao et al., 2025; Cawley and Gillmor, 2008; Gao and Wu, 2017). At the same time, the carbon emissions and resource consumption generated by tourism activities have received growing attention. Related studies use input-output analysis and carbon-footprint accounting to reveal environmental pressure along the tourism value chain (Gössling and Peeters, 2015; Lenzen et al., 2018; Chen et al., 2024a; Zhang et al., 2022). In most studies, however, the ecological environment is treated as a pre-existing condition, while the mechanisms that form and improve that environment receive less attention. The effects of the environment on tourism have been repeatedly demonstrated, but the production-structure adjustments that improve the environment have not been examined with equal intensity. Agricultural production systems and tourism consumption systems therefore remain relatively separated in theory.

## 2.3 Coupling mechanism between the agricultural circular economy and rural tourism

Research on agriculture-tourism linkage and destination competitiveness provides a useful basis for this study. Studies of integrated rural tourism describe rural tourism as both a tourism product and a territorial development process involving agriculture, local culture, community participation, and landscape management (Saxena et al., 2007; Moscardo, 2014; Cawley and Gillmor, 2008). Tourism-management studies further show that rural tourism performance depends on accessibility, service capacity, visitor demand, environmental quality, and destination competitiveness (Park and Yoon, 2009; Su, 2011; Gao and Wu, 2017; Wang et al., 2022a; Dwyer and Kim, 2003; Crouch, 2011). Research on whether rural tourism benefits from agriculture also suggests that agriculture and tourism reinforce each other when production functions, landscape functions, and market demand are effectively connected (Yang et al., 2023; Fleischer and Tchetchik, 2005). These arguments point to a mutually embedded and dynamically evolving relationship between agricultural circularity and rural tourism. If analysis remains limited to one-way regression or static correlation, this interactive structure cannot be fully captured.

The disagreement in circular economy research therefore points to a more holistic question: do different subsystems evolve in coordination? If agricultural circularity remains limited to internal efficiency improvement and fails to improve rural industrial structure and spatial form, its transformative significance becomes questionable. If rural tourism growth lacks an interaction mechanism with agricultural greening, green development will also lack a stable foundation. Single-sector performance evaluation cannot reveal this degree of matching or the underlying structural relationship.

Against this background, the coupling coordination model provides an operational tool for analyzing cross-system relationships. By constructing composite evaluation indices for the agricultural circular economy and rural tourism and measuring their coupling intensity and coordination level, it is possible to evaluate whether the two systems develop synchronously and whether structural imbalance exists (Zhang et al., 2023; Liu et al., 2022; Tang, 2015; Li et al., 2012). The model separates interaction intensity from coordination quality: two systems may be closely linked while still developing at different speeds or with structural mismatches. Coupling coordination analysis therefore makes it possible to examine system transformation through both connection and matched development.

Overall, clear research gaps remain in the scale definition of the circular economy, the spillover effects of agricultural circularity, and the formation mechanism of the rural tourism environment. Placing the agricultural circular economy and rural tourism within a unified analytical framework helps move beyond the limits of single-sector evaluation. Existing empirical studies have examined digital rural transformation, agricultural eco-efficiency, green innovation and rural resilience, rural livelihoods, farmers' income growth, regional green development, tourism-led ecological protection, digital governance, agricultural waste recycling, climate constraints, tourism carbon mitigation, rural green transformation, agricultural modernization, tourism competitiveness, circular-agriculture pathways, and rural sustainable development under circular-economy frameworks (Zhang et al., 2022; Liu et al., 2022, 2024b; Sun et al., 2022; He et al., 2023; Guo et al., 2022; Huang et al., 2023; Li et al., 2022; Zhou et al., 2024; Ma et al., 2023; Tang et al., 2024; Feng et al., 2023; Wu et al., 2023; Li et al., 2023; Gao et al., 2022; Peng et al., 2023; Chen et al., 2024b; Wang et al., 2024b). These studies provide important context, but a more integrated analysis is still needed to explain whether agricultural circular transformation and rural tourism development move together over time, whether their development levels become more balanced, and which factors continue to constrain coordinated upgrading.

# 3 Materials and methods

## 3.1 Study area and sample description

This study takes China as the empirical setting and uses provincial administrative units as the research objects. China is selected because its rural revitalization strategy, agricultural green transformation policies, and rapid rural tourism expansion provide a typical national context in which the relationship between production-side circularity and consumption-side rural tourism can be observed. To ensure consistency in statistical standards and data availability, the sample covers 30 provinces, autonomous regions, and municipalities and forms a balanced panel for 2011–2022.

Tibet, Hong Kong, Macao, and Taiwan are excluded for different reasons. Hong Kong, Macao, and Taiwan are not included because their statistical systems and tourism/agricultural data are not directly comparable with mainland provincial statistics. Tibet is excluded because several core agricultural circular economy and rural tourism indicators are missing or use inconsistent statistical calibers for parts of the study period. This exclusion may slightly understate the heterogeneity of western China, particularly in high-altitude ecological and tourism-resource regions. However, the remaining western sample still includes 11 provincial units, including Xinjiang, Qinghai, Gansu, Ningxia, Inner Mongolia, Sichuan, Chongqing, Guizhou, Yunnan, Guangxi, and Shaanxi. This helps preserve the representativeness of the western-region comparison while maintaining balanced-panel comparability. The provincial scale is adopted because provincial statistics provide the most consistent and comparable long-term data for both agricultural circular economy and rural tourism indicators. Moreover, provincial governments play an important role in policy implementation, resource allocation, and regional tourism planning, making this scale suitable for policy-oriented comparison.

## 3.2 Data sources and preprocessing

Provincial indicators are mainly drawn from official Chinese national and provincial statistical yearbooks and government bulletins, including statistical yearbooks for agriculture, tourism, culture and tourism, ecological environment, transportation, and public services. The dataset contains 30 provinces over 2011–2022, producing 360 province-year observations after matching the two subsystem datasets. For preprocessing, a small number of isolated missing tourism observations are replaced with full-sample means when this treatment does not alter the time span. Indicators with inconsistent definitions are transformed into ratios or intensities to improve comparability.

## 3.3 Indicator system construction

### 3.3.1 Agricultural circular economy subsystem (ACE)

To measure the agricultural circular economy, this study takes the principles of Reduce, Reuse, and Recycle as the theoretical foundation and links each selected indicator to recent studies on the circular economy, agricultural sustainability, manure-resource utilization, and agricultural low-carbon transformation, mainly published after 2023. Table 1 reports the indicator-specific reference basis so that the selection of each variable is traceable rather than supported only by collective citations (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024; Lin et al., 2025; Wang et al., 2024a; Xie et al., 2025). The indicator system focuses on agricultural economic output and efficiency, reduced resource inputs, circular use of agricultural resources, and resource-environment pressure. This design keeps the measurement object clear: it evaluates the development level of the agricultural circular economy rather than a broad and ambiguous notion of general high-quality agricultural development.

On this basis, this study constructs a four-dimensional first-level indicator system. First, the economic output and efficiency dimension uses agricultural value added (X1) and output per unit of land (X2). Recent studies on agricultural circular-economy efficiency and sustainable grain-family-farm evaluation emphasize that circular agriculture should not only reduce resource inputs but also maintain agricultural production capacity and land-output performance; therefore, X1 and X2 are used to capture the production-performance foundation of the subsystem (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024). Second, the reduced-input dimension uses fertilizer application intensity (X3), pesticide application intensity (X4), and agricultural water-use intensity (X5). These indicators correspond to the “reduce” principle of the circular economy and are closely related to agricultural digitalization, mechanization, and low-carbon transformation, where excessive chemical inputs and water-use pressure are treated as important sources of environmental burden (OECD, 2024; Duan and Pan, 2024; Wang et al., 2024a; Xie et al., 2025). Third, the resource circular-use dimension uses the utilization rate of livestock and poultry manure (X6), multiple cropping index (X7), agricultural machinery output efficiency (X8), and fertilizer output efficiency (X9). X6 directly reflects the policy focus on livestock-manure resource utilization, while X7–X9 describe land-use intensity, equipment-use efficiency, and the conversion of fertilizer input into agricultural output, which are repeatedly emphasized

TABLE 1 Indicator system for the agricultural circular economy.

| First-level indicator | Second-level indicator | Code | Type | Unit | Reference basis |
|---|---|---|---|---|---|
| Economic output and efficiency (ACE-benefit) | Agricultural value added | X1 | Positive indicator | 100 million yuan | (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024) |
| Economic output and efficiency (ACE-benefit) | Output per unit of land | X2 | Positive indicator | Tons per 1,000 hectares | (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024) |
| Reduced inputs (ACE-reduction) | Fertilizer application intensity | X3 | Negative indicator | Tons per 1,000 hectares | (OECD, 2024; Wang et al., 2024a) |
| Reduced inputs (ACE-reduction) | Pesticide application intensity | X4 | Negative indicator | Tons per 1,000 hectares | (OECD, 2024; Wang et al., 2024a) |
| Reduced inputs (ACE-reduction) | Agricultural water-use intensity | X5 | Negative indicator | Tons per 1,000 hectares | (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024) |
| Resource circular use (ACE-circulation) | Livestock and poultry manure utilization rate | X6 | Positive indicator | % | (Lin et al., 2025) |
| Resource circular use (ACE-circulation) | Multiple cropping index | X7 | Positive indicator | % | (Duan and Pan, 2024; Xie et al., 2025) |
| Resource circular use (ACE-circulation) | Agricultural machinery output efficiency | X8 | Positive indicator | 100 million yuan per 10,000 kW | (Xie et al., 2025) |
| Resource circular use (ACE-circulation) | Fertilizer output efficiency | X9 | Positive indicator | 100 million yuan per 10,000 tons | (Guo et al., 2023; Wang et al., 2024a) |
| Resource-environment security/pressure (ACE-environment) | Agricultural non-point source pollution intensity | X10 | Negative indicator | 100 million cubic meters | (OECD, 2024; Guo et al., 2023) |
| Resource-environment security/pressure (ACE-environment) | Agricultural carbon emission intensity | X11 | Negative indicator | 10,000 tons | (Wang et al., 2024a; Xie et al., 2025) |

in recent circular-agriculture and agricultural modernization studies (OECD, 2024; Guo et al., 2023; Duan and Pan, 2024; Lin et al., 2025; Xie et al., 2025). Fourth, the resource-environment security/pressure dimension uses agricultural non-point source pollution intensity (X10) and agricultural carbon emission intensity (X11). These two indicators capture the environmental and carbon constraints of agricultural green transformation, especially under agricultural carbon-emission reduction and pollution-control requirements (Duan and Pan, 2024; Wang et al., 2024a; Xie et al., 2025). The system therefore follows a progressive logic of output improvement, input reduction, resource reuse, and environmental-pressure control.

### 3.3.2 Rural tourism development subsystem (RTD)

To describe the overall level of rural tourism development, this study draws on recent studies on rural tourism evaluation, high-quality rural tourism indices, sustainable tourism, digital public services, and tourism resilience, mainly published from 2023 to 2025. Table 2 reports the indicator-specific reference basis for the rural tourism subsystem, covering industrial scale and benefits, reception capacity and service level, ecological-environmental quality, sharing and income-increasing effects, and governance and innovation support (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023; Yang et al., 2024; Wu et al., 2024; World Economic Forum, 2024; Wang and Liu, 2024; Sun and Zhou, 2025). These dimensions are selected because rural tourism development depends not only on visitor flows and revenue, but also on accessibility, ecological quality, income-sharing capacity, public services, and digital support.

For industrial scale and benefits, tourism revenue share (Y1), domestic tourism revenue (Y2), and domestic tourist arrivals (Y3) measure the market scale and economic contribution of rural tourism. Recent studies on high-quality rural tourism indices and tourism-development indices usually treat tourist flows and tourism income as core scale indicators, but they also emphasize that scale should be interpreted together with quality and sustainability conditions (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023). For reception capacity and services, star-rated hotels (Y4), tourism employees (Y5), and transportation network density (Y6) describe accommodation capacity, labor support, and accessibility conditions. These indicators are retained because rural tourism destinations need reception infrastructure, service labor, and transport accessibility before ecological and cultural resources can be converted into tourism demand (Zhao and Jaafar, 2025a; Liu et al., 2025b; Yan et al., 2023; World Economic Forum, 2024). For ecological-environmental quality, built-up area green coverage rate (Y7), urban sewage treatment rate (Y8), and $CO_2$ emissions (Y9, negative) capture environmental support and pressure. Sustainable rural tourism and tourism-village resilience studies

TABLE 2 Indicator system for rural tourism development level.

| First-level indicator | Second-level indicator | Code | Type | Unit | Reference basis |
|---|---|---|---|---|---|
| Industrial scale and benefits | Share of tourism revenue | Y1 | Positive indicator | % | (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023) |
| | Domestic tourism revenue | Y2 | Positive indicator | 100 million yuan | (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023) |
| | Domestic tourist arrivals | Y3 | Positive indicator | 10,000 person-times | (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023) |
| Reception capacity and services | Accommodation capacity (number of star-rated hotels) | Y4 | Positive indicator | Units | (Zhao and Jaafar, 2025a; Liu et al., 2025b; World Economic Forum, 2024) |
| | Number of tourism employees | Y5 | Positive indicator | Persons | (Zhao and Jaafar, 2025a; Liu et al., 2025b; World Economic Forum, 2024) |
| | Transportation network density | Y6 | Positive indicator | km per square km | (Liu et al., 2025b; World Economic Forum, 2024) |
| Ecological-environmental quality | Built-up area green coverage rate | Y7 | Positive indicator | % | (Wu et al., 2024; Wang and Liu, 2024; Sun and Zhou, 2025) |
| | Centralized domestic sewage treatment rate | Y8 | Positive indicator | % | (Wang and Liu, 2024; Sun and Zhou, 2025) |
| | CO2 emissions | Y9 | Negative indicator | Tons | (Wu et al., 2024; Wang and Liu, 2024; Sun and Zhou, 2025) |
| Sharing and income-increasing effects | Per capita disposable income of rural residents | Y10 | Positive indicator | Yuan | (Zhao and Jaafar, 2025a,b; Yan et al., 2023) |
| | Urban–rural income ratio | Y11 | Negative indicator | % | (Zhao and Jaafar, 2025a,b; Yan et al., 2023) |
| | Share of value added in the tertiary industry | Y12 | Positive indicator | % | (Zhao and Jaafar, 2025a,b; Liu et al., 2025b; Yan et al., 2023) |
| Governance and innovation support | Internet penetration rate | Y13 | Positive indicator | % | (Yang et al., 2024; World Economic Forum, 2024) |
| | General public service budget expenditure | Y14 | Positive indicator | 100 million yuan | (Yang et al., 2024; World Economic Forum, 2024) |
| | Beds in health institutions per 1,000 people | Y15 | Positive indicator | Beds | (Yang et al., 2024; World Economic Forum, 2024) |

highlight that rural tourism depends on ecological carrying capacity and environmental governance, while carbon emissions represent the environmental pressure associated with tourism-related development (Zhao and Jaafar, 2025a; Wu et al., 2024; Wang and Liu, 2024; Sun and Zhou, 2025). For sharing and income-increasing effects, rural resident disposable income (Y10), the urban-rural income ratio (Y11, negative), and the tertiary-industry value-added share (Y12) reflect whether tourism development is connected with rural income improvement and service-sector upgrading rather than limited to visitor reception (Zhao and Jaafar, 2025a,b; Yan et al., 2023). For governance and innovation support, internet penetration (Y13), general public service expenditure (Y14), and health-institution beds per 1,000 people (Y15) measure digital capacity, public-service provision, and resilience support. Recent research on digital public services and rural tourism resilience shows that these conditions shape destination management, online visibility, risk response, and visitor-service quality (Zhao and Jaafar, 2025a,b; Yang et al., 2024; Sun and Zhou, 2025). The selected indicators therefore combine standard tourism scale indicators with rural sustainability and destination-competitiveness indicators rather than treating tourism development as simple visitor growth.

Because direct and continuous province-level statistical indicators for rural tourism destinations remain limited, this study uses several environmental and public-service variables as destination-support proxies. These indicators do not directly measure tourist flows or tourism revenue, but they capture ecological conditions, infrastructure, governance capacity, and public-service foundations that shape rural tourism development at the provincial level.

The entropy-weight results show that the agricultural circular economy index is mainly driven by output per unit of land (X2, 0.2154), agricultural value added (X1, 0.1781), agricultural machinery output efficiency (X8, 0.1574), and fertilizer output efficiency (X9, 0.1449). For rural tourism, domestic tourism revenue (Y2, 0.1145), domestic tourist arrivals (Y3, 0.1132), tourism employees (Y5, 0.1114), tourism revenue share (Y1, 0.0912), and public service expenditure (Y14, 0.0910) carry

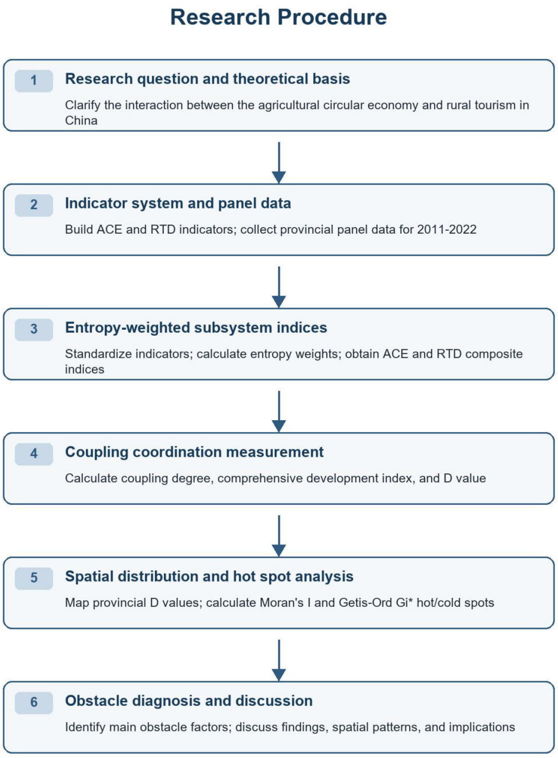


FIGURE 1
Research procedure and empirical analysis framework. ACE denotes the agricultural circular economy subsystem; RTD denotes the rural tourism development subsystem; *D* denotes the coupling coordination value.

the largest weights. The detailed entropy weights are moved to Appendix Table A1 because they are derived from the same indicators listed in Tables 1, 2; the main text reports only the largest contributors to avoid repetition.

## 3.4 Comprehensive evaluation method and variable measurement

Figure 1 summarizes the overall research procedure. The detailed calculation procedures are presented in Equations (1)-(19). The empirical strategy contains four core methodological modules: the entropy weight method, the coupling coordination model, Getis-Ord Gi* hot-spot analysis, and obstacle diagnosis. Moran's *I*, province-level spatial visualization, and convergence diagnostics are used as supporting analyses to strengthen the interpretation of spatial and temporal patterns.

### 3.4.1 Weight determination and subsystem index synthesis (entropy weight method)

To reduce bias from subjective weighting, this study uses the entropy weight method to assign objective weights to all indicators and synthesize the composite development index for each subsystem. The entropy weight method is an objective weighting approach for multi-attribute decision analysis. It determines indicator weights by calculating the entropy value of each indicator. A higher entropy value indicates smaller variation and lower information contribution, whereas a larger difference coefficient indicates greater variation and a higher weight. This method reduces the influence of subjective judgment on indicator weights and improves the comparability of the evaluation results. Because this study uses provincial panel data, entropy values and weights are calculated uniformly over the full sample, covering all provinces and all years, so that the weights remain consistent throughout the study period and intertemporal comparability is maintained.

#### 3.4.1.1 Indicator standardization

Let the original value of the jth indicator for province i in year $t$ be denoted by $x_{ijt}$. To remove dimensional effects, range standardization is used.

Positive indicators:

$$z_{ijt} = \frac{x_{ijt} - min(x_{jt})}{\max(x_{jt}) - min(x_{jt})} \tag{1}$$

Negative indicators:

$$z_{ijt} = \frac{\max(x_{jt}) - x_{ijt}}{\max(x_{jt}) - min(x_{jt})} \tag{2}$$

where the maximum and minimum values are taken over the full sample, covering all provinces and all years, to ensure intertemporal comparability.

#### 3.4.1.2 Calculating indicator proportions

Each province-year observation is treated as a sample unit, with sample size $N = n \times T$. The proportion of the jth indicator for observation $(i, t)$ is defined as follows:

$$p_{ijt} = \frac{\tilde{z}_{ijt}}{\sum_{i=1}^{n} \sum_{t=1}^{T} \tilde{z}_{ijt}},\ \ 0 < p_{ijt} < 1\ ,\sum_{i=1}^{n} \sum_{t=1}^{T} p_{ijt} = 1 \tag{3}$$

This step follows the information-theoretic idea of converting indicator values into a distribution, thereby allowing the uncertainty of each indicator to be measured.

#### 3.4.1.3 Calculating entropy values and difference coefficients

The information entropy of the *j*th indicator is:

$$e_j = -k\sum_{i=1}^{n} \sum_{t=1}^{T} p_{ijt} \ln(p_{ijt}), k = \frac{1}{\ln(N)} \tag{4}$$

A larger entropy value indicates smaller differences across samples and lower information contribution. The difference coefficient, or redundancy, is then obtained as follows:

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

A larger difference coefficient indicates stronger indicator variation and a higher information contribution, so the indicator receives a larger weight.

#### 3.4.1.4 Determining indicator weights

The weight of the jth indicator is determined from the difference coefficient as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{m} d_j}, w_j \geq 0, \sum_{j=1}^{m} w_j = 1 \tag{6}$$

#### 3.4.1.5 Synthesizing the composite subsystem Index

Let subsystem $k$ have indicator set $\Omega$ and number of indicators $\Omega k$. The composite subsystem index for province $i$ in year $t$ is defined as follows:

$$U_{k,it} = \sum_{j \in \Omega k} w_j \cdot z_{ijt} \tag{7}$$

where a larger value indicates a higher development level of the subsystem. The entropy-weighted composite index has been widely applied in panel-data analysis and in comprehensive evaluations of regional sustainability, tourism development, and regional development.

For easier interpretation, the composite index can be renormalized to the 0–1 interval:

$$U'_{k,it} = \frac{U_{k,it} - min(U_k)}{\max(U_k) - min(U_k)} \tag{8}$$

### 3.4.2. Coupling coordination model

To characterize the interaction intensity and coordinated development level between the agricultural circular economy and rural tourism subsystems, this study introduces the coupling coordination model. The model originates from coupling theory in systems science and has been widely used to analyze coordinated relationships in composite systems, including economy-resource-environment systems, industrial development systems, and ecosystems. In this study, the model is used to calculate the $D$ value, which reflects whether the two subsystem development levels are mutually matched rather than merely associated.

First, based on the entropy weight results above, this study constructs the composite development index of the agricultural circular economy subsystem, and the composite development index of the rural tourism subsystem, where $i$ denotes the province, $t$ denotes the year, and both subsystem indices fall within the 0–1 interval. On this basis, the coupling degree between the agricultural circular economy and rural tourism, is defined as:

$$C_{it} = \frac{2\sqrt{U_{1,it} \times U_{2,it}}}{U_{1,it} + U_{2,it}} \tag{9}$$

where the coupling degree lies within [0,1], and a larger value indicates stronger interaction between the agricultural circular economy and rural tourism. The classification of coupling degree levels is shown in Table 3. However, this indicator reflects only the strength of intersystem coupling and cannot fully describe the coordination of development between the two systems.

TABLE 3 Classification of coupling degree levels.

| Level | Range of coupling degree C | Stage | Stage classification |
|---|---|---|---|
| 1 | [0, 0.200) | Coupling | Low |
| 2 | [0.200, 0.400) | Coupling | Relatively low |
| 3 | [0.400, 0.600) | Coupling | Moderate |
| 4 | [0.600, 0.800) | Coupling | Relatively high |
| 5 | [0.800, 1.000] | Coupling | High |

TABLE 4 Classification of coupling coordination levels.

| Level | Range of coupling coordination value D | Stage | Stage classification |
|---|---|---|---|
| 1 | [0, 0.100) | Imbalance | Extreme |
| 2 | [0.100, 0.200) | Imbalance | High |
| 3 | [0.200, 0.300) | Imbalance | Moderate |
| 4 | [0.300, 0.400) | Imbalance | Low |
| 5 | [0.400, 0.500) | Imbalance | Weak |
| 6 | [0.500, 0.600) | Coordination | Weak |
| 7 | [0.600, 0.700) | Coordination | Low |
| 8 | [0.700, 0.800) | Coordination | Moderate |
| 9 | [0.800, 0.900) | Coordination | High |
| 10 | [0.900, 1.000] | Coordination | Extreme |

Therefore, the comprehensive development index is further constructed to represent the overall development level of the agricultural circular economy and rural tourism:$T_{it}$

$$T_{it} = \alpha U_{1,it} + \beta U_{2,it} \tag{10}$$

where the two parameters are weight coefficients. Considering the equal importance of the agricultural circular economy and rural tourism in regional sustainable development, this study follows common practice in prior research and sets alpha = beta = 0.5.

Based on the coupling degree and the comprehensive development index, the coupling coordination value $D$ is further constructed:

$$D_{it} = \sqrt{C_{it} \times T_{it}} \tag{11}$$

$D$ falls within the 0–1 interval. A larger value indicates closer interaction and a higher matched development level between the agricultural circular economy and rural tourism. Because $D$ incorporates subsystem development levels through the comprehensive development index, it provides stronger regional discrimination than coupling degree alone. The detailed classification of coupling coordination levels is shown in Table 4. The classification thresholds are adopted from commonly used coupling coordination studies and adjusted to maintain comparability with prior regional sustainability research (Zhang et al., 2022; Wang et al., 2022a).

### 3.4.3 Hot spot analysis and spatial diagnostics

The spatial module is used to examine whether coupling coordination is randomly distributed across provinces or shows spatial dependence. Global Moran's *I* is calculated annually as an exploratory global statistic using an inverse-distance spatial weight matrix based on provincial capital coordinates, and 999 random permutations are used to evaluate statistical significance (Moran, 1950). Its value in year t is defined as follows:

$$I_t = \frac{n}{S_0}\frac{\sum_i \sum_j w_{ij}\left(D_{it}-\bar{D}_t\right)\left(D_{jt}-\bar{D}_t\right)}{\sum_i \left(D_{it}-\bar{D}_t\right)^2},\quad S_0 = \sum_i \sum_j w_{ij} \tag{12}$$

where n is the number of provinces, $D_{it}$ is the coupling coordination value of province i in year t, $D_t$ is the annual mean value, and $w_{ij}$ is the spatial weight between provinces *i* and *j*. Moran's *I* is retained only to determine whether weak overall spatial association exists; it is not used to infer local clustering or causal spillover effects.

To identify local high-value and low-value clusters, this study further applies the Getis-Ord Gi* statistic (Getis and Ord, 1992; Ord and Getis, 1995). For province *i*, Gi* compares the weighted sum of the *D* value in province i and neighboring provinces with the expected value under spatial randomness. The standardized Gi* statistic is calculated as follows:

$$G_i^* = \frac{\sum_j w_{ij}D_j - \bar{D}\sum_j w_{ij}}{S\sqrt{\left[n\sum_j w_{ij}^2 - \left(\sum_j w_{ij}\right)^2\right]/(n-1)}} \tag{13}$$

$$S = \sqrt{\frac{\sum_j D_j^2}{n} - \bar{D}^2} \tag{14}$$

The standardized *z*-score is used to classify hot spots and cold spots. Values of $z \geq 1.65$, 1.96, and 2.58 indicate hot spots at the 10%, 5%, and 1% significance levels, respectively, while values of $z \leq -1.65$, $-1.96$, and $-2.58$ indicate cold spots. The selected years 2011, 2015, 2019, and 2022 represent the initial, middle, pre-pandemic, and latest available stages of the sample period. For visualization, Figure 2 presents province-level choropleth maps based on the standard provincial administrative boundary map of China, and the hot-spot and cold-spot classifications are summarized according to the Gi* results reported in Table 5.

In addition, a region-adjusted trend regression and beta/sigma convergence tests are used as auxiliary diagnostics for temporal evolution. The annual trend regression examines whether national coordination improves over time after accounting for regional differences; beta convergence examines whether provinces with lower initial coordination levels grow faster; and sigma convergence is evaluated by the coefficient of variation of the *D* value across provinces. The corresponding specifications are as follows:

$$D_{it} = \gamma_0 + \gamma_1 t + \mu_r + \varepsilon_{it} \tag{15}$$

$$\ln\left(\frac{D_{i,2022}}{D_{i,2011}}\right) = \theta_0 + \theta_1 \ln\left(D_{i,2011}\right) + u_i \tag{16}$$

$$CV_t = \frac{\sigma\left(D_t\right)}{\bar{D}_t} \tag{17}$$

### 3.4.4 Obstacle-degree model

The obstacle-degree model is used to identify the indicators that constrain coordinated development. After standardization, the deviation degree of indicator j for province i in year *t* is measured as the distance from the ideal normalized value. The obstacle contribution combines this deviation degree with the entropy weight of the indicator:

$$F_{ijt} = 1 - z_{ijt},\quad M_{ijt} = W_j F_{ijt} \tag{18}$$

$$O_{ijt} = \frac{W_j F_{ijt}}{\sum_j \left(W_j F_{ijt}\right)} \times 100\% \tag{19}$$

where $F_{ijt}$ is the deviation degree, $z_{ijt}$ is the standardized value of indicator *j*, $W_j$ is the entropy weight, $M_{ijt}$ is the obstacle contribution, and $O_{ijt}$ is the obstacle degree. A main obstacle factor is therefore not a negative causal coefficient; rather, it is a bottleneck indicator that is both important in the composite system and relatively far from the best observed level. Higher obstacle-degree values indicate that improving this indicator would contribute more to raising the overall coordination level under the current indicator system.

## 4 Results

### 4.1 Measurement and analysis of agricultural circular economy development

Tables 6, 7 report the measurement results. The agricultural circular economy index rose continuously from 2011 to 2022. This indicates that agricultural green transformation advanced steadily during the study period, with clear improvements in resource-recycling efficiency, ecological carrying adaptability, and the allocation efficiency of green production factors. Over time, the index followed a relatively stable upward path, suggesting that China's agricultural circular development has gradually shifted from policy-driven promotion toward institutional deepening and structural optimization.

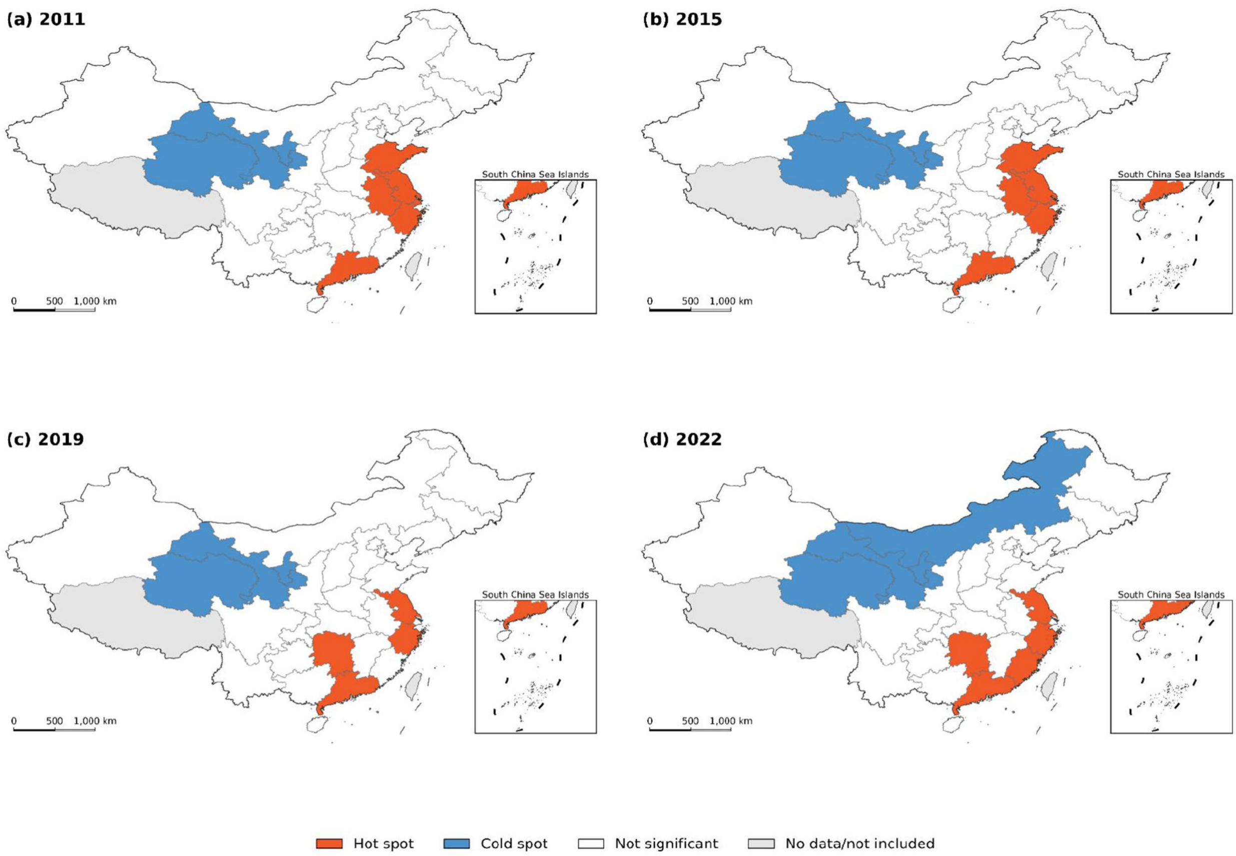


FIGURE 2
Province-level Getis-Ord Gi* hot-spot and cold-spot maps of coupling coordination. **(a)** 2011, **(b)** 2015, **(c)** 2019, and **(d)** 2022. Hot and cold spots are identified according to Table 5. The base map uses the standard administrative boundary map of China GS(2024)0650. Hong Kong, Macao, Taiwan, and Tibet are shown for cartographic completeness but are not included in the empirical sample because of data availability and statistical comparability.

TABLE 5 Getis-Ord Gi* hot and cold spot results in selected years.

| Year | Mean D | Hot spots (Gi* $z \geq 1.65$) | Cold spots (Gi* $z \leq -1.65$) | No. hot | No. cold |
|---|---|---|---|---|---|
| 2011 | 0.474 | Shanghai; Zhejiang; Jiangsu; Guangdong; Shandong; Anhui | Qinghai; Gansu; Ningxia | 6 | 3 |
| 2015 | 0.537 | Jiangsu; Zhejiang; Shanghai; Guangdong; Anhui; Shandong | Qinghai; Ningxia; Gansu | 6 | 3 |
| 2019 | 0.612 | Guangdong; Zhejiang; Jiangsu; Hunan | Ningxia; Qinghai; Gansu | 4 | 3 |
| 2022 | 0.620 | Guangdong; Jiangsu; Zhejiang; Fujian; Hunan | Ningxia; Gansu; Qinghai; Inner Mongolia | 5 | 4 |

In terms of regional averages, the agricultural circular economy development level in the eastern region increased from 0.307 in 2011 to 0.517 in 2022, a rise of 68.40%. The central region rose from 0.266 to 0.435, and the western region from 0.211 to 0.401. The overall pattern shows a clear gradient: the east leads, the central region follows, and the west catches up. Regional differences display a relatively stable hierarchy, indicating strong path dependence and regional development inertia. With stronger economic development, a more complete industrial system, and greater technological innovation capacity, the eastern region has formed a more mature institutional and market environment for promoting green agricultural technologies, valorizing agricultural waste, and extending industrial chains.

At the provincial level, eastern coastal provinces generally show higher development levels, with clear first-mover advantages and scale effects. The indices for Guangdong, Jiangsu, Shandong, Zhejiang, and Fujian continued to rise. Guangdong reached 0.723 in 2022, the highest level nationwide, showing strong advantages in agricultural resource recycling efficiency, green technology input intensity, and agricultural industrial coordination. Jiangsu and Shandong also maintained rapid growth, reflecting the eastern region's combined strengths in institutional supply, marketization,

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TABLE 6 Comprehensive evaluation index of the agricultural circular economy in China's 30 Provinces, autonomous regions, and municipalities, 2011–2022.

| Region | Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | Shanghai | 0.410 | 0.425 | 0.415 | 0.408 | 0.404 | 0.381 | 0.362 | 0.422 | 0.405 | 0.421 | 0.459 | 0.443 |
| | Beijing | 0.306 | 0.325 | 0.334 | 0.332 | 0.324 | 0.324 | 0.304 | 0.312 | 0.369 | 0.372 | 0.428 | 0.415 |
| | Tianjin | 0.184 | 0.189 | 0.213 | 0.207 | 0.216 | 0.225 | 0.237 | 0.267 | 0.307 | 0.341 | 0.367 | 0.364 |
| | Shandong | 0.335 | 0.343 | 0.381 | 0.377 | 0.393 | 0.405 | 0.419 | 0.435 | 0.459 | 0.480 | 0.540 | 0.541 |
| | Guangdong | 0.367 | 0.394 | 0.404 | 0.419 | 0.431 | 0.467 | 0.463 | 0.491 | 0.613 | 0.612 | 0.630 | 0.723 |
| | Jiangsu | 0.352 | 0.372 | 0.378 | 0.403 | 0.416 | 0.439 | 0.450 | 0.436 | 0.471 | 0.498 | 0.521 | 0.560 |
| | Hebei | 0.277 | 0.287 | 0.312 | 0.311 | 0.305 | 0.328 | 0.318 | 0.342 | 0.355 | 0.395 | 0.392 | 0.415 |
| | Zhejiang | 0.262 | 0.282 | 0.302 | 0.317 | 0.318 | 0.352 | 0.339 | 0.376 | 0.438 | 0.444 | 0.475 | 0.499 |
| | Hainan | 0.260 | 0.284 | 0.279 | 0.297 | 0.295 | 0.328 | 0.319 | 0.403 | 0.410 | 0.447 | 0.501 | 0.576 |
| | Fujian | 0.315 | 0.342 | 0.354 | 0.369 | 0.381 | 0.423 | 0.404 | 0.461 | 0.549 | 0.582 | 0.615 | 0.635 |
| Central region | Anhui | 0.252 | 0.266 | 0.283 | 0.281 | 0.299 | 0.299 | 0.324 | 0.330 | 0.331 | 0.367 | 0.392 | 0.400 |
| | Shanxi | 0.202 | 0.215 | 0.222 | 0.227 | 0.220 | 0.246 | 0.240 | 0.258 | 0.272 | 0.301 | 0.317 | 0.318 |
| | Jiangxi | 0.258 | 0.265 | 0.308 | 0.304 | 0.331 | 0.338 | 0.354 | 0.359 | 0.397 | 0.421 | 0.424 | 0.427 |
| | Henan | 0.299 | 0.324 | 0.336 | 0.342 | 0.351 | 0.357 | 0.372 | 0.378 | 0.416 | 0.452 | 0.478 | 0.492 |
| | Hubei | 0.270 | 0.294 | 0.296 | 0.312 | 0.329 | 0.346 | 0.365 | 0.371 | 0.401 | 0.431 | 0.464 | 0.486 |
| | Hunan | 0.312 | 0.329 | 0.337 | 0.344 | 0.352 | 0.360 | 0.351 | 0.365 | 0.423 | 0.468 | 0.472 | 0.491 |
| Western region | Yunnan | 0.190 | 0.207 | 0.238 | 0.254 | 0.289 | 0.320 | 0.368 | 0.403 | 0.496 | 0.354 | 0.382 | 0.414 |
| | Inner Mongolia | 0.117 | 0.137 | 0.155 | 0.173 | 0.194 | 0.199 | 0.238 | 0.257 | 0.284 | 0.243 | 0.227 | 0.230 |
| | Sichuan | 0.209 | 0.238 | 0.266 | 0.278 | 0.334 | 0.355 | 0.397 | 0.431 | 0.491 | 0.478 | 0.487 | 0.453 |
| | Ningxia | 0.090 | 0.110 | 0.122 | 0.129 | 0.138 | 0.150 | 0.163 | 0.168 | 0.178 | 0.179 | 0.181 | 0.191 |
| | Guangxi | 0.143 | 0.173 | 0.194 | 0.215 | 0.253 | 0.267 | 0.303 | 0.350 | 0.416 | 0.373 | 0.405 | 0.372 |
| | Xinjiang | 0.155 | 0.172 | 0.178 | 0.180 | 0.203 | 0.223 | 0.235 | 0.257 | 0.287 | 0.246 | 0.261 | 0.259 |
| | Gansu | 0.094 | 0.118 | 0.136 | 0.151 | 0.171 | 0.191 | 0.215 | 0.243 | 0.276 | 0.243 | 0.254 | 0.228 |
| | Guizhou | 0.172 | 0.197 | 0.226 | 0.236 | 0.265 | 0.303 | 0.353 | 0.409 | 0.475 | 0.356 | 0.375 | 0.349 |
| | Chongqing | 0.202 | 0.227 | 0.241 | 0.258 | 0.280 | 0.295 | 0.316 | 0.347 | 0.380 | 0.337 | 0.313 | 0.325 |
| | Shaanxi | 0.173 | 0.193 | 0.214 | 0.228 | 0.266 | 0.277 | 0.303 | 0.328 | 0.364 | 0.295 | 0.313 | 0.310 |
| | Qinghai | 0.060 | 0.074 | 0.094 | 0.112 | 0.128 | 0.133 | 0.161 | 0.171 | 0.194 | 0.185 | 0.191 | 0.188 |
| Northeastern region | Heilongjiang | 0.239 | 0.280 | 0.308 | 0.306 | 0.308 | 0.312 | 0.349 | 0.360 | 0.369 | 0.378 | 0.380 | 0.401 |
| | Jilin | 0.209 | 0.226 | 0.228 | 0.233 | 0.230 | 0.232 | 0.226 | 0.230 | 0.237 | 0.245 | 0.245 | 0.276 |
| | Liaoning | 0.284 | 0.311 | 0.335 | 0.343 | 0.344 | 0.336 | 0.336 | 0.357 | 0.368 | 0.385 | 0.425 | 0.410 |

TABLE 7 Comprehensive evaluation index of the agricultural circular economy by region in China, 2011–2022.

| Region | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | 0.307 | 0.324 | 0.337 | 0.344 | 0.348 | 0.367 | 0.362 | 0.395 | 0.438 | 0.459 | 0.493 | 0.517 |
| Central region | 0.266 | 0.282 | 0.297 | 0.302 | 0.314 | 0.324 | 0.335 | 0.344 | 0.373 | 0.407 | 0.424 | 0.435 |
| Western region | 0.211 | 0.222 | 0.234 | 0.241 | 0.250 | 0.271 | 0.280 | 0.296 | 0.328 | 0.355 | 0.381 | 0.401 |
| Northeastern region | 0.244 | 0.272 | 0.290 | 0.294 | 0.294 | 0.293 | 0.304 | 0.316 | 0.325 | 0.336 | 0.350 | 0.362 |

and the concentration of capital and technological factors. These strengths further reinforce innovation diffusion and technology spillovers within the region.

By contrast, some western provinces, such as Qinghai and Ningxia, remained at relatively low levels for a long period. Although the overall trend was upward, their development levels still lagged clearly behind the eastern region because of more limited resource endowments, insufficient agricultural scale operation, weak foundations for green technology diffusion, and limited industrial support capacity. This gap shows that agricultural circular economy development depends heavily on capital input intensity, technology diffusion efficiency, and the regional economic base. It also reflects how differences in regional factor endowments constrain green transformation pathways.

Some western provinces experienced phased fluctuations around 2019. For example, the indices for Yunnan and Guizhou declined briefly after rapid growth. This volatility may be related to adjustments in agricultural industrial structure, stronger ecological-environmental governance, and changes in the macroeconomic environment. Stronger ecological governance may have constrained some high-pollution or low-efficiency production methods in the short term, producing a temporary adjustment in the index. At the same time, external economic shocks and differences in the pace of industrial transition may have affected green investment and technology diffusion. This suggests that agricultural circular economy development is driven by technological progress and capital accumulation, but it also involves phased fluctuations and sensitivity to the external environment.

Overall, China's agricultural circular economy shows a clear upward temporal trend and a spatially uneven pattern. Regional gaps remain, but from a dynamic perspective the central and western regions grew faster, and interregional gaps showed slow convergence. Under policy guidance, optimized factor flows, and stronger regional coordination mechanisms, the agricultural circular economy is gradually shifting from polarized expansion toward coordinated upgrading. This trend provides an important foundation for subsequent coupling coordination between agriculture and rural tourism systems.

## 4.2 Measurement and analysis of rural tourism development

According to the results in Tables 8, 9, China's rural tourism development level rose continuously from 2011 to 2019, with steady growth in the comprehensive evaluation index across all regions. At the regional level, the eastern region increased from 0.291 to 0.440, the central region from 0.205 to 0.427, the western region from 0.146 to 0.349, and the northeastern region from 0.180 to 0.322.

Further analysis shows that growth during this stage was not limited to increases in reception scale and revenue. It also reflected structural improvements in industrial integration, product innovation, and service quality. Factor reorganization between agriculture and tourism extended the value chain and improved the comprehensive-use efficiency of rural resources. In addition, better infrastructure and digital platform development improved market accessibility and information-flow efficiency, providing institutional and technical support for the continued expansion of rural tourism. Therefore, 2011–2019 can be viewed as an important transition period in which rural tourism moved from factor-driven growth toward structurally optimized growth.

Since 2020, however, rural tourism indices have declined to varying degrees across regions. The eastern region fell from 0.440 in 2019 to 0.391 in 2020, a relatively large decrease. The central, western, and northeastern regions also showed phased declines. This change has the characteristics of an external shock and reflects the high sensitivity of rural tourism to macro-environmental volatility. In terms of industry attributes, rural tourism depends heavily on visitor flows and consumer confidence. It is more affected by public emergencies and macroeconomic uncertainty, and its demand elasticity and volatility are clearly higher than those of foundational industrial systems such as the agricultural circular economy.

Regional indices gradually recovered in 2021–2022. Although they had not fully returned to their 2019 peaks, they showed an overall pattern of restorative growth. This indicates that the rural tourism system displayed a degree of recovery capacity and structural resilience after the external shock. Its recovery path mainly involved three channels. First, the substitution growth of local and short-distance tourism strengthened regional internal circulation. Second, digital marketing and online platform promotion improved market response efficiency. Third, special government support policies for rural tourism helped cushion the short-term shock. Thus, although rural tourism is highly volatile, it has some capacity for self-repair under institutional regulation and market adjustment mechanisms.

At the provincial level, Sichuan, Guangdong, Jiangsu, and Shandong remained at relatively high development levels over the long term. Sichuan reached an index value of 0.606 in 2022, the highest in the western region, reflecting its combined advantages in ecological resources, deep culture-tourism integration, and sustained policy support. Guangdong and

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TABLE 8 Evaluation index of rural tourism development level in China's 30 provinces, autonomous regions, and municipalities, 2011–2022.

| Region | Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | Shanghai | 0.329 | 0.351 | 0.348 | 0.355 | 0.368 | 0.390 | 0.406 | 0.415 | 0.425 | 0.403 | 0.422 | 0.410 |
| | Beijing | 0.383 | 0.403 | 0.414 | 0.416 | 0.433 | 0.431 | 0.457 | 0.458 | 0.472 | 0.424 | 0.450 | 0.439 |
| | Tianjin | 0.205 | 0.221 | 0.236 | 0.248 | 0.267 | 0.284 | 0.299 | 0.310 | 0.336 | 0.285 | 0.295 | 0.283 |
| | Shandong | 0.338 | 0.358 | 0.377 | 0.391 | 0.438 | 0.457 | 0.483 | 0.513 | 0.523 | 0.458 | 0.484 | 0.464 |
| | Guangdong | 0.384 | 0.403 | 0.425 | 0.430 | 0.474 | 0.484 | 0.507 | 0.524 | 0.562 | 0.464 | 0.460 | 0.442 |
| | Jiangsu | 0.359 | 0.384 | 0.405 | 0.412 | 0.444 | 0.467 | 0.486 | 0.508 | 0.524 | 0.453 | 0.509 | 0.479 |
| | Hebei | 0.197 | 0.215 | 0.234 | 0.245 | 0.284 | 0.309 | 0.352 | 0.384 | 0.420 | 0.337 | 0.353 | 0.349 |
| | Zhejiang | 0.354 | 0.379 | 0.406 | 0.418 | 0.438 | 0.451 | 0.483 | 0.491 | 0.522 | 0.490 | 0.482 | 0.471 |
| | Hainan | 0.143 | 0.156 | 0.167 | 0.176 | 0.189 | 0.203 | 0.217 | 0.230 | 0.249 | 0.257 | 0.296 | 0.278 |
| | Fujian | 0.217 | 0.246 | 0.258 | 0.263 | 0.283 | 0.297 | 0.317 | 0.340 | 0.365 | 0.337 | 0.337 | 0.337 |
| Central region | Anhui | 0.198 | 0.227 | 0.347 | 0.255 | 0.288 | 0.308 | 0.350 | 0.377 | 0.413 | 0.349 | 0.376 | 0.377 |
| | Shanxi | 0.183 | 0.203 | 0.222 | 0.237 | 0.259 | 0.286 | 0.305 | 0.342 | 0.379 | 0.281 | 0.279 | 0.267 |
| | Jiangxi | 0.171 | 0.188 | 0.208 | 0.230 | 0.277 | 0.312 | 0.341 | 0.394 | 0.433 | 0.376 | 0.410 | 0.386 |
| | Henan | 0.226 | 0.248 | 0.270 | 0.278 | 0.302 | 0.354 | 0.378 | 0.413 | 0.456 | 0.389 | 0.427 | 0.382 |
| | Hubei | 0.225 | 0.245 | 0.272 | 0.303 | 0.330 | 0.345 | 0.371 | 0.384 | 0.411 | 0.381 | 0.406 | 0.403 |
| | Hunan | 0.226 | 0.248 | 0.265 | 0.284 | 0.358 | 0.389 | 0.400 | 0.421 | 0.472 | 0.454 | 0.426 | 0.430 |
| Western region | Yunnan | 0.201 | 0.221 | 0.240 | 0.245 | 0.253 | 0.257 | 0.256 | 0.301 | 0.363 | 0.386 | 0.424 | 0.452 |
| | Inner Mongolia | 0.188 | 0.193 | 0.208 | 0.214 | 0.205 | 0.221 | 0.234 | 0.233 | 0.235 | 0.250 | 0.247 | 0.273 |
| | Sichuan | 0.336 | 0.361 | 0.366 | 0.377 | 0.383 | 0.424 | 0.447 | 0.458 | 0.515 | 0.557 | 0.572 | 0.606 |
| | Ningxia | 0.162 | 0.156 | 0.164 | 0.170 | 0.171 | 0.189 | 0.184 | 0.202 | 0.196 | 0.221 | 0.232 | 0.244 |
| | Guangxi | 0.241 | 0.247 | 0.259 | 0.267 | 0.271 | 0.295 | 0.302 | 0.327 | 0.377 | 0.394 | 0.440 | 0.452 |
| | Xinjiang | 0.189 | 0.203 | 0.208 | 0.203 | 0.214 | 0.218 | 0.225 | 0.235 | 0.225 | 0.251 | 0.288 | 0.305 |
| | Gansu | 0.169 | 0.182 | 0.181 | 0.183 | 0.195 | 0.215 | 0.223 | 0.234 | 0.251 | 0.272 | 0.286 | 0.302 |
| | Guizhou | 0.189 | 0.208 | 0.225 | 0.257 | 0.294 | 0.327 | 0.358 | 0.372 | 0.418 | 0.450 | 0.499 | 0.509 |
| | Chongqing | 0.256 | 0.272 | 0.287 | 0.286 | 0.304 | 0.330 | 0.339 | 0.351 | 0.398 | 0.430 | 0.453 | 0.468 |
| | Shaanxi | 0.228 | 0.229 | 0.244 | 0.259 | 0.262 | 0.289 | 0.292 | 0.305 | 0.361 | 0.397 | 0.422 | 0.438 |
| | Qinghai | 0.163 | 0.169 | 0.195 | 0.194 | 0.195 | 0.215 | 0.222 | 0.232 | 0.271 | 0.299 | 0.326 | 0.366 |
| Northeastern region | Heilongjiang | 0.239 | 0.280 | 0.308 | 0.306 | 0.308 | 0.312 | 0.349 | 0.360 | 0.369 | 0.378 | 0.380 | 0.401 |
| | Jilin | 0.209 | 0.226 | 0.228 | 0.233 | 0.230 | 0.232 | 0.226 | 0.230 | 0.237 | 0.245 | 0.245 | 0.276 |
| | Liaoning | 0.284 | 0.311 | 0.335 | 0.343 | 0.344 | 0.336 | 0.336 | 0.357 | 0.368 | 0.385 | 0.425 | 0.410 |

TABLE 9 Comprehensive evaluation index of rural tourism development level by region in China, 2011–2022.

| Region | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | 0.291 | 0.312 | 0.327 | 0.336 | 0.362 | 0.377 | 0.401 | 0.417 | 0.440 | 0.391 | 0.409 | 0.395 |
| Central region | 0.205 | 0.227 | 0.264 | 0.265 | 0.302 | 0.332 | 0.358 | 0.389 | 0.427 | 0.372 | 0.387 | 0.374 |
| Western region | 0.146 | 0.168 | 0.188 | 0.201 | 0.229 | 0.247 | 0.277 | 0.306 | 0.349 | 0.299 | 0.308 | 0.302 |
| Northeastern region | 0.180 | 0.196 | 0.213 | 0.222 | 0.241 | 0.258 | 0.276 | 0.297 | 0.322 | 0.286 | 0.302 | 0.281 |

Jiangsu, supported by strong economic foundations and mature market systems, developed significant scale and spillover effects in agriculture-tourism integration innovation and brand building. By contrast, Hainan, Qinghai, and Ningxia had relatively low development levels but grew quickly, showing clear latecomer catch-up characteristics. This indicates that, with stronger policy support and more efficient resource integration, low-base regions have considerable room for marginal improvement and structural upgrading.

Overall, China's rural tourism development followed a phased path of rapid growth, short-term decline, and gradual recovery. Over time, the industry experienced a dynamic process of expansion, shock, and repair. Spatially, regional differences remained clear: the eastern region led overall, the central and western regions accelerated their catch-up, and the northeastern region developed relatively steadily but with limited improvement. These results show that rural tourism development is shaped by structural differences in regional economic foundations, resource endowments, and market size, and that it is also highly sensitive to macro-environmental change. Its long-term development still depends on deeper industrial integration, stronger institutional innovation capacity, and continued green transformation.

## 4.3 Coupling and coordination between the agricultural circular economy and rural tourism

According to the results in Table 10, the coupling degree between the agricultural circular economy and rural tourism subsystems in China's 30 provinces remained above 0.95 from 2011 to 2022 and approached 1 in most years. This indicates a high degree of association.

From the perspective of theoretical mechanisms, the agricultural circular economy provides an ecological foundation and green product supply for rural tourism by improving resource-use efficiency and environmental quality. At the same time, rural tourism creates product premiums and value-realization channels for the agricultural circular economy through expanded market demand and value-chain extension. Functionally, the two systems form a two-way feedback mechanism between supply and demand, which explains their high coupling intensity. This high-coupling state indicates that the two systems have built a relatively stable interaction framework in factor flows, industrial-chain linkages, and ecological value conversion.

However, high coupling does not necessarily indicate high-quality coordinated development. Coupling degree mainly reflects the closeness of intersystem association and interaction intensity. It cannot reveal whether subsystem development levels are matched or whether structures are balanced. When two subsystems develop at very different levels, frequent interaction may still coexist with a high-coupling but low-coordination imbalance. Therefore, coupling degree alone cannot fully evaluate the quality of system coordination. Coupling coordination is needed to assess the matching level and structural coordination of the two systems and to describe the coordinated development state of the composite system more accurately.

The results in Table 11 show that the coupling coordination between China's agricultural circular economy and rural tourism increased overall from 2011 to 2022. Compared with the coupling degree, which remained high and compressed near the upper bound, the coordination degree offers more useful regional discrimination. The stage distribution also improved: in 2011, 19 provinces were still in imbalance stages, while by 2022 only one province remained in weak imbalance, 8 were in weak coordination, 17 entered low coordination, and 4 reached moderate coordination.

A further issue is how to interpret the generally high coupling degree found in this study. The quality of the agricultural ecological environment is an important basis for rural tourism appeal, while the expansion of the tourism market can create reverse incentives for agricultural production methods through changes in demand structure and branding effects. Under this interaction logic, it is not surprising that the two systems are strongly correlated in statistical terms. Yet association strength is not the same as coordination level. When the agricultural circular economy is in a quality-improvement stage but the tourism industry remains in a scale-expansion stage, high coupling may still coexist with inconsistent development rhythms. Including coordination degree in the analytical framework therefore helps avoid overly optimistic judgments based only on coupling intensity and makes the identification of structural matching more robust.

The spatial distribution further reveals this differentiated evolutionary pattern. Overall, coupling coordination shows a clear regional gradient: relative maturity in the east, accelerated improvement in the central region, differentiated development in the west, and stable but slower progress in the northeast. These layered trajectories are closely related to long-standing differences in China's economic foundations, industrial structures, and resource endowments.

In the eastern region, most provinces have entered a relatively advanced coordination stage, and overall fluctuations are small. In

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TABLE 10 Coupling degree between the agricultural circular economy and rural tourism in China's 30 provinces, autonomous regions, and municipalities, 2011–2022.

| Region | Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | Shanghai | 0.994 | 0.995 | 0.996 | 0.998 | 0.999 | 1.000 | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 | 0.999 |
| | Beijing | 0.994 | 0.994 | 0.994 | 0.994 | 0.990 | 0.990 | 0.980 | 0.982 | 0.993 | 0.998 | 1.000 | 1.000 |
| | Tianjin | 0.999 | 0.997 | 0.999 | 0.996 | 0.994 | 0.993 | 0.993 | 0.997 | 0.999 | 0.996 | 0.994 | 0.992 |
| | Shandong | 1.000 | 1.000 | 1.000 | 1.000 | 0.999 | 0.998 | 0.997 | 0.997 | 0.998 | 1.000 | 0.999 | 0.997 |
| | Guangdong | 1.000 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 | 0.999 | 0.999 | 0.999 | 0.990 | 0.988 | 0.971 |
| | Jiangsu | 1.000 | 1.000 | 0.999 | 1.000 | 0.999 | 1.000 | 0.999 | 0.997 | 0.999 | 0.999 | 1.000 | 0.997 |
| | Hebei | 0.986 | 0.990 | 0.990 | 0.993 | 0.999 | 1.000 | 0.999 | 0.998 | 0.996 | 0.997 | 0.999 | 0.996 |
| | Zhejiang | 0.989 | 0.989 | 0.989 | 0.990 | 0.987 | 0.992 | 0.985 | 0.991 | 0.996 | 0.999 | 1.000 | 1.000 |
| | Hainan | 0.957 | 0.957 | 0.968 | 0.967 | 0.976 | 0.972 | 0.982 | 0.962 | 0.970 | 0.963 | 0.966 | 0.937 |
| | Fujian | 0.983 | 0.986 | 0.987 | 0.986 | 0.989 | 0.985 | 0.993 | 0.989 | 0.979 | 0.964 | 0.956 | 0.952 |
| Central region | Anhui | 0.993 | 0.997 | 0.995 | 0.999 | 1.000 | 1.000 | 0.999 | 0.998 | 0.994 | 1.000 | 1.000 | 1.000 |
| | Shanxi | 0.999 | 1.000 | 1.000 | 1.000 | 0.997 | 0.997 | 0.993 | 0.990 | 0.986 | 0.999 | 0.998 | 0.996 |
| | Jiangxi | 0.979 | 0.985 | 0.981 | 0.990 | 0.996 | 0.999 | 1.000 | 0.999 | 0.999 | 0.998 | 1.000 | 0.999 |
| | Henan | 0.990 | 0.991 | 0.994 | 0.995 | 0.997 | 1.000 | 1.000 | 0.999 | 0.999 | 0.997 | 0.998 | 0.992 |
| | Hubei | 0.996 | 0.996 | 0.999 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 | 0.998 | 0.998 | 0.996 |
| | Hunan | 0.987 | 0.990 | 0.993 | 0.995 | 1.000 | 0.999 | 0.998 | 0.997 | 0.998 | 1.000 | 0.999 | 0.998 |
| Western region | Yunnan | 1.000 | 0.999 | 1.000 | 1.000 | 0.998 | 0.994 | 0.984 | 0.989 | 0.988 | 0.999 | 0.999 | 0.999 |
| | Inner Mongolia | 0.972 | 0.985 | 0.989 | 0.994 | 1.000 | 0.999 | 1.000 | 0.999 | 0.996 | 1.000 | 0.999 | 0.996 |
| | Sichuan | 0.972 | 0.979 | 0.987 | 0.988 | 0.998 | 0.996 | 0.998 | 1.000 | 1.000 | 0.997 | 0.997 | 0.989 |
| | Ningxia | 0.959 | 0.985 | 0.989 | 0.991 | 0.994 | 0.993 | 0.998 | 0.996 | 0.999 | 0.994 | 0.992 | 0.993 |
| | Guangxi | 0.967 | 0.984 | 0.990 | 0.994 | 0.999 | 0.999 | 1.000 | 0.999 | 0.999 | 1.000 | 0.999 | 0.995 |
| | Xinjiang | 0.995 | 0.997 | 0.997 | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 | 0.993 | 1.000 | 0.999 | 0.997 |
| | Gansu | 0.959 | 0.977 | 0.990 | 0.995 | 0.998 | 0.998 | 1.000 | 1.000 | 0.999 | 0.998 | 0.998 | 0.990 |
| | Guizhou | 0.999 | 1.000 | 1.000 | 0.999 | 0.999 | 0.999 | 1.000 | 0.999 | 0.998 | 0.993 | 0.990 | 0.982 |
| | Chongqing | 0.993 | 0.996 | 0.996 | 0.999 | 0.999 | 0.998 | 0.999 | 1.000 | 1.000 | 0.993 | 0.983 | 0.984 |
| | Shaanxi | 0.990 | 0.996 | 0.998 | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 | 1.000 | 0.989 | 0.989 | 0.985 |
| | Qinghai | 0.887 | 0.921 | 0.936 | 0.963 | 0.978 | 0.972 | 0.988 | 0.989 | 0.986 | 0.972 | 0.966 | 0.947 |
| Northeastern region | Heilongjiang | 0.970 | 0.965 | 0.964 | 0.962 | 0.979 | 0.986 | 0.983 | 0.986 | 0.989 | 0.982 | 0.984 | 0.976 |
| | Jilin | 0.986 | 0.985 | 0.990 | 0.995 | 0.998 | 1.000 | 0.999 | 0.996 | 0.991 | 0.999 | 0.996 | 1.000 |
| | Liaoning | 0.997 | 0.997 | 0.997 | 0.998 | 0.999 | 1.000 | 1.000 | 1.000 | 1.000 | 0.997 | 0.995 | 0.992 |

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TABLE 11 Coupling coordination between the agricultural circular economy and rural tourism in China's 30 provinces, autonomous regions, and municipalities, 2011–2022.

| Region | Province | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | 2021 | 2022 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eastern region | Shanghai | 0.606 | 0.621 | 0.617 | 0.617 | 0.621 | 0.621 | 0.619 | 0.647 | 0.644 | 0.642 | 0.663 | 0.653 |
| | Beijing | 0.585 | 0.602 | 0.610 | 0.610 | 0.612 | 0.611 | 0.610 | 0.615 | 0.646 | 0.630 | 0.662 | 0.653 |
| | Tianjin | 0.441 | 0.452 | 0.473 | 0.476 | 0.490 | 0.503 | 0.516 | 0.537 | 0.567 | 0.558 | 0.574 | 0.567 |
| | Shandong | 0.580 | 0.592 | 0.616 | 0.620 | 0.644 | 0.656 | 0.671 | 0.687 | 0.700 | 0.685 | 0.715 | 0.708 |
| | Guangdong | 0.613 | 0.631 | 0.644 | 0.652 | 0.673 | 0.689 | 0.696 | 0.712 | 0.766 | 0.730 | 0.734 | 0.752 |
| | Jiangsu | 0.596 | 0.615 | 0.625 | 0.639 | 0.655 | 0.673 | 0.684 | 0.686 | 0.705 | 0.689 | 0.718 | 0.720 |
| | Hebei | 0.483 | 0.498 | 0.520 | 0.525 | 0.542 | 0.564 | 0.579 | 0.602 | 0.621 | 0.604 | 0.610 | 0.617 |
| | Zhejiang | 0.552 | 0.572 | 0.591 | 0.603 | 0.611 | 0.631 | 0.636 | 0.656 | 0.691 | 0.683 | 0.692 | 0.696 |
| | Hainan | 0.439 | 0.459 | 0.465 | 0.478 | 0.486 | 0.508 | 0.513 | 0.552 | 0.565 | 0.582 | 0.620 | 0.633 |
| | Fujian | 0.511 | 0.539 | 0.550 | 0.558 | 0.573 | 0.595 | 0.598 | 0.629 | 0.669 | 0.666 | 0.675 | 0.680 |
| Central region | Anhui | 0.473 | 0.496 | 0.560 | 0.518 | 0.542 | 0.551 | 0.581 | 0.594 | 0.608 | 0.598 | 0.620 | 0.623 |
| | Shanxi | 0.438 | 0.457 | 0.471 | 0.482 | 0.489 | 0.515 | 0.520 | 0.545 | 0.566 | 0.539 | 0.545 | 0.540 |
| | Jiangxi | 0.459 | 0.472 | 0.503 | 0.514 | 0.551 | 0.570 | 0.589 | 0.613 | 0.644 | 0.631 | 0.646 | 0.637 |
| | Henan | 0.510 | 0.533 | 0.549 | 0.555 | 0.571 | 0.596 | 0.612 | 0.629 | 0.660 | 0.647 | 0.672 | 0.658 |
| | Hubei | 0.497 | 0.518 | 0.533 | 0.554 | 0.574 | 0.588 | 0.607 | 0.615 | 0.637 | 0.636 | 0.659 | 0.665 |
| | Hunan | 0.515 | 0.535 | 0.546 | 0.559 | 0.596 | 0.612 | 0.612 | 0.626 | 0.668 | 0.679 | 0.670 | 0.678 |
| Western region | Yunnan | 0.442 | 0.462 | 0.489 | 0.500 | 0.520 | 0.535 | 0.554 | 0.590 | 0.651 | 0.608 | 0.634 | 0.658 |
| | Inner Mongolia | 0.385 | 0.403 | 0.424 | 0.439 | 0.447 | 0.458 | 0.486 | 0.495 | 0.508 | 0.497 | 0.487 | 0.500 |
| | Sichuan | 0.515 | 0.541 | 0.559 | 0.569 | 0.598 | 0.623 | 0.649 | 0.667 | 0.709 | 0.718 | 0.727 | 0.724 |
| | Ningxia | 0.348 | 0.362 | 0.376 | 0.385 | 0.392 | 0.410 | 0.416 | 0.429 | 0.432 | 0.446 | 0.453 | 0.465 |
| | Guangxi | 0.431 | 0.455 | 0.474 | 0.490 | 0.512 | 0.530 | 0.550 | 0.582 | 0.629 | 0.619 | 0.650 | 0.640 |
| | Xinjiang | 0.414 | 0.433 | 0.439 | 0.437 | 0.457 | 0.470 | 0.479 | 0.496 | 0.504 | 0.498 | 0.524 | 0.530 |
| | Gansu | 0.355 | 0.382 | 0.396 | 0.407 | 0.428 | 0.450 | 0.468 | 0.488 | 0.513 | 0.507 | 0.519 | 0.512 |
| | Guizhou | 0.424 | 0.450 | 0.475 | 0.496 | 0.528 | 0.561 | 0.596 | 0.624 | 0.667 | 0.633 | 0.658 | 0.649 |
| | Chongqing | 0.477 | 0.499 | 0.513 | 0.521 | 0.540 | 0.559 | 0.572 | 0.591 | 0.624 | 0.617 | 0.614 | 0.624 |
| | Shaanxi | 0.446 | 0.458 | 0.478 | 0.493 | 0.514 | 0.532 | 0.545 | 0.562 | 0.602 | 0.585 | 0.603 | 0.607 |
| | Qinghai | 0.314 | 0.335 | 0.368 | 0.384 | 0.397 | 0.411 | 0.435 | 0.446 | 0.479 | 0.485 | 0.500 | 0.512 |
| Northeastern region | Heilongjiang | 0.420 | 0.436 | 0.445 | 0.458 | 0.467 | 0.480 | 0.486 | 0.501 | 0.521 | 0.508 | 0.518 | 0.521 |
| | Jilin | 0.514 | 0.535 | 0.557 | 0.567 | 0.573 | 0.574 | 0.582 | 0.600 | 0.610 | 0.596 | 0.619 | 0.601 |
| | Liaoning | 0.432 | 0.463 | 0.484 | 0.481 | 0.501 | 0.513 | 0.538 | 0.551 | 0.565 | 0.560 | 0.564 | 0.567 |

2022, Guangdong (0.752), Jiangsu (0.720), and Shandong (0.708) ranked at the top. These results are closely related to their higher economic development levels, sound institutional environments, and mature market systems. In these regions, agricultural ecological improvements can often be quickly incorporated into rural tourism products and converted into competitive advantages through branding and digital marketing. At the same time, stable tourism consumption demand provides continuous incentives for green agricultural production, creating a relatively stable interaction pattern. The high coordination in the eastern region therefore reflects deeper industrial integration rather than growth in a single sector.

The central region shows a clear catch-up pattern. In 2022, Henan (0.658), Hubei (0.665), and Hunan (0.678) all exceeded 0.65, indicating that the synergistic relationship is strengthening more quickly. In recent years, the central region has increased efforts in agricultural structural adjustment and green investment. At the same time, improvements in transportation infrastructure and support from culture-tourism policies have steadily expanded the tourism market. Improvements in the agricultural ecological environment are beginning to translate into stronger tourism appeal, and the interaction between the two systems is becoming more visible. Compared with the east, the central region is still in a stage of institutional integration and deeper industrial convergence, but its coordination degree has improved more sharply. This latecomer advantage is already reflected in the data.

The western region is more complex. Its coordination degree has improved rapidly overall, but interprovincial differences remain pronounced. Sichuan (0.724) has entered a relatively advanced coordination range. Its rich ecological resources and foundation in cultural tourism provide practical support for agriculture-tourism integration and allow the results of agricultural circularity to be embedded in tourism product structures. However, Qinghai (0.512), Ningxia (0.465), and some other provinces remain at medium-low coordination levels. This gap is closely related to industrial scale, market capacity, and infrastructure conditions. Although agricultural green transformation is advancing, its results have not yet been fully converted into tourism growth momentum, and the linkage effect between the two systems still needs to be strengthened.

The northeastern region evolved at a relatively steady pace. In 2022, Heilongjiang (0.521), Jilin (0.601), and Liaoning (0.567) maintained growth, but the overall increase was limited. Pressures from industrial restructuring, population mobility, and insufficient tourism market vitality have prevented a strong reinforcing mechanism from forming between agricultural circular transformation and tourism expansion. This stable but slow change also reflects the influence of structural inertia in regional economic transformation.

Changes over time are also notable. From 2011 to 2019, coordination improved steadily, closely linked to the continued advance of agricultural green policies and the implementation of the rural revitalization strategy. During this stage, agriculture-tourism integration gradually moved from exploration to institutionalized practice, and the matching level between the systems increased. The phased decline in 2020 came mainly from a short-term contraction in rural tourism demand that disrupted the pace of development, rather than from a clear decline in the agricultural circular economy. When the tourism market gradually recovered in 2021–2022, the coordination degree rebounded. This shows that the agricultural circular system remained relatively stable under external shocks and provided a foundation for tourism recovery. The two systems have therefore formed a degree of structural resilience.

Taken together, the analysis shows that China's agricultural circular economy and rural tourism are moving from simple association toward structural optimization. In the early stage, high coupling mainly meant that the systems were closely connected, while development quality was not yet fully synchronized. As agricultural green efficiency improved and the tourism structure adjusted, coordination levels rose. The central and western regions improved more quickly, suggesting some convergence. Nevertheless, regional gaps have not been fully closed. In regions with weaker resource endowments or limited market size, coordinated development continues to face real constraints.

This raises an important question: where should future breakthroughs in coordinated development come from? The current results suggest that improving efficiency within a single sector is no longer sufficient to further raise coordination. Deeper institutional integration and industrial convergence may be the key pathway toward high-quality coordination. In this sense, the interaction between the agricultural circular economy and rural tourism is not only the outcome of structural matching. It is also an institutional process that continues to evolve. The empirical value of this finding is that it reframes agriculture-tourism integration from a simple industrial-linkage issue into a system-coordination issue. It shows that rural sustainable development depends on the conversion of agricultural ecological gains into tourism value and on the reverse incentives generated by tourism markets for greener agricultural production.

## 4.4 Spatial association and convergence diagnostics

The spatial exploration confirms that coordination has a weak but persistent clustering tendency. Global Moran's $I$ remains positive in every year, ranging from 0.096 in 2017 to 0.119 in 2022, and all annual values pass the 999-permutation significance test (maximum annual $p$-value = 0.024; Table 12). Because Moran's $I$ is a global statistic, this result should not be overinterpreted as strong nationwide clustering. It shows that similar coordination levels tend to be geographically closer, but the clustering intensity is limited.

Figure 3 presents a province-grouped heatmap of coupling coordination for four selected benchmark years (2011, 2015, 2019, and 2022). The visualization shows that coordination improved substantially from 2011 to 2022 and that high-value provinces expanded from the eastern coastal area toward several central and western growth poles. Because the empirical sample is a balanced provincial panel, the visualization is used to compare statistical units in the sample rather than to make administrative-boundary claims.

TABLE 12 Global Moran's *I* of coupling coordination, 2011–2022.

| Year | Moran's I | Permutation *p*-value | Interpretation |
|---|---|---|---|
| 2011 | 0.109 | 0.006 | Positive spatial association |
| 2012 | 0.104 | 0.011 | Positive spatial association |
| 2013 | 0.119 | 0.001 | Positive spatial association |
| 2014 | 0.104 | 0.005 | Positive spatial association |
| 2015 | 0.103 | 0.009 | Positive spatial association |
| 2016 | 0.101 | 0.015 | Positive spatial association |
| 2017 | 0.096 | 0.024 | Positive spatial association |
| 2018 | 0.107 | 0.005 | Positive spatial association |
| 2019 | 0.097 | 0.019 | Positive spatial association |
| 2020 | 0.108 | 0.006 | Positive spatial association |
| 2021 | 0.111 | 0.002 | Positive spatial association |
| 2022 | 0.119 | 0.004 | Positive spatial association |

TABLE 13 Main obstacle factors in selected years.

| Year | Rank | Code | Indicator | Obstacle degree (%) |
|---|---|---|---|---|
| 2011 | 1 | X2 | Output per unit of land | 12.62 |
| 2011 | 2 | X1 | Agricultural value added | 8.84 |
| 2011 | 3 | X9 | Fertilizer output efficiency | 8.72 |
| 2011 | 4 | X8 | Agricultural machinery output efficiency | 8.54 |
| 2011 | 5 | Y3 | Domestic tourist arrivals | 7.04 |
| 2015 | 1 | X2 | Output per unit of land | 13.23 |
| 2015 | 2 | X9 | Fertilizer output efficiency | 8.98 |
| 2015 | 3 | X8 | Agricultural machinery output efficiency | 8.76 |
| 2015 | 4 | X1 | Agricultural value added | 8.64 |
| 2015 | 5 | Y3 | Domestic tourist arrivals | 7.34 |
| 2019 | 1 | X2 | Output per unit of land | 13.54 |
| 2019 | 2 | X9 | Fertilizer output efficiency | 9.27 |
| 2019 | 3 | X1 | Agricultural value added | 9.05 |
| 2019 | 4 | X8 | Agricultural machinery output efficiency | 8.71 |
| 2019 | 5 | Y3 | Domestic tourist arrivals | 7.75 |
| 2022 | 1 | X2 | Output per unit of land | 12.83 |
| 2022 | 2 | Y3 | Domestic tourist arrivals | 8.65 |
| 2022 | 3 | X9 | Fertilizer output efficiency | 7.99 |
| 2022 | 4 | X1 | Agricultural value added | 7.72 |
| 2022 | 5 | X8 | Agricultural machinery output efficiency | 7.64 |

Figure 2 presents province-level Getis-Ord Gi* hot-spot and cold-spot choropleth maps for the selected benchmark years. Hot spots are mainly concentrated in eastern coastal provinces and gradually include several central provinces, whereas cold spots are concentrated in the northwest. This spatial pattern is consistent with the regional-gradient results: market access, public-service capacity, tourism demand, and agricultural production efficiency jointly shape high-value clusters, whereas remote western provinces still face constraints in transforming ecological resources into coordinated agriculture-tourism development.

The trend and convergence diagnostics further strengthen the empirical evidence. After controlling for regional fixed differences, coupling coordination increases significantly year by year (coefficient = 0.0139, robust SE = 0.0009, $p < 0.001$). The beta-convergence test gives a significantly negative coefficient for the initial 2011 coordination level (coefficient = −0.368, robust SE = 0.077, $p < 0.001$), indicating that provinces with lower initial coordination tended to grow faster. The sigma-convergence result is consistent with this pattern: the coefficient of variation declined from 0.162 in 2011 to 0.120 in 2022, a decrease of 26.1%. These results show that the improvement in coordination is statistically supported rather than merely descriptive.

## 4.5 Obstacle-factor diagnosis

The obstacle-degree results further reveal where coordinated development is constrained. Across the sample period, the leading obstacles are concentrated in agricultural circular economy efficiency indicators. Output per unit of land (X2) ranks first in every year, with an obstacle degree of 12.83% in 2022. This means that the coordination system is still constrained by land productivity and intensive agricultural output capacity rather than by interaction intensity alone. Fertilizer output efficiency (X9) and agricultural machinery output efficiency (X8) indicate whether agricultural input and equipment investment are effectively converted into output; their high obstacle degrees show that circular agriculture must improve input-output efficiency, not only reduce inputs. Agricultural value added (X1) reflects the economic carrying capacity of agriculture itself; when this factor remains a bottleneck, rural tourism lacks a stronger production-side foundation for product development, branding, and value-chain extension. On the rural tourism side, domestic tourist arrivals (Y3) becomes increasingly important, rising to the second-largest obstacle in 2022 (8.65%). This does not simply mean that more tourists are always better; rather, it indicates that after the 2020 shock, demand recovery and stable tourism flows became key conditions for converting agricultural ecological improvement into market value. Therefore, obstacle diagnosis has substantive meaning: it identifies the specific levers through which coordination can move from low-level association to higher-quality integration. The main obstacle factors in selected years are summarized in Table 13.

# 5 Discussion

## 5.1 Findings on coupling coordination

The findings help clarify the theoretical relationship between agricultural circular economy development and rural tourism.

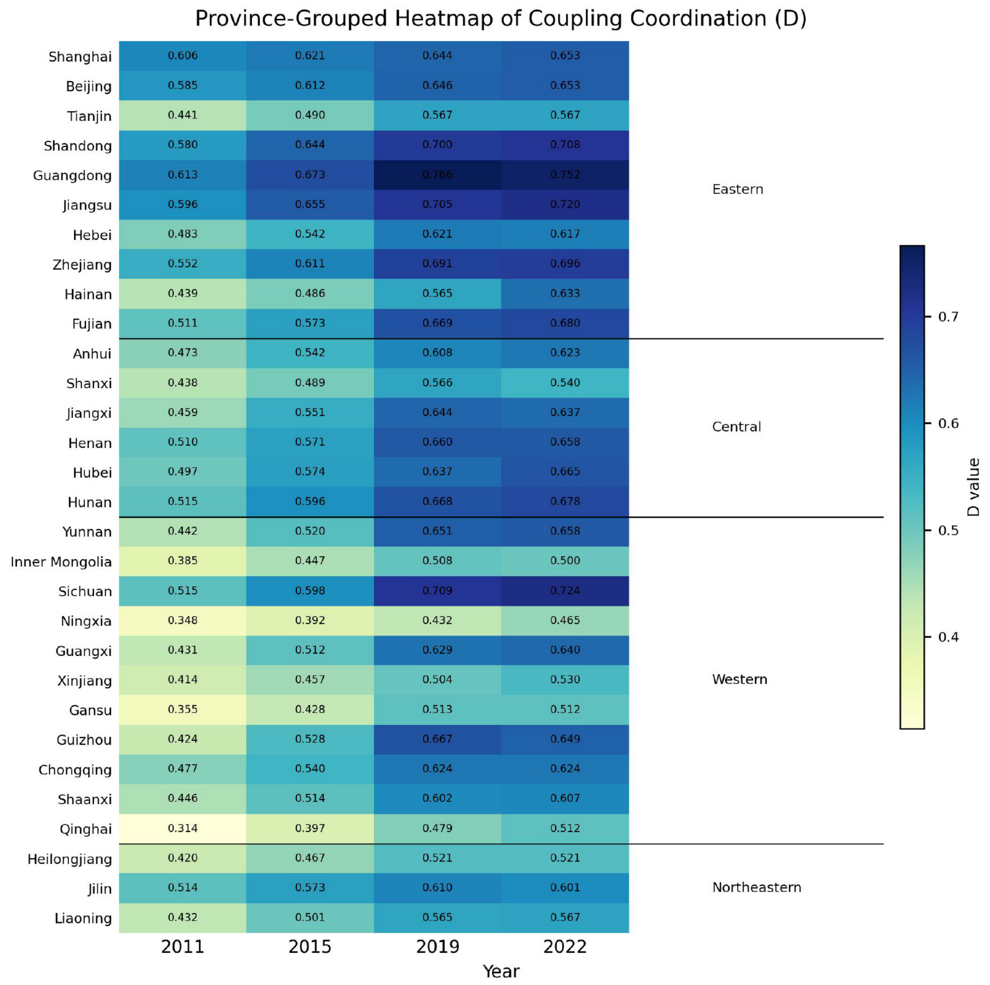


FIGURE 3
Province-grouped heatmap of coupling coordination in 30 Chinese provincial-level units, 2011, 2015, 2019, and 2022. *D* values are shown for four benchmark years. Provinces are grouped by region. Source: Authors' calculations based on the coupling coordination model; heatmap design follows common regional panel visualization practice.

Agricultural circular transformation improves the ecological and efficiency foundation of rural space, while rural tourism creates demand-side incentives for ecological value conversion. This two-way relationship explains why the two subsystems remain closely connected. However, the coordination results also show that connection alone is insufficient. Coordinated development depends on whether ecological improvement, agricultural efficiency, tourism demand, and public-service support improve together.

The distinction between coupling degree and coupling coordination is therefore important. The high coupling degree confirms that the two systems are strongly associated, but it has limited ability to distinguish regional development quality when values are compressed near the upper bound. The coordination degree, together with the significant annual trend and convergence tests, provides a more meaningful picture: coordination has improved over time, lower-level provinces show catch-up tendencies, and regional dispersion has narrowed, but most provinces have not yet reached a high-coordination stage.

These findings also extend existing studies on rural tourism, agriculture-tourism integration, and circular economy evaluation. Prior rural tourism research mainly emphasizes sustainability, destination competitiveness, community participation, visitor demand, and agriculture-tourism integration performance (Lane and Kastenholz, 2015; Sharpley, 2020; Park and Yoon, 2009; Su, 2011; Saxena et al., 2007; Moscardo, 2014; Zhao et al., 2025; Cawley and Gillmor, 2008; Gao and Wu, 2017; Gössling and Peeters, 2015; Lenzen et al., 2018; Wang et al., 2022a; Dwyer and Kim, 2003; Crouch, 2011; Fleischer and Tchetchik, 2005; Zhang et al., 2023), while circular-economy studies focus more on resource efficiency, material circulation, and production-side green transformation (Geissdoerfer et al., 2017; Kirchherr et al., 2017; Korhonen et al., 2018; Haas et al., 2015; Niero and Kalbar, 2019; Bringezu, 2015; Zhang et al., 2021; Moraga et al., 2019; Velenturf and Purnell, 2021; Saidani et al., 2019; Li et al., 2021; Peng et al., 2025a). By placing the two subsystems in a unified framework, this study shows that high interaction intensity does not necessarily imply high-quality coordination. The empirical pattern of high coupling but uneven coordination suggests that ecological production upgrading, tourism demand recovery, public-service support, and regional governance capacity must improve together before agriculture-tourism linkage can become a stable rural transformation mechanism.

## 5.2 Spatial distribution of coupling coordination

The spatial results further enrich the explanation of regional differentiation. The positive and significant Moran's $I$ values and the Gi* hot spot results show that coordination is not randomly distributed, but rather has weak global association and identifiable local clustering. Neighboring market conditions, transportation links, policy diffusion, ecological resource endowments, and public-service capacity may jointly shape this pattern. Eastern provinces benefit from mature markets and stronger service systems, while some western and northeastern provinces still face constraints in converting agricultural ecological resources into stable tourism competitiveness. These findings support differentiated governance rather than a uniform national policy package.

## 5.3 Obstacles to coupling coordination

The obstacle-factor results make the empirical analysis more interpretable and policy-relevant because they shift the focus from whether coordination is improving to why coordination remains at a relatively low level in many provinces. The main obstacles are not abstract institutional slogans, but measurable bottlenecks in land-output efficiency, fertilizer and machinery conversion efficiency, agricultural value creation, and tourism demand recovery. This pattern suggests that the next stage of coordination should not rely only on expanding tourism scale or promoting circular agriculture separately. It requires a joint upgrading process in which agricultural production becomes more efficient and cleaner, while rural tourism becomes better able to absorb and monetize ecological and cultural value. Together, the province-level spatial visualization, Moran's $I$, Gi* hot-spot analysis, convergence tests, and obstacle-degree diagnosis clarify the temporal trend, regional catch-up, local clustering, and policy levers of the coupling coordination results.

## 5.4 Methodological and practical implications

The results have two methodological implications. First, coupling degree and coupling coordination should not be treated as interchangeable indicators. The former captures interaction intensity, whereas the latter better reflects whether the development levels of the two subsystems are matched. Second, obstacle diagnosis is useful because it translates the abstract idea of coordinated development into measurable bottlenecks, including land-output efficiency, fertilizer and machinery conversion efficiency, agricultural value added, and tourism demand recovery.

The practical implication is that agriculture-tourism coordination should be understood as a joint upgrading process rather than as a simple industrial-linkage project. Provinces with higher $D$ values need to consolidate product quality, ecological certification, digital services, and cross-regional tourism routes, whereas lower-value provinces should first strengthen agricultural efficiency, manure-resource utilization, chemical-input reduction, transport accessibility, and basic public services.

## 5.5 Limitations and future research

Several limitations should be noted. First, this study is conducted at the provincial level. This scale improves statistical comparability over 2011–2022, but it cannot fully capture within-province differences among counties, villages, and specific rural tourism destinations. In addition, several variables in the rural tourism subsystem are destination-support proxies, such as public-service and environmental indicators, because continuous province-level rural-tourism statistics remain limited. Future studies should incorporate destination-level data, firm or farm survey data, and visitor-flow data when they become available.

Second, the methods used in this study are mainly descriptive and diagnostic. The entropy weight method depends on the selected indicator system, the coupling coordination model measures matched development rather than causal mechanisms, and the obstacle-degree model identifies bottlenecks within the evaluation framework rather than causal coefficients. Similarly, Moran's $I$ and Gi* are exploratory spatial statistics. They reveal global association and local clustering but cannot by themselves establish spatial spillovers or causal transmission. Future research can compare adjacency, inverse-distance, and economic-distance matrices and further use spatial econometric models or policy-shock designs to test mechanisms more directly.

Third, the sample excludes Tibet, Hong Kong, Macao, and Taiwan because of data availability and differences in statistical caliber. This exclusion helps maintain balanced-panel comparability but may understate spatial heterogeneity in some border, island, and high-altitude tourism-resource regions. The figures are therefore interpreted as statistical visualizations of the empirical sample rather than as administrative-boundary evidence. Future research should update the sample when consistent data become available. For the present study, the province-level maps are used as statistical visualizations of the empirical sample, and officially approved standard base-map materials are used for cartographic completeness.

# 6 Conclusions

Based on Chinese provincial panel data from 2011 to 2022, this study examines the coordinated relationship between the agricultural circular economy and rural tourism development. The analysis reports entropy weights, clarifies the sample of 30 provinces, specifies the methodological formulas, and supplements the coupling coordination model with spatial association, convergence, and obstacle-factor diagnostics. The findings show that the two subsystems differ in development rhythm and volatility, but they are gradually moving from weak imbalance and weak coordination toward higher coordination stages.

First, the agricultural circular economy subsystem follows a path of continuous and steady structural evolution. Its overall volatility is limited, and it shows clear path dependence and gradual optimization. Regions with lower initial development levels grew faster, displaying a degree of catch-up. This suggests that agricultural green transformation has a spatial diffusion mechanism rather than being locked into a small number of highly developed regions. At the same time, marginal improvements in high-development regions gradually converged, and the focus of development shifted from scale expansion to efficiency improvement, technological upgrading, and institutional optimization. Overall, the agricultural circular economy has moved from extensive expansion to a stage centered on intensive improvement. Its evolution is driven more by long-term structural adjustment and institutional refinement than by short-term market-demand fluctuations.

Second, the rural tourism subsystem shows strong growth elasticity and phased volatility. Its development is strongly affected by changes in market demand and shocks from the macro environment. Compared with the agricultural circular economy, rural tourism fluctuates more sharply, and regional differences are more pronounced. Resource endowments, location conditions, and industrial foundations have significant effects on its development level. This structural feature indicates that rural tourism is a high-elasticity service system. Its sustainability depends not only on market expansion, but also on institutional regulation, risk-prevention mechanisms, and public-service provision. Under external shocks, tourism-system resilience becomes a key prerequisite for long-term stable growth.

Third, at the system-interaction level, the coupling degree remains high over the long term, but this should be interpreted as evidence of close association rather than proof of high-quality coordination. Coupling coordination provides stronger explanatory value because it incorporates both interaction intensity and subsystem development levels. Its annual trend is significantly positive (coefficient = 0.0139, $p < 0.001$), and by 2022, 17 provinces had entered low coordination and four had reached moderate coordination, indicating clear improvement but also room for further upgrading.

Fourth, the province-level visualizations, Moran's I, Getis-Ord Gi* hot-spot analysis, convergence, and obstacle-factor diagnostics show that coordination has a weak but significant positive spatial clustering tendency and clear local hot-spot/cold-spot differentiation, while regional gaps are narrowing to some extent. The beta-convergence coefficient is negative and significant (coefficient = $-0.368$, $p < 0.001$), and the coefficient of variation declined from 0.162 in 2011 to 0.120 in 2022. Key constraints are concentrated in agricultural efficiency and tourism demand indicators, especially output per unit of land, fertilizer output efficiency, agricultural value added, agricultural machinery output efficiency, and domestic tourist arrivals. These results identify the areas on which future coordinated development should focus.

## 6.1 Policy implications

Based on these empirical findings, policy should promote the long-term coordinated development of the agricultural circular economy and rural tourism through system integration, efficiency improvement, spatial coordination, and obstacle-oriented governance.

First, policy should strengthen the support function of the agricultural circular economy as an ecological foundation system. The policy focus should shift from scale expansion to efficiency improvement and technological innovation. Closed-loop agricultural models should be promoted, agricultural waste valorization systems improved, and digital management and precision-input technologies advanced. These steps can continuously improve resource-use efficiency and environmental carrying capacity in agricultural ecosystems. Only by consolidating the ecological foundation function of the agricultural circular economy can rural tourism gain stable environmental support and reduce the sensitivity of the dual system to external shocks. At the institutional level, land-use intensification, agricultural waste recycling, low-carbon energy transition, digital green innovation, and farmer participation should be coordinated rather than implemented as isolated projects (Moraga et al., 2019; Velenturf and Purnell, 2021; Saidani et al., 2019; Li et al., 2021; Peng et al., 2025a; Wang et al., 2022b, 2026; Bai et al., 2026; Zhao et al., 2026, 2025; Liu et al., 2026; Meng et al., 2026).

Second, rural tourism should be upgraded from scale-driven to quality-driven development. During this process, deeper integration with agricultural production and ecological resource management should be strengthened. Diverse formats such as farming experiences, ecological education, and rural cultural and creative products should be developed to improve the comprehensive value conversion of agricultural resources. At the same time, public-service systems and infrastructure should be continuously improved to enhance the tourism system's risk-response capacity and sustained operating capacity, thereby reducing its dependence on short-term market fluctuations.

Third, a multilevel collaborative governance mechanism should be established to narrow regional gaps. In policy design, central and local governments should strengthen differentiated support. For the central and western regions, greater support should be provided for technology diffusion, institutional innovation, and fiscal investment to promote the replication and diffusion of coordinated development models. For highly developed regions, policy should encourage demonstration and leadership in efficiency optimization and institutional innovation, creating integration pathways that can be replicated elsewhere. Cross-regional cooperation and experience-sharing mechanisms can improve overall coordination efficiency and promote more balanced regional development.

Fourth, an obstacle-oriented evaluation and monitoring system should be established. Local governments should not focus only on whether the two systems interact, but should also track the indicators that most constrain coordination, especially land-output efficiency, fertilizer and machinery efficiency, agricultural value added, and rural tourism demand recovery. Continuous monitoring of coupling coordination, spatial clustering, hot-spot/cold-spots, and obstacle factors can improve the precision and adaptability of policy regulation.

In conclusion, the coordinated development of the agricultural circular economy and rural tourism is not only a matter of industrial integration. It is also an important pathway for strengthening rural economic resilience, optimizing resource allocation, and advancing ecologically sustainable transformation. Future efforts should center on efficiency improvement and institutional integration. By strengthening system interaction mechanisms and governance capacity, the two subsystems can continue moving toward a higher level of coordination.

## Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

## Author contributions

GY: Data curation, Investigation, Resources, Formal analysis, Methodology, Project administration, Writing – original draft, Software. YY: Software, Methodology, Writing – original draft. SF: Investigation, Writing – original draft, Project administration. YZ: Formal analysis, Data curation, Visualization, Writing – original draft. HC: Data curation, Resources, Formal analysis, Writing – original draft. GT: Investigation, Funding acquisition, Visualization, Formal analysis, Validation, Data curation, Writing – review & editing. XZ: Validation, Software, Writing – review & editing, Methodology, Supervision.

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## Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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# Appendix A

The entropy-weight table is reported in the Appendix to avoid repeating the indicator definitions already shown in Tables 1, 2 while preserving transparency about the contribution of each indicator to the composite indices.

Appendix A1 Entropy weights of the agricultural circular economy and rural tourism indicators.

| Subsystem | Code | Indicator | Direction | Weight |
|---|---|---|---|---|
| ACE | X1 | Agricultural value added | Positive | 0.1781 |
| ACE | X2 | Output per unit of land | Positive | 0.2154 |
| ACE | X3 | Fertilizer application intensity | Negative | 0.0223 |
| ACE | X4 | Pesticide application intensity | Negative | 0.0145 |
| ACE | X5 | Agricultural water-use intensity | Negative | 0.0192 |
| ACE | X6 | Livestock and poultry manure utilization rate | Positive | 0.1111 |
| ACE | X7 | Multiple cropping index | Positive | 0.0660 |
| ACE | X8 | Agricultural machinery output efficiency | Positive | 0.1574 |
| ACE | X9 | Fertilizer output efficiency | Positive | 0.1449 |
| ACE | X10 | Agricultural non-point source pollution intensity | Negative | 0.0323 |
| ACE | X11 | Agricultural carbon emission intensity | Negative | 0.0388 |
| RTD | Y1 | Share of tourism revenue | Positive | 0.0912 |
| RTD | Y2 | Domestic tourism revenue | Positive | 0.1145 |
| RTD | Y3 | Domestic tourist arrivals | Positive | 0.1132 |
| RTD | Y4 | Star-rated hotels | Positive | 0.0881 |
| RTD | Y5 | Tourism employees | Positive | 0.1114 |
| RTD | Y6 | Transportation network density | Positive | 0.0794 |
| RTD | Y7 | Built-up area green coverage rate | Positive | 0.0193 |
| RTD | Y8 | Urban sewage treatment rate | Positive | 0.0121 |
| RTD | Y9 | CO2 emissions | Negative | 0.0229 |
| RTD | Y10 | Rural resident disposable income | Positive | 0.0790 |
| RTD | Y11 | Urban-rural income ratio | Negative | 0.0273 |
| RTD | Y12 | Tertiary-industry value-added share | Positive | 0.0535 |
| RTD | Y13 | Internet penetration rate | Positive | 0.0467 |
| RTD | Y14 | General public service budget expenditure | Positive | 0.0910 |
| RTD | Y15 | Health-institution beds per 1,000 people | Positive | 0.0504 |