



Reconstruction and Interpretability Analysis of China's Rural Tourism Development Level Based on SVR and SHAP Algorithms

Zhikun Xu^{1,*} and Yi Wang²

¹ School of Digital Economy and Finance, Guizhou University of Commerce, Guiyang 550014, Guizhou, China

² Academic Affairs Office, Party School of the CPC Hecheng District Committee, Huaihua 418000, Hunan, China

SUMMARY: *Rural tourism is a key industry promoted across regions in China and serves as a crucial driver for rural revitalization, socioeconomic development, and common prosperity. Assessing the development level of rural tourism and identifying the contributions of different indicators are essential for fostering sustainable growth. Based on provincial-level data from 2012 to 2023, this study constructs an evaluation index system for rural tourism development in China. Using the entropy method as a foundation, the SVR and SHAP algorithms are applied to reassess the relative importance of influencing variables. The results show that (1) overall, the level of rural tourism development in China exhibited an upward trend during 2012-2023, with a temporary decline observed in 2020. (2) In terms of dimensional scores, Tourism Assets contributed the most and increased the fastest, while Supportive Services showed a relatively stable but gradual rise, and Environmental Factors together with Supportive Services remained weak links in the rural tourism system. (3) regarding associated factors, the key drivers influencing rural tourism development include the number of traditional villages, the number of China's beautiful leisure villages, forest coverage rate, and the number of employees in travel agencies. Accordingly, policy recommendations are proposed in four areas: prioritizing the protection and revitalization of traditional villages, strengthening the brand of beautiful leisure villages, improving service quality and organizational supply, and promoting differentiated regional development strategies.*

KEYWORDS: *rural tourism; SVR; SHAP; comprehensive evaluation*

1 Introduction

In recent years, within the exploration of revitalization pathways, rural tourism—an industry form grounded in natural, historical, and cultural resources—has demonstrated the potential to attract external revenue, stimulate the growth of small enterprises, create employment opportunities, and promote investment in infrastructure and public services, thereby becoming a vital strategic choice for local economic development [1]. As a key engine for advancing rural revitalization and a crucial pathway for fostering rural–urban integration, rural tourism not only exhibits significant potential for economic growth but also plays a distinctive role in improving living environments, enriching cultural expression, and enhancing social cohesion [2]. At present, the global rural tourism market is experiencing rapid expansion. Accompanied by the accelerated growth of the tourism industry and the continuous improvement of the

*xzk_8103@163.com

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tertiary sector, rural tourism has evolved into an interdisciplinary research field and has increasingly become a subject of great concern for policymakers and the academic community worldwide [3]. Entering a stage of high-quality development, rural tourism now demonstrates strong momentum in terms of scale expansion, industrial chain extension, and comprehensive spillover effects, thereby emerging as an important driver for sustainable rural transformation.

However, alongside the rapid and vigorous growth of rural tourism, a number of challenges have also emerged [4]. Significant disparities exist in the development levels of different types of rural tourism destinations, with some regions experiencing restricted market growth, erosion of residents' interests, and mounting pressure on the ecological environment [5]. These practical constraints not only hinder the sustainable development of rural tourism but also exacerbate regional imbalances. Against this backdrop, how to scientifically and systematically evaluate the level of rural tourism development and formulate feasible optimization strategies has become an urgent issue. In particular, conducting objective and rigorous assessments, diagnosing the obstacles to rural tourism development across different regions, and adopting targeted and effective measures are critical for identifying weaknesses, correcting developmental deviations, and ultimately advancing the high-quality and sustainable development of rural tourism.

Against this backdrop, re-examining the evaluation system of rural tourism and introducing new methodological frameworks holds significant theoretical and practical value. On the one hand, it can contribute to deepening research on rural tourism and enriching the perspectives within the tourism discipline; on the other hand, it can provide policymakers and practitioners with a sound scientific basis for decision-making, thereby fostering the high-quality and sustainable development of rural tourism and advancing comprehensive revitalization of rural areas in the context of the new era.

2 Literature review

Rural tourism originated in European countries during the mid-19th century. In 1865, following the establishment of the National Association of Agriculture and Tourism in Italy, the public was encouraged to engage in rural activities, marking the official emergence of rural tourism under the association's strong promotion. Reference [6] and others defined the locations and services associated with rural tourism, viewing it as a form of tourism conducted in specific rural environments such as farms and ranches, where visitors can obtain food and accommodation while participating in leisure activities. Subsequently, Reference [7] provided a more comprehensive interpretation of the concept, arguing that rural tourism refers to tourism activities undertaken in rural areas, and that its forms vary across different countries and regions.

Existing research has primarily focused on the development models of rural tourism destinations and their impacts on host areas, consumer behavior characteristics and satisfaction, as well as government regulation and its effects. Reference [8] argued that evaluating the competitiveness of rural tourism in China is critical for tourism planning. However, due to the lack of suitable data and systematic methodologies, related studies remain insufficient. To address this, It adopted a modified version of Michael Porter's Diamond Model to integrate multiple data sources. Using 1,806 township-level units in Henan Province as a case study, It constructed an evaluation framework of rural tourism competitiveness and a typology of development models, identifying four types: balanced development driven by multiple advantages, complementary industries-driven, eco-resource-

oriented, and rural landscape–experience models. From the perspective of tourism empowerment and community participation, Reference [9] employed a structural equation model to examine the interactions among destination system construction, tourism empowerment, community participation, and participation capacity. The results showed that institutional construction significantly promotes both tourism empowerment and community participation; tourism empowerment exerts a strong positive effect on community participation; and participation capacity positively moderates the relationship between institutional construction and tourism empowerment. Reference [10] investigated tourist satisfaction by proposing a mixed-method approach based on online reviews to sustain rural tourism. Using 5,832 online reviews from two adjacent rural tourism destinations, Wu applied K-means clustering and importance–performance analysis to identify service attributes of concern to tourists, while opinion mining was used to reveal sources of dissatisfaction. The study suggested targeted strategies for sustainable development, highlighting natural environment, pricing, catering, hospitality, and cultural heritage as the core service dimensions. Specifically, Hongcun required urgent improvement in natural environment and pricing, with catering and hospitality also identified as weaknesses, providing data-driven managerial insights for rural tourism sustainability. Reference [11], drawing on 545 visitor questionnaires, developed a "Tourist Motivation–Destination Image–Satisfaction–Revisit Intention" framework using a structural equation model (SEM). The study examined the influence of learning and recreation motivations, novelty-seeking motivations, natural and cultural environments, social environment, and infrastructure on tourist behavior. Findings indicated that learning and recreation motivations, the natural environment, the social environment, and tourist satisfaction all had significant positive impacts on revisit intention. Moreover, satisfaction served as a mediating variable in the process through which tourist motivations and destination image influence revisit intention, offering empirical evidence for enhancing destination brand value and revisit rates. Reference [12], based on landscape perception theory, constructed a SEM pathway of "Landscape Perception–Satisfaction–Revisit Intention." Empirical analysis revealed that landscape perception had significant positive effects on both satisfaction and revisit intention, with satisfaction mediating the relationship. More specifically, five dimensions—natural ecology, historical culture, leisure and entertainment, educational experience, and overall itineraries—significantly enhanced revisit intention, with historical culture and overall itineraries exerting the greatest influence. The study further suggested in-depth exploration of rural historical and cultural resources, the creation of red-culture brands, and the optimization of high-quality itineraries to improve revisit intention, providing valuable insights for rural tourism planning. Reference [13], using data from the China County Statistical Yearbook (2006–2022), adopted a difference-in-differences (DID) approach to investigate the mechanisms through which government intervention influences rural tourism and farmers' income growth. The findings indicated that government-supported rural tourism development significantly promoted farmers' income growth, primarily by stimulating entrepreneurial activity, driving related industries, and optimizing resource allocation. However, its effects on narrowing the rural–urban income gap and reversing the declining share of labor income were limited. Further analysis revealed that the positive impact was more pronounced in regions with stronger economic foundations, higher agricultural development levels, and more favorable geographic conditions. The study suggested that developing countries need to employ more targeted and inclusive policy tools to effectively advance rural revitalization.

At the same time, most existing studies have evaluated the development level of rural tourism using weighting methods such as the AHP and the entropy method [14]. However, traditional approaches exhibit certain limitations when dealing with multidimensional and

complex variables, making it difficult to fully uncover the intrinsic mechanisms of rural tourism development. In addition, the identification and quantification of deep-seated influencing factors remain insufficient, resulting in a lack of robust scientific evidence for policymaking in practice. With the increasing application of machine learning in evaluation research [15], it has become imperative to re-examine the evaluation system for rural tourism development, as well as to further explore underlying influencing factors and quantify the contribution of each variable to rural tourism growth. Against this backdrop, the present study constructs an evaluation index system for rural tourism development in China based on four dimensions—Industrial Benefits, Tourism Assets, Supportive Services, and Environmental Factors. Subsequently, the study employs SVR and SHAP algorithms to identify key influencing factors, thereby providing effective decision support for the formulation of scientific rural tourism development policies and the promotion of sustainable growth in the sector.

3 Method Selection and Model Construction

3.1 Support Vector Regression (SVR) Algorithm

Support Vector Regression (SVR) is a self-learning algorithm that establishes correlations between low-dimensional and high-dimensional spaces through kernel mapping [16]. A distinctive advantage of SVR is its ability to achieve relatively accurate predictions even with limited training samples, making it well-suited for nonlinear forecasting problems characterized by high levels of uncertainty and relatively large datasets. Commonly used kernel functions include polynomial, RBF, σ , and linear kernels, which transform the data into higher-dimensional spaces to enhance predictive performance.

Let the training sample set $\{(x_i, y_i), i=1, \dots, n\}$ consist of n training samples. In the training set, x_i denotes the input vector, where $x_i \in R^d$ and d represents the dimensionality of the space; y_i denotes the output variable, $y_i \in R$. The discriminant function of the SVM can be expressed as follows [17]:

$$f(x) = \omega \cdot \varphi(x) + b \quad (1)$$

In this formulation, $\varphi(x)$ denotes the mapping function, ω represents the linear weight vector, and b is the bias term. Since, in practical applications, linear inseparability in high-dimensional space often occurs to some extent, slack variables can be introduced to relax the constraints and thereby improve the computational efficiency of the algorithm. The optimization problem of SVR can thus be defined as follows:

$$\begin{cases} \min & \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \\ s.t. & y_i - \omega \cdot \varphi(x) - b \leq \varepsilon + \xi_i \\ & \omega \cdot \varphi(x) + b - y_i \leq \varepsilon + \xi_i^* \\ & \xi_i \geq 0, \xi_i^* \geq 0 \end{cases} \quad (2)$$

Here, C represents the penalty parameter; ε denotes the error loss coefficient; ξ_i and ξ_i^* are slack variables, whose values are determined according to the allowable deviation

error specified by the model.

For the optimization problem in Equation (2), the solution can be obtained by constructing the Lagrangian function:

$$\begin{aligned}
 \max \quad & \sum_{i=1}^n y_i (a_i - a_i^*) - \frac{1}{2} \sum_{i,j=1}^n (a_i - a_i^*)(a_j - a_j^*) \\
 & - \varepsilon \sum_{i=1}^n (a_i + a_i^*) \\
 \text{s.t.} \quad & \sum_{i=1}^n (a_i - a_i^*) = 0 \\
 & a_i \geq 0, a_i^* \leq C
 \end{aligned} \tag{3}$$

where a_i , a_i^* denotes the Lagrange multipliers, and $k(x_i, x)$ represents the kernel function.

From Equation (3), the solution to Equation (1) can be obtained, and the SVR prediction model can be expressed as follows:

$$f(x) = \sum_{i=1}^n (a_i - a_i^*) k(x_i, x) + b \tag{4}$$

The SVR prediction model demonstrates strong generalization capability. By introducing kernel functions, it enables precise mapping from low-dimensional space to high-dimensional space, thereby effectively addressing multi-factor nonlinear prediction problems. Among them, the selection of the kernel function parameter σ has a substantial impact on the prediction accuracy of the model. Therefore, it is necessary to determine an appropriate σ value to achieve more accurate predictions.

3.2 SHAP Interpretability Analysis

SHAP is a widely used feature attribution mechanism in explainable artificial intelligence, which employs concepts from game theory to quantify the contribution of individual features to machine learning model predictions. Its core principle lies in computing the average marginal contribution of each feature when added to the model, thereby assessing its influence on the prediction outcome [18]. Compared with other approaches to evaluating variable importance, the SHAP method offers two major advantages: (1) it provides a unified framework for ranking feature importance, and (2) it satisfies the condition of consistency when assessing contribution values.

In SHAP, given an input $x = [x_1, \dots, x_p]$ and a trained model T, SHAP employs a simplified surrogate model M to approximate T. The surrogate model M can be readily interpreted to reveal the contribution of each feature value. Formally, the model M can be expressed as follows [19]:

$$M(z) = \phi_0 + \sum_{i=1}^p \phi_i z_i \tag{5}$$

In this formulation, p denotes the total number of features, and $z = [z_1, \dots, z_p]^T$ represents a simplified binary encoding of the input $x = [x_1, \dots, x_p]$, where the value of 1 indicates that

the corresponding feature is included in the prediction and 0 otherwise. The term ϕ denotes the contribution of each feature to the model. Accordingly, the SHAP value for the i^{th} feature is defined as follows: denotes the contribution of each feature to the model. Accordingly, the SHAP value for the i^{th} feature is defined as follows [20]:

$$\phi_i(T, x) = \sum_{z \subseteq x} \frac{|z|!(p-|z|-1)!}{p!} (T(z) - T(z \setminus i)) \quad (6)$$

4 Indicator System and Data Description

4.1 Indicator System

Compared with urban tourism, rural tourism overlaps more closely with the living and production spaces of local residents. Consequently, rural tourism entails more complex social and industrial relationships [21]. Building upon existing research findings and integrating the new connotations of rural tourism, an evaluation indicator system for rural tourism development was constructed. The design adheres to the principles of systematicity, scientific rigor, objectivity, comparability, and operability. Specifically, the system is structured around four dimensions—Industrial Benefits, Tourism Assets, Supportive Services, and Environmental Factors—to comprehensively assess the development level of rural tourism in China. The detailed indicator framework is presented in **Table 1**.

Table 1: Evaluation Indicator System for the Development Level of Rural Tourism in China

Dimension	Factor index	Unit	Property	Weight
Industrial Benefits	Total Number Of Tourists Received	10,000 Persons	+	0.0557
	Total Income From Tourism	100 Million Rmb \	+	0.0750
	Tourist Turnover	100 Million Person-Kilometers	+	0.0629
	Gdp	10 Thousand Rmb \	+	0.0722
	Employees Of Tourism Industry	Person	+	0.0613
Tourism Assets	Number Of Star-Rated Hotels	Number	+	0.0418
	Number Of A-Grade Tourist Attractions	Number	+	0.0515
	Number Of Travel Agencies	Number	+	0.0488
	Number Of China's Beautiful Leisure Villages	Number	+	0.0866
	Demonstration Counties (Sites) For Leisure Agriculture And Rural Tourism	Number	+	0.0284
	Number Of Traditional Villages	Number	+	0.1440
Supportive Services	Employees Of Star-Rated Hotels	Person	+	0.0638
	Employees Of Travel Agencies	Person	+	0.0734
	Employees Of Tourist Attractions	Person	+	0.0858
Environmental Factors	Forest Coverage Rate	%	+	0.0444
	Harmless Treatment Rate Of Household Waste	%	+	0.0043

4.2 Industrial Benefits

In the Industrial Benefits dimension, the selected indicators construct an evaluation framework from three perspectives: economic output, market scale, and social contribution. Total tourism revenue directly quantifies the capacity of rural tourism to generate economic value, serving as the core benchmark for assessing industrial profitability [22]. Gross Domestic Product (GDP) reflects the sector's contribution to overall regional economic growth and thus functions as the key macro-level indicator of Industrial Benefits. Total number of tourist arrivals captures market attractiveness and spatial reach from the demand side, where expansion in scale reveals the potential for sustainable development. Passenger turnover integrates both the volume of visitors and their travel distances, thereby measuring the sector's capacity to activate regional transportation networks and spatial linkages. Number of employees in the sector intuitively reflects the industry's ability to absorb rural labor, serving as a direct embodiment of its social benefits. Collectively, these indicators constitute the "output–scale–employment" evaluation framework of Industrial Benefits, providing a comprehensive representation of rural tourism's overall driving effect on regional development.

4.3 Tourism Assets

In the Tourism Assets dimension, the selected indicators focus on the core resources and infrastructural carriers that support industrial development [23]. The number of A-grade tourist attractions, as standardized and rated core attractions, directly reflects the capacity of rural tourism to transform resources into large-scale and regulated offerings, thereby serving as a key marker of core competitiveness. Officially recognized units such as Beautiful Leisure Villages of China and National Demonstration Counties (or Sites) for Leisure Agriculture and Rural Tourism indicate the level of standardized development and demonstration effect achieved under policy guidance, while also carrying the value of brand endorsement. The number of traditional villages reflects the preservation and utilization of cultural heritage and historical resources, constituting an essential asset for the development of culture-oriented experiential tourism and shaping the cultural distinctiveness of the industry. Meanwhile, the number of star-rated hotels and travel agencies represent, respectively, the maturity of accommodation facilities and the market capacity of visitor-organizing channels, jointly forming the critical support system for transforming resources into tourism products.

4.4 Supportive Services

In the Supportive Services dimension, the selected indicators emphasize the core human resources that ensure the quality of the tourism experience. The number of employees in star-rated hotels, number of employees in travel agencies, and number of employees in tourist attractions correspond respectively to the three core scenarios of rural tourism—"accommodation services, visitor organization, and on-site experiences." The scale of these workforces directly determines the capacity for service provision. As the direct executors of service delivery, the size and professionalization of these employees form the foundation for the efficient operation of the service system and constitute a central factor shaping visitor perceptions of the tourism experience [24]. Such indicators effectively measure the stability and professionalism of the rural tourism service system, thereby providing an assessment of the industry's capacity for sustainable development.

4.5 Environmental Factors

In the Environmental Factors dimension, the selected indicators are grounded in the fundamental ecological attributes of rural tourism. Forest coverage rate, as a key measure of natural ecological quality, directly reflects the integrity and stability of regional ecosystems. It not only constitutes the material basis of rural tourism's "ecological attractiveness", but also underpins critical ecosystem services such as climate regulation and biodiversity conservation, thereby serving as a prerequisite for the development of eco-tourism. Meanwhile, the harmless treatment rate of domestic waste reflects the level of governance of the rural living environment, directly linking to environmental sustainability in tourism activities. This indicator simultaneously measures a region's capacity to respond to environmental pressures generated by tourism and demonstrates the degree of coordination between "tourism development and environmental carrying capacity," thus constituting a core criterion for ensuring the industry's sustainable development.

4.6 Data Sources

This study selects 30 provincial-level administrative regions in China from 2012 to 2023 (excluding Hong Kong, Macao, Taiwan, and Tibet) as the research objects [25]. The data are derived from the China Statistical Yearbook, the China Culture and Tourism Statistical Yearbook (formerly the China Tourism Statistical Yearbook), provincial statistical yearbooks, provincial statistical bulletins on national economic and social development, ecological and environmental status bulletins, and officially released data on government websites. The entropy-weight method was employed to assign weights to the evaluation indicators of rural tourism development in China, and the resulting weight coefficients are presented in Table 1.

5 Results and Analysis

5.1 Descriptive Statistical Analysis

The rural tourism development levels of 30 provinces in China from 2012 to 2023 are shown in **Table 2**. First, the overall development level of rural tourism in China demonstrates a steady upward trend, rising from 0.1478 in 2012 to 0.3083 in 2023—an increase of approximately 109 percentage points. This indicates that under the combined influence of policy guidance, market demand, and industrial integration, rural tourism in China has achieved a leap forward from its initial stage to steady growth. Its overall strength, spatial coverage, and social influence have all been significantly enhanced. Second, in 2023, the provinces ranking at the top in rural tourism development level include Zhejiang (0.5620), Guangdong (0.5151), Sichuan (0.5003), Hunan (0.5001), Shandong (0.4682), Yunnan (0.4340), Jiangsu (0.4318), Fujian (0.4017), Anhui (0.3728), and Guizhou (0.3664). These provinces, by virtue of their superior natural endowments, profound cultural heritage, and early industrial deployment, have established relatively complete rural tourism systems, making them leading regions in China's rural tourism development. Third, between 2019 and 2020, the rural tourism development levels in most provinces experienced a temporary decline due to the impact of the COVID-19 pandemic. This highlights the sensitivity and vulnerability of the tourism industry to public health emergencies. From 2021 onward, with the normalization of pandemic prevention and control measures and the implementation of supportive policies for the cultural and tourism industries, rural tourism development levels in most provinces gradually recovered and showed an upward trend. However, some regions, constrained by differences in resource endowments, market environments, and recovery

capacities, continued to show signs of decline. By 2023, rural tourism development levels nationwide had generally achieved rapid growth, reflecting a trend of comprehensive recovery and accelerated improvement, thereby demonstrating the resilience and growth potential of the rural tourism system.

Table 2: Evaluation of Rural Tourism Development Levels in China, 2012–2023

LOCALTY	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
ANHUI	0.1666	0.1695	0.2089	0.2134	0.2221	0.2560	0.2741	0.3393	0.3000	0.3167	0.3171	0.3728
BEIJING	0.2184	0.2251	0.2464	0.2537	0.2385	0.2521	0.2858	0.2979	0.2599	0.2377	0.2276	0.2702
CHONGQING	0.1105	0.1136	0.1427	0.1510	0.1540	0.1631	0.1728	0.1970	0.1842	0.1984	0.2057	0.2423
FUJIAN	0.1907	0.1950	0.2269	0.2372	0.2643	0.2813	0.2816	0.3628	0.3533	0.3523	0.3571	0.4017
GANSU	0.0894	0.0907	0.0952	0.1052	0.1192	0.1349	0.1566	0.1844	0.1421	0.1420	0.1430	0.1847
GUANGDONG	0.3757	0.3774	0.4414	0.4380	0.4206	0.4481	0.4525	0.5047	0.4604	0.4469	0.4494	0.5151
GUANGXI	0.1456	0.1462	0.1769	0.2037	0.2106	0.2300	0.2465	0.3002	0.2951	0.3019	0.3016	0.3489
GUIZHOU	0.1005	0.1466	0.1923	0.2011	0.2338	0.2600	0.2827	0.3412	0.3219	0.3304	0.3320	0.3664
HAINAN	0.0757	0.0765	0.0847	0.0914	0.0959	0.1031	0.1038	0.1192	0.1221	0.1268	0.1270	0.1431
HEBEI	0.1618	0.1670	0.2034	0.2099	0.2297	0.2625	0.2886	0.2943	0.2593	0.2666	0.2646	0.3275
HEILONGJIANG	0.0976	0.0932	0.1133	0.1233	0.1235	0.1363	0.1447	0.1539	0.1465	0.1511	0.1549	0.1802
HENAN	0.1737	0.1727	0.1993	0.2073	0.2368	0.2596	0.2868	0.3178	0.2813	0.2918	0.2810	0.3555
HUBEI	0.1697	0.1785	0.2226	0.2323	0.2386	0.2574	0.2613	0.3005	0.2722	0.2878	0.2959	0.3547
HUNAN	0.1916	0.1987	0.2948	0.2969	0.3125	0.3834	0.3155	0.4493	0.4386	0.4430	0.4357	0.5001
JIANGSU	0.2751	0.2817	0.3279	0.3281	0.3515	0.3693	0.3744	0.3989	0.3641	0.3748	0.3668	0.4318
JIANGXI	0.1369	0.1531	0.1977	0.2099	0.2216	0.2344	0.3053	0.3005	0.2898	0.3095	0.3088	0.3575
JILIN	0.0795	0.0875	0.0982	0.1088	0.1150	0.1176	0.1268	0.1340	0.1315	0.1388	0.1401	0.1636
LIAONING	0.1535	0.1637	0.2613	0.2125	0.2020	0.2253	0.2477	0.2517	0.2355	0.2354	0.2263	0.2640
NEIMENGGU	0.0833	0.0883	0.1040	0.1180	0.1168	0.1319	0.1496	0.1641	0.1489	0.1520	0.1588	0.1921
NINGXIA	0.0180	0.0216	0.0269	0.0278	0.0343	0.0419	0.0439	0.0473	0.0514	0.0560	0.0614	0.0730
QINGHAI	0.0166	0.0209	0.0361	0.0439	0.0521	0.0705	0.0722	0.0971	0.0905	0.0943	0.1011	0.1249
SHAANXI	0.1270	0.1360	0.1655	0.1846	0.1885	0.2139	0.2189	0.2534	0.2285	0.2408	0.2445	0.3016
SHANDONG	0.2759	0.2715	0.3532	0.3721	0.3681	0.4213	0.4540	0.4444	0.4025	0.4013	0.3952	0.4682
SHANGHAI	0.1404	0.1368	0.1469	0.1564	0.1727	0.1865	0.1940	0.1957	0.1885	0.1822	0.1666	0.1904
SHANXI	0.1044	0.1092	0.1301	0.1319	0.1672	0.1805	0.2035	0.2646	0.2416	0.2549	0.2616	0.2986
SICHUAN	0.1640	0.1767	0.2066	0.2255	0.2413	0.2860	0.3255	0.3946	0.4359	0.4490	0.4462	0.5003
TIANJIN	0.0491	0.0519	0.0623	0.0665	0.0723	0.0813	0.0762	0.0852	0.0801	0.0821	0.0778	0.0935
XINJIANG	0.0786	0.0797	0.0994	0.1095	0.1184	0.1274	0.1501	0.1588	0.1599	0.1879	0.1907	0.2311
YUNNAN	0.1587	0.2176	0.2796	0.2930	0.3065	0.3273	0.3377	0.4649	0.3532	0.3644	0.3857	0.4340
ZHEJIANG	0.3046	0.3212	0.3658	0.3654	0.3830	0.4491	0.4415	0.5342	0.5143	0.5127	0.5126	0.5620
AVERAGE	0.1478	0.1556	0.1904	0.1973	0.2070	0.2297	0.2425	0.2784	0.2584	0.2643	0.2646	0.3083

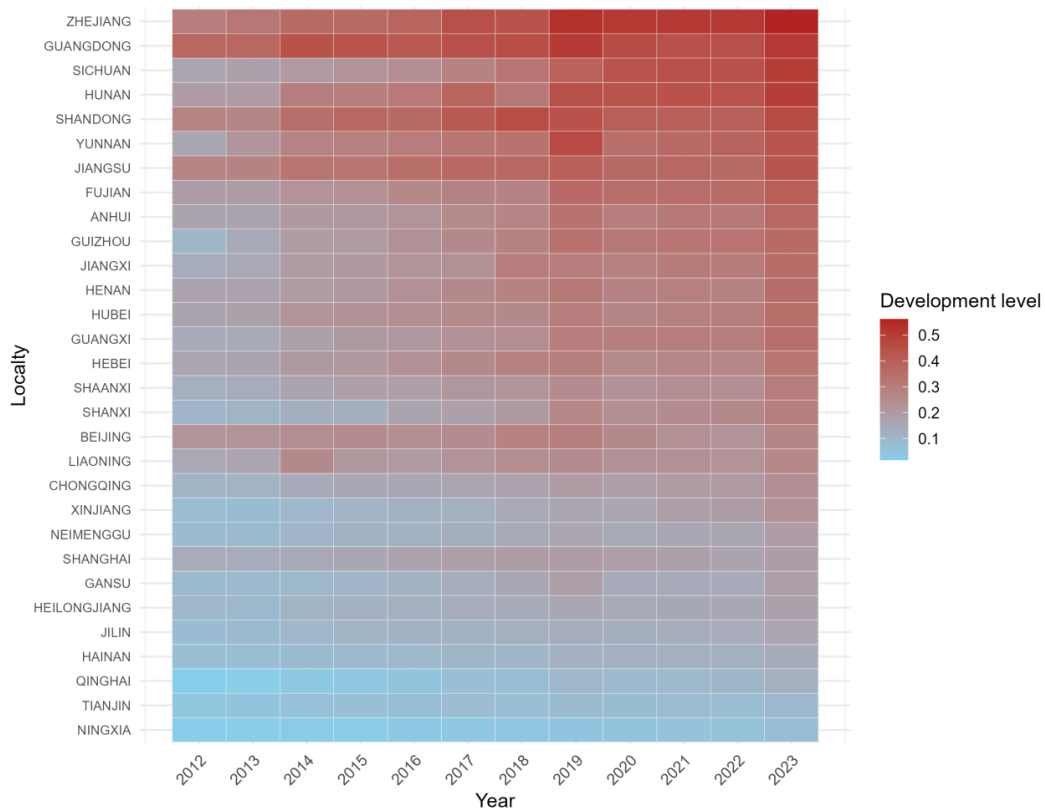


Figure 1: Rural Tourism Development Levels in China, 2012-2023

As shown in **Figure 1**, the overall level of rural tourism development in China exhibited a continuous upward trend between 2012 and 2023. Eastern coastal provinces (e.g., Zhejiang, Guangdong, Jiangsu, and Shandong) consistently maintained leading positions, while central provinces demonstrated steady improvement. In contrast, western and northeastern regions lagged behind but nevertheless showed signs of progress. The overall spatial pattern can be summarized as "leading in the east, catching up in the center, and lagging in the west and northeast." At the same time, several western provinces, such as Sichuan, Yunnan, and Guizhou, stood out with notable performance, reflecting a coexistence of regional disparities and development potential.

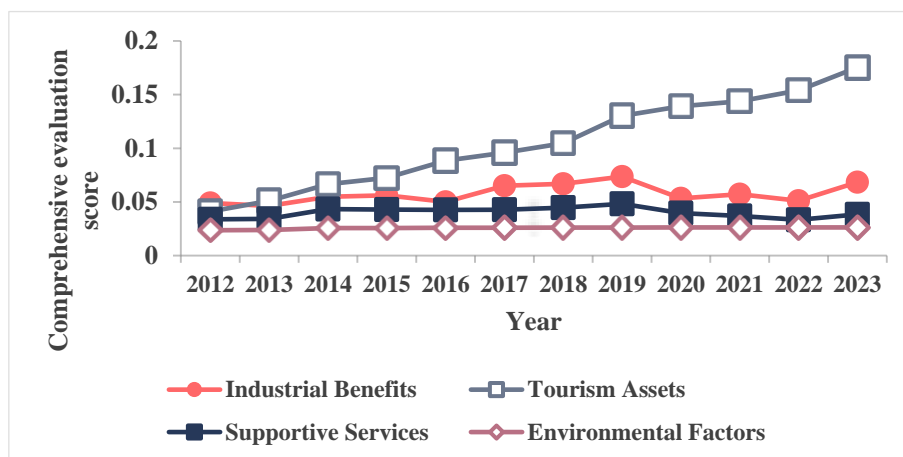


Figure 2: Subsystem Scores of Rural Tourism Development in China, 2012–2023

Figure 2 illustrates the evolutionary trends in the comprehensive evaluation scores of four subsystems of rural tourism in China from 2012 to 2023: Industrial Benefits, Tourism Assets, Supportive Services, and Environmental Factors.

From a dimensional perspective, Tourism Assets consistently scored the highest among the four subsystems, confirming that rural tourism in China remains primarily driven by a "supply-side-capital stock" model [26]. The upgrading and expansion of A-grade scenic areas, the establishment of traditional villages and Beautiful Leisure Villages, as well as the improvement of the star-rated hotel and travel agency systems—spurred by integrated tourism initiatives and the Rural Revitalization strategy—have significantly enhanced the efficiency of transforming "resources-facilities-products." Moreover, this subsystem registered the largest increase, largely attributable to combined policy-driven investments and market-oriented capital inflows, improved transportation accessibility, and the amplification effect of online distribution channels on asset utilization. The Supportive Services subsystem exhibited relatively stable yet gradually increasing scores, suggesting steady improvement in human resources and operational support at destinations. However, the pace of progress has been constrained by limitations in training systems and levels of organizational development. By contrast, the comparatively lower levels of Environmental Factors and Supportive Services reveal systemic shortcomings. In particular, insufficient ecological governance, underdeveloped clean operations, limited grassroots service capacity, and inadequate standardization have emerged as critical bottlenecks, restricting the high-quality and sustainable development of rural tourism.

5.2 Evaluation of Model Prediction Performance Based on Different Methods

The provincial-level rural tourism development dataset for the period 2012–2023 was divided into training and testing sets in a 2:8 ratio. Grid search combined with five-fold cross-validation was employed for parameter optimization. After hyperparameter tuning, the performance of all eight machine learning models improved significantly, with the prediction results summarized in **Table 3**. Among them, the SVR model achieved an R^2 value of 0.9991, which is nearly equal to 1, while its RMSE and MAE values were the lowest at 0.0036 and 0.0020, respectively. These results indicate highly accurate predictive performance. Therefore, this study adopts the SVR model as the primary analytical tool.

Table 3: Evaluation of Predictive Performance of Machine Learning Models

Machine Learning method	R^2	RMSE	MAE
XGBoost	0.9787	0.0178	0.0135
Decision tree	0.8711	0.0438	0.0324
Random forest	0.9663	0.0224	0.0167
GBDT	0.9782	0.0180	0.0134
AdaBoost	0.9827	0.0161	0.0122
LightGBM	0.9775	0.0183	0.0131
SVR	0.9991	0.0036	0.0020
KNN	0.9696	0.0213	0.0155

5.3 Interpretability Analysis Based on SHAP

To address the "black-box" problem of machine learning and to gain deeper insights into the key factors driving demand changes, SHAP values were employed to quantitatively assess the influence of multiple factors on the development level of rural tourism in China. On the basis

of prediction results, SHAP was further used to rank variable importance. Figures 3 and 4 illustrate the relative importance of different variables in the model’s predictions. The selected indicators provided positive contributions to rural tourism development, suggesting that these variables exerted significant positive effects on enhancing China’s rural tourism development level.

Global feature importance measures the overall impact of each variable on the model’s predictions, represented by the mean absolute SHAP value. As shown in **Figure 3**, the Number of Traditional Villages emerged as the most important driving factor, with a mean absolute SHAP value of 0.0245. The Number of China’s Beautiful Leisure Villages ranked second (0.0159), followed by Forest Coverage Rate (0.0121) and Employees of Travel Agencies (0.0107). These results indicate that while Forest Coverage Rate and Employees of Travel Agencies exert relatively smaller effects, they nevertheless play meaningful roles in shaping rural tourism development. By contrast, variables such as Demonstration Counties (Sites) for Leisure Agriculture and Rural Tourism, Number of Star-Rated Hotels, and Total Income from Tourism had lower mean SHAP values, suggesting that their influence on rural tourism development is comparatively limited.

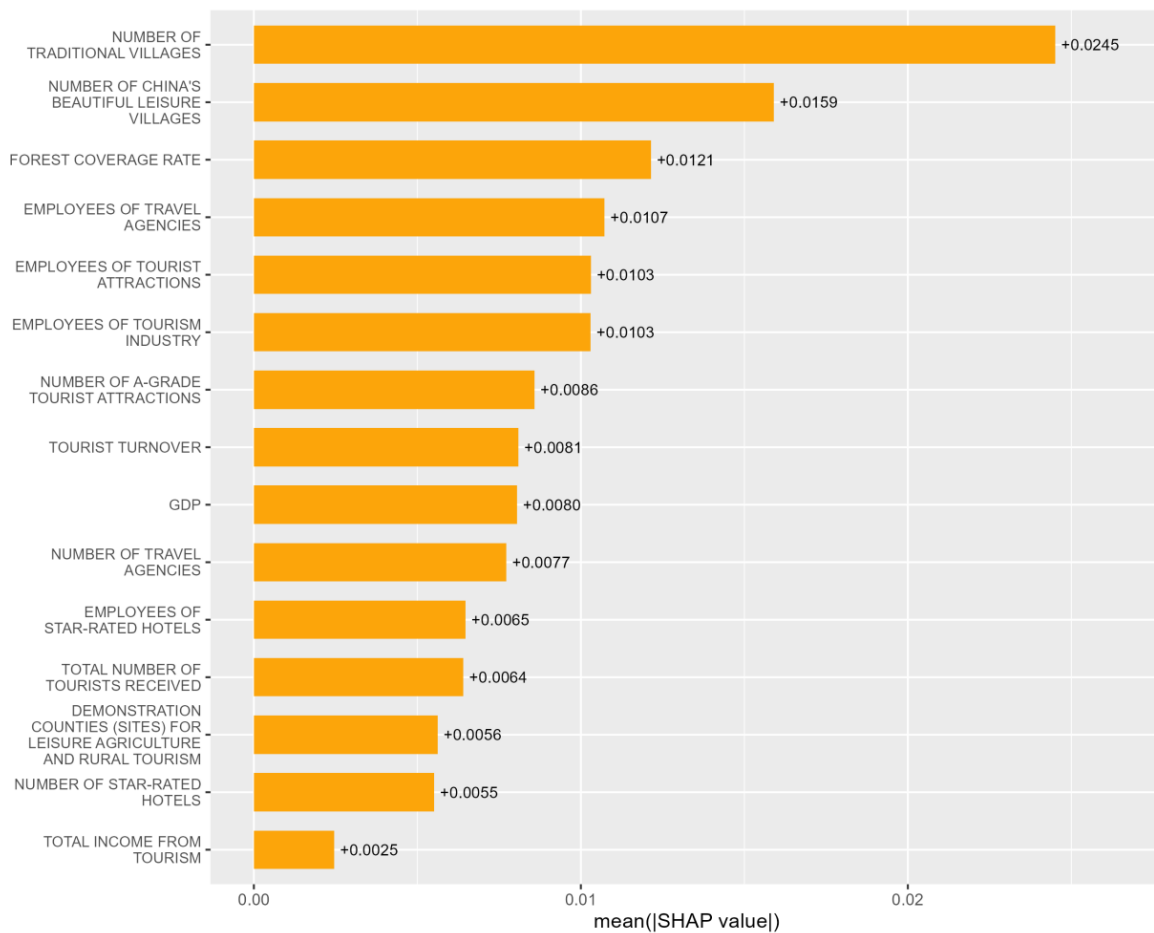


Figure 3: Mean (SHAP value) (average impact on model output magnitude)



Figure 4: Overview of SHAP Feature Analysis

Further analysis reveals that when the value of an indicator is relatively high, the corresponding SHAP value is positive; conversely, when the indicator value is relatively low, the SHAP value becomes negative. This indicates that the selected indicators exert varying degrees of promoting effects on the development level of rural tourism. A wider distribution of SHAP values suggests that the feature exhibits greater heterogeneity in its influence across samples, implying that it may act as a strong driving factor and that non-linear or interaction effects with the target variable may exist. As shown in **Figure 4**, the primary drivers of rural tourism development are cultural and ecological resources (e.g., Number of Traditional Villages, Number of China's Beautiful Leisure Villages, and Forest Coverage Rate), followed by service provision and human resources (e.g., Number of Travel Agencies, Tourist Attractions, Employees in the Tourism Industry, and A-Level Scenic Spots). High values of these indicators generally shift the prediction to the right, significantly enhancing development levels. Forest Coverage Rate contributes positively overall, though it exhibits a "Threshold of Diminishing Marginal Returns" effect. By contrast, scale-oriented indicators such as Total Tourist Arrivals, Total Tourism Income, and GDP have contributions concentrated around zero, providing relatively little information. These findings suggest that revitalizing cultural resources and strengthening human and organizational capacities yield higher-quality improvements than merely expanding hotel capacity or pursuing larger visitor volumes.

5.4 Evaluation of Rural Tourism Development Levels

Using the weights derived from the SVR model, the rural tourism development levels of China’s provinces were re-evaluated, with the results presented in **Table 4**. In 2023, the leading provinces in terms of rural tourism development included Zhejiang (0.5609), Guangdong (0.5154), Hunan (0.5010), Sichuan (0.4992), Shandong (0.4675), Jiangsu (0.4306), Yunnan (0.4248), Fujian (0.4012), Anhui (0.3723), and Guizhou (0.3653).

Compared with traditional multiple linear regression, the evolution of rural tourism development levels reconstructed using SVR is more reasonable and provides clearer insights into the dynamic changes among provinces. This, in turn, offers important references for future policy formulation and resource allocation. The primary advantages of SVR lie in its ability to capture nonlinear relationships, its robustness to outliers, its suitability for high-dimensional and small-sample problems, and its stronger generalization capacity.

Table 4: Evaluation of Rural Tourism Development Levels in China Based on SVR Reconstruction

LOCALTY	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
ANHUI	0.1678	0.1701	0.2085	0.2127	0.2213	0.2554	0.2731	0.3405	0.3012	0.3178	0.3179	0.3723
BEIJING	0.2196	0.2247	0.2451	0.2548	0.2373	0.2500	0.2847	0.2970	0.2611	0.2365	0.2274	0.2701
CHONGQING	0.1100	0.1134	0.1415	0.1503	0.1535	0.1628	0.1723	0.1964	0.1830	0.1976	0.2057	0.2431
FUJIAN	0.1918	0.1947	0.2261	0.2370	0.2641	0.2808	0.2805	0.3640	0.3541	0.3516	0.3560	0.4012
GANSU	0.0916	0.0919	0.0941	0.1040	0.1204	0.1428	0.1632	0.1856	0.1429	0.1409	0.1430	0.1834
GUANGDONG	0.3746	0.3763	0.4402	0.4368	0.4218	0.4493	0.4537	0.5023	0.4594	0.4463	0.4483	0.5154
GUANGXI	0.1455	0.1467	0.1772	0.2049	0.2104	0.2292	0.2457	0.2990	0.2945	0.3016	0.3011	0.3477
GUIZHOU	0.0994	0.1452	0.1914	0.2005	0.2345	0.2614	0.2839	0.3399	0.3225	0.3305	0.3311	0.3653
HAINAN	0.0768	0.0781	0.0855	0.0916	0.0954	0.1019	0.1031	0.1181	0.1216	0.1260	0.1266	0.1430
HEBEI	0.1609	0.1659	0.2023	0.2087	0.2286	0.2613	0.2883	0.2934	0.2580	0.2656	0.2640	0.3274
HEILONGJIANG	0.0970	0.0939	0.1130	0.1242	0.1246	0.1368	0.1459	0.1534	0.1471	0.1515	0.1562	0.1812
HENAN	0.1749	0.1726	0.1982	0.2064	0.2358	0.2584	0.2858	0.3184	0.2804	0.2906	0.2804	0.3530
HUBEI	0.1685	0.1797	0.2232	0.2322	0.2386	0.2564	0.2601	0.3016	0.2719	0.2879	0.2963	0.3576
HUNAN	0.1928	0.1990	0.2958	0.2975	0.3113	0.3823	0.3152	0.4481	0.4375	0.4439	0.4369	0.5010
JIANGSU	0.2748	0.2805	0.3272	0.3274	0.3525	0.3706	0.3740	0.4001	0.3677	0.3759	0.3680	0.4306
JIANGXI	0.1381	0.1537	0.1966	0.2088	0.2209	0.2331	0.3065	0.2994	0.2890	0.3085	0.3080	0.3563
JILIN	0.0807	0.0869	0.0970	0.1079	0.1143	0.1174	0.1272	0.1341	0.1316	0.1388	0.1412	0.1643
LIAONING	0.1544	0.1650	0.2625	0.2123	0.2026	0.2246	0.2467	0.2505	0.2359	0.2356	0.2275	0.2647
NEIMENGGU	0.0826	0.0887	0.1044	0.1174	0.1163	0.1307	0.1486	0.1620	0.1482	0.1508	0.1590	0.1916
NINGXIA	0.0192	0.0227	0.0277	0.0286	0.0362	0.0433	0.0451	0.0489	0.0522	0.0566	0.0616	0.0723
QINGHAI	0.0198	0.0229	0.0364	0.0436	0.0517	0.0693	0.0721	0.0967	0.0904	0.0935	0.1002	0.1245
SHAANXI	0.1253	0.1353	0.1643	0.1840	0.1873	0.2128	0.2180	0.2531	0.2273	0.2402	0.2445	0.3022
SHANDONG	0.2767	0.2712	0.3534	0.3709	0.3645	0.4184	0.4454	0.4432	0.4013	0.4025	0.3941	0.4675
SHANGHAI	0.1416	0.1380	0.1474	0.1566	0.1734	0.1869	0.1947	0.1960	0.1897	0.1815	0.1673	0.1907
SHANXI	0.1024	0.1080	0.1281	0.1307	0.1661	0.1798	0.2030	0.2658	0.2413	0.2540	0.2604	0.2982
SICHUAN	0.1643	0.1776	0.2070	0.2266	0.2408	0.2864	0.3266	0.3958	0.4164	0.4367	0.4450	0.4992
TIANJIN	0.0508	0.0527	0.0618	0.0656	0.0713	0.0801	0.0758	0.0855	0.0796	0.0811	0.0774	0.0933
XINJIANG	0.0798	0.0796	0.0982	0.1097	0.1190	0.1274	0.1489	0.1576	0.1611	0.1879	0.1916	0.2290
YUNNAN	0.1594	0.2189	0.2799	0.2927	0.3062	0.3272	0.3369	0.4638	0.3525	0.3637	0.3821	0.4248
ZHEJIANG	0.3054	0.3200	0.3647	0.3656	0.3785	0.4519	0.4425	0.5363	0.5155	0.5162	0.5114	0.5609
AVERAGE	0.1482	0.1558	0.1900	0.1970	0.2066	0.2296	0.2423	0.2782	0.2578	0.2637	0.2643	0.3077

5.5 Robustness Test

To ensure the robustness of the empirical results, this study conducted a comparative analysis based on the top 10 features ranked by both the SVR and SHAP algorithms. The results are presented in **Table 5**. The findings show that Number of Traditional Villages and Number of

China's Beautiful Leisure Villages consistently ranked as the top two predictive factors, confirming the robustness of the empirical results obtained in this study.

Table 5: Comparison of Feature Importance between SVR and SHAP Algorithms

Rank	SVR model		SHAP algorithm		Entropy method	
	Feature	Value	Feature	Value	Feature	Weight
1	Number Of Traditional Villages	0.0365	Number Of Traditional Villages	0.0245	Number Of Traditional Villages	0.144
2	Number Of China's Beautiful Leisure Villages	0.0220	Number Of China's Beautiful Leisure Villages	0.0159	Number Of China's Beautiful Leisure Villages	0.0866
3	Employees Of Travel Agencies	0.0152	Forest Coverage Rate	0.0121	Employees Of Tourist Attractions	0.0858
4	Gdp	0.0138	Employees Of Travel Agencies	0.0107	Total Income From Tourism	0.075
5	Forest Coverage Rate	0.0127	Employees Of Tourist Attractions	0.0103	Employees Of Travel Agencies	0.0734
6	Employees Of Tourist Attractions	0.0118	Employees Of Tourism Industry	0.0103	Gdp	0.0722
7	Employees Of Tourism Industry	0.0118	Number Of A-Grade Tourist Attractions	0.0086	Employees Of Star-Rated Hotels	0.0638
8	Tourist Turnover	0.0108	Tourist Turnover	0.0081	Tourist Turnover	0.0629
9	Number Of Travel Agencies	0.0101	Gdp	0.0080	Employees Of Tourism Industry	0.0613
10	Number Of A-Grade Tourist Attractions	0.0094	Number Of Travel Agencies	0.0077	Total Number Of Tourists Received	0.0557

6 Conclusions and Recommendations

6.1 Conclusions

Based on the entropy-weight method, this study constructed an evaluation indicator system for China's rural tourism development levels from 2012 to 2023. Eight machine learning models—including SVR, XGBoost, Decision Tree, and Random Forest—were compared, and the SVR model demonstrated superior predictive performance. To further investigate the specific roles of influencing factors, the SHAP method was applied. The key conclusions are as follows:

According to the entropy-weight method, rural tourism development in China—except for the decline in 2020 due to the COVID-19 pandemic—showed an overall upward trajectory. The national average rose from 0.1478 in 2012 to 0.3083 in 2023, representing a cumulative increase of 108.6%. Although 2020 fell 7.2% compared with 2019, by 2023 it had exceeded the 2019 level by 10.7%. At the provincial scale, Zhejiang, Guangdong, Sichuan, Hunan, and

Shandong formed a high-ranking cluster; the central, western, and southwestern regions became growth hotspots, driven by infrastructure improvement and product supply upgrading; meanwhile, the northeast and smaller provinces remained at a low-to-mid development plateau.

Using the SVR model, the provinces ranking at the top of rural tourism development include Zhejiang, Guangdong, Hunan, Sichuan, and Shandong, with Jiangsu, Yunnan, Fujian, Anhui, and Guizhou on the edge of the first tier. Over the long term, Sichuan, Hunan, Guizhou, Yunnan, and Zhejiang showed the most significant improvements. Overall, eastern coastal regions continue to provide high baselines and stable supply, while the southwest has become the major source of incremental growth; by contrast, the northeast and smaller provinces remain in a relatively stagnant phase.

SHAP-based feature contributions reveal that the Number of Traditional Villages and Number of China's Beautiful Leisure Villages exert the strongest impacts on rural tourism development. These are followed by service-related variables such as the number of travel agencies, scenic spots, and employees in the tourism industry, as well as A-grade scenic spots, passenger turnover, and GDP, representing "supply and carrying capacity" factors. By contrast, traditional "scale-oriented" indicators such as total tourism income, total tourist arrivals, and number of star-rated hotels have limited marginal contributions. This suggests that high-quality rural tourism development should prioritize the protection and revitalization of traditional villages, strengthening leisure-village branding and ecological restoration, and enhancing professional services and organizational capacity—rather than merely pursuing greater visitor volumes and revenue.

6.2 Recommendations

Prioritize the protection and revitalization of traditional villages to strengthen cultural foundations. Establish a full-chain mechanism of "protection, revitalization, and utilization." For protection, designate core preservation areas, strictly regulate destructive construction, and use dedicated fiscal funds to support architectural restoration and intangible cultural heritage transmission. For revitalization, promote "village+" model innovations that integrate traditional villages with homestay experiences, handicraft workshops, educational programs, and folk festivals. For utilization, build digital preservation platforms, employ VR technology to reconstruct historical village scenes for remote experiences, and limit daily visitor numbers to balance conservation and development.

Strengthen the branding of Beautiful Leisure Villages to enhance ecological and brand synergies. In central and southwestern growth regions, efforts should focus on creating more nationally recognized Beautiful Leisure Villages. On one hand, leverage ecological advantages to build a distinctive cultural IP (brand identity in the cultural and creative industries); on the other, integrate rural leisure with agricultural industries through activities such as fruit-picking, farm-work experiences, and rural complexes, thus forming a composite value chain of "production + tourism + education." Moreover, establish a national dynamic evaluation system for Beautiful Leisure Villages, incorporating ecological outcomes and resident participation into assessments to avoid hollow branding.

Optimize services and organizational supply to enhance professional capacities. Deeper integration between travel agencies and rural tourism resources should be promoted to design customized rural tourism routes. In the southwest—where incremental growth is most pronounced—greater emphasis should be placed on training tourism personnel, with a focus on tour guiding, emergency management, and cultural interpretation. A joint training mechanism involving government, enterprises, and industry associations should be established to raise standardization. Additionally, rural tourism cooperatives should be

encouraged to enhance villagers' organizational capacity.

Implement differentiated regional development strategies to address imbalance. Development strategies should be tailored according to regional disparities. For provinces already at a higher level of rural tourism development, the focus should shift from "scale expansion" to "quality upgrading," emphasizing thematic operations of A-grade scenic areas. For the southwest, infrastructural support should be reinforced by leveraging ecological advantages, particularly to address transportation bottlenecks and promote linkages between scenic spots and surrounding villages. For the northeast and smaller provinces, replication of eastern models should be avoided; instead, local distinctive resources—such as ice-and-snow landscapes and wetlands—should be harnessed to create differentiated tourism products.

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