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Research article

Research on the efficiency of agro-tourism integration in China: Based on the DEA cross-efficiency model

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Abstract: The efficiency of agro-tourism integration has become an important research object in evaluating agricultural efficiency. However, traditional efficiency evaluation theories and methods assume that all decision-making units are independent of each other and cannot effectively deal with the complex relationship between agriculture and tourism development. Based on the cooperative relationship between agriculture and tourism, this study constructed a data envelopment analysis (DEA) model based on cross-efficiency. It used ten input variables and six output variables from the agricultural and tourism systems to analyze the efficiency of agro-tourism integration in 31 provinces in mainland China from 2010 to 2019. The research results show that the efficiency of agro-tourism integration in China is relatively high and tourism significantly promotes agriculture. Still, the promotion efficiency of agriculture on tourism is low and the integration efficiency of agriculture and tourism in different provinces is significantly different with spatially differentiated features. From the perspective of dynamic trends, hot and sub-hot spots continue to gather in the developed eastern provinces, while cold spots and sub-cold spots mainly gather in the northwest region. Finally, eight indicators were selected to analyze the reasons for forming the spatial differentiation characteristics of China's efficiency of agro-tourism integration.

Keywords: efficiency of agro-tourism integration; DEA cross-efficiency model; spatially differentiated features; geographic detectors
Mathematics Subject Classification: 90C08

1. Introduction

The integrated development of and tourism is essential in enriching rural business forms [1], promoting agricultural transformation and upgrading, optimizing industrial structure [2] and increasing farmers' income [3,4]. Moreover, it is a crucial breakthrough in promoting the development of modern farming and industrial systems [5]. The idea of the integrated development of agriculture and tourism began in 1850 in Germany's "Citizens Paradise" [6,7]. The world's tourism-developed countries successively adopted policies to support and guide the integrated development of agriculture and tourism. For example, the United States established the "Rural Tourism Development Fund" in 1992 [8]; Japan proposed the concept of a "Green Tourism Lifestyle" in 1993 [9]; South Korea formulated the "Agricultural and Rural Basic Law" in 1999 to promote the development of green tourism [10]; France launched the "National Suburban Agricultural Development Network" in 2000 to guide the development of the agricultural tourism industry [11,12].

Recently, the Chinese government has also attached great importance to the integrated development of agriculture and tourism. Since the central government's "No. 1 Document" proposed "promoting the integrated development of primary [13], secondary, and tertiary industries in rural areas" in 2015, the agro-tourism integration has accelerated significantly and a large number of new agriculture-related industries, new formats and new models have emerged [14]. As a result, it has gradually become an important starting point and a significant sector for local governments to promote the development of agricultural integration. In 2019, China's leisure agriculture and rural tourism received about 3.2 billion tourists, with an operating income of more than 850 billion yuan [5]. This directly drove the employment of 12 million people and benefited more than 8 million rural households [15]. The rapid growth of leisure agriculture and rural tourism has contributed to the economic development of China's agriculture and rural areas as well as employment and income increase. However, problems such as insufficient overall industrial development [16], poor service and supply of mid-to-high-end products [17] and homogeneous operations still exist, leading to issues such as extensive utilization of resources, low efficiency of industrial integration and unbalanced regional development in the process of integrated development of agriculture and tourism [18]. The law of difference and its influencing factors can improve the efficiency of agro-tourism integration, promote deep agro-tourism integration and promote high-quality economic and social development.

From the perspective of research objects, the relevant research on the efficiency of agricultural tourism integration in the existing literature mainly focuses on the evaluation of a farming park [19]; the analysis of the operating efficiency of farmhouses and leisure villas in specific areas [20]; the assessment of the efficiency of agricultural tourism development based on leisure agriculture and rural tourist attractions [21,22], agricultural sightseeing park as the research object; the evaluation of the efficiency of leisure agriculture in each unit in a specific area; the research on the spatial distribution difference of rural tourism development efficiency [7,22].

From the perspective of research methods, the current efficiency evaluation methods mainly include parametric and non-parametric methods represented by stochastic frontier analysis (SFA) and data envelopment analysis (DEA) [23]. Since DEA avoids subjective setting of production function and distribution form [24], it is widely used to measure the relative efficiency of multi-input and multi-output units [25–27]. However, since the traditional DEA model is a self-evaluation evaluation model, it is prone to problems such as superficial DEA effectiveness and exaggerated evaluation weights and does not consider the cooperative and competitive relationship between decision-making units [28]. Therefore, scholars have begun to introduce the DEA cross-efficiency model and extend the DEA method to mutual evaluation [29]. Some proposed an improved DEA cross-efficiency model [30] that can objectively evaluate the decision-making unit through the mutual evaluation model and better solve the problems of non-unique optimal solutions and non-Pareto optimality in other DEA models [31,32]. Several scholars combined the DEA model with the game cross-efficiency model, constructed a two-stage model and evaluated China's regional research and development (R&D) efficiency in connection with the overall cross-efficiency model [31]. Other scholars measured the environmental efficiency of Asian countries based on the cross-efficiency model of ideal decision-making units [33]. However, there are few studies on cross-efficiency to measure the efficiency of agro-tourism integration. Only one study used the benevolent DEA cross-efficiency model to evaluate the eco-efficiency of agricultural practices in China [34].

Overall, existing studies have explored the efficiency of agro-tourism integration to varying degrees. However, from the perspective of research methods, the traditional efficiency evaluation method is mainly used for static efficiency analysis. The dynamic evaluation of the trend of efficiency of agro-tourism integration is relatively lacking, especially since the research using the DEA cross-efficiency model is relatively small. From the perspective of research depth, most of them are typical cases, regional overall efficiency or local efficiency evaluation and there are relatively few studies based on the general description of internal efficiency differences. From the perspective of research content, few studies have further analyzed the reasons for forming internal efficiency differences. This study strives to form the following two contributions based on existing research. First, the mathematical statistical method DEA efficiency model is applied to evaluate agricultural economic efficiency. A DEA cross-efficiency model for integrating agriculture and tourism is constructed based on the cooperative relationship between the agricultural and tourism systems. This model can be used to integrate agriculture and tourism in different periods. The cross-efficiency evaluation effectively overcomes the shortcomings of the traditional DEA self-evaluation evaluation method. They were second, using ArcGIS analysis, geographic detectors and other spatial geographic analysis methods, to analyze the spatial differences and causes of the efficiency of agro-tourism integration in different provinces in China, which is conducive to further enriching the research on the efficiency of agro-tourism integration. The content provides a methodological reference for developing cross-disciplinary research in related disciplines.

2. Materials and methods

2.1. Measurement

2.1.1. DEA benevolent cross-efficiency model

Agriculture and tourism are complementary rather than antagonistic games and the efficiency of decision-making units of agriculture and tourism is most likely to come from cooperation [35,36]. Therefore, this paper chooses the DEA collaborative cross-efficiency model, which regards all decision-making units as cooperative relations [37]. Its operation characteristic is to maximize the cross-efficiency of other decision-making units on the premise that each decision-making unit ensures the maximum value of its efficiency, which overcomes the deficiency of traditional DEA based on self-evaluation [38,39]. The specific calculation process is as follows:

Suppose there are n decision-making units corresponding to the input X of m dimensions and output index Y of s dimensions. For decision-making units j $(1 \leq \mathrm{j} \leq \mathrm{n}, 1 \leq \mathrm{k} \leq \mathrm{n}, \mathrm{j} \neq \mathrm{k})$, where t input is $x_{ij}(1 \leq \mathrm{i} \leq \mathrm{n})$ and the r output is y_{rj} $(1 \leq \mathrm{r} \leq \mathrm{s})$. First, the self-evaluation efficiency e_{ii} of each unit is obtained by using the traditional DEA-CCR model [40]. The calculation model is as follows:

$$e_{ii} = \max \frac{y_i^T u}{x_i^T v},$$

$$\mathrm{s.t.} \frac{u^T y_i}{v^T x_i} \leq 1 (i = 1,2,\cdots,n) \tag{1}$$

Where u and v are the weight vector of output and input, the self-evaluation efficiency of decision-making unit k is obtained through the model and the best weight of the decision-making unit is recorded (u_k, v_k, e_k). The cross-efficiency of the j-th unit is represented by the decision-making unit E_j:

$$E_j = \frac{1}{n} \frac{\sum_{i=1}^{n} u_i^T y_i}{\sum_{i=1}^{n} v_i^T x_i} \tag{2}$$

The benevolent cross-efficiency of the decision unit based on i is:

$$e_{ik} = max \frac{u^T y_i}{v^T x_i} \tag{3}$$

Then, according to the equivalent linear programming, assuming that $\mathrm{t} = {}^{1}/_{x_i^T}$, $\omega = \mathrm{tv}$, $\mu = \mathrm{tu}$ and $\omega, \mu \geq 0$, there are:

$$\max y_i^T \mu,$$

$$\mathrm{s.t.}\, y_i^T \mu \leq x_i^T \omega,$$

$$x_i^T \omega = 1,$$

$$y_i^T \mu - e_i x_i^T \omega = 0.$$

The evaluation benevolent cross-efficiency formula of decision-making unit k is expressed as follows:

$$E_k = \frac{1}{n} \sum_{i=1}^{n} e_{ik} \tag{4}$$

2.1.2. Geographic detector

The geographic detector is a model to detect the influence of independent variables on the spatial differentiation of geographical phenomena. Its basic principle is that if independent variables strongly influence dependent variables, their spatial distribution will have a certain degree of similarity and consistency [17,41]. There are four kinds of geographic detectors: factor detector, interaction detector, risk zone detector and ecological detector [42]. Factor detection is to detect the extent to which the dependent variable X explains the spatial differentiation of the independent variable Y. Interactive detection is mainly used to compare whether there is a significant difference in the influence of any combination of two dependent variables on the spatial distribution of the independent variable Y. To explore the influencing factors of the spatial differentiation of the efficiency of agro-tourism integration in China and referring to the relevant experiences of other scholars, this paper chooses factor detection and interactive detection to quantitatively explore the influence of the influencing factors and the interaction between them on the spatial differentiation of the efficiency of agro-tourism integration and then analyze the driving force of the influencing factors on the differentiation of the efficiency of agro-tourism integration [43]. The formula for factor detection is:

$$q = 1 - \left(\frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N\sigma^2}\right) \tag{5}$$

Among them, q is the influence of the factors influencing the spatial differentiation of the efficiency of agro-tourism integration and the range of values is [0,1]. The higher the value of q is, the greater the influence of this factor on the spatial differentiation; h is the number of sub-regions of the influencing factor X; L is the stratification of variables; N and N_h are the total number of samples and the number of regional h samples and σ^2 and σ_h^2 are the variance of the entire region and the variance of the region h, respectively.

2.2. Study design

2.2.1. Index selection

The all-factor evaluation index system of the efficiency of agro-tourism integration includes input and output indexes. Using the index selection method of related research for reference, agriculture and tourism input factors are determined as land, labor, capital and other inputs [44]. Specifically, the total sown area of crops is used as the index of agricultural land input and the abundance of tourism resources (e.g., the number of scenic spots) is used as the index of land input of tourism [16]. The number of employees in agriculture and tourism is used as the index of labor input in agriculture and tourism [22]. The investment in fixed assets of agriculture, forestry, animal husbandry and fishery is used as the investment index of agricultural capital [13]. The investment of fixed assets in the accommodation and catering industry is used as the capital input index of tourism. The effective irrigated area of crops and the total power of agricultural machinery are used as the indicators of other agricultural input factors and the number of travel agencies and star hotels are used as the indicators of different input factors of tourism [45]. In terms of output indicators, the total output value of agriculture, forestry, animal husbandry and fishery and the per capita disposable income of rural households are used as agricultural output indicators; the number of inbound tourists, domestic tourism income and inbound tourism foreign exchange income are used as tourism output indicators (Table 1).

Table 1. Evaluation index system of efficiency of agro-tourism integration in China.

Tier 1 indicators	Secondary indicators	Agriculture tier 3 indicator	Tourism tier 3 indicator
Input	Labor factor	Number of employees in primary industry (10,000 people)	Number of employees in the tourism industry (persons)
	Capital factor	Investment in fixed assets in agriculture, forestry, animal husbandry and fishery (CNY billion)	Investment in fixed assets in accommodation and catering (CNY billion)
	Land factor	The total sown area of crops (thousand hectares)	The richness of tourism resources (number of scenic spots)
	Other factors	Total power of agricultural machinery (million kilowatts) Effective irrigated area of arable land (thousand hectares)	Number of travel agencies (number) Number of star-rated hotels (number)
Output	Value of output	The total output value of agriculture, forestry, animal husbandry and fishery (CNY billion)	Total domestic tourist arrivals (million) Number of inbound tourist arrivals (million)
	Income	Per capita disposable income of rural households (CNY)	Domestic tourism revenue (CNY billion) Foreign exchange earnings from inbound tourism (USD million)

2.2.2. Data description

Based on data availability, this paper selects the agricultural and tourism panel data of 31 provinces, autonomous regions and municipalities in China from 2010 to 2019 as research samples. After the original value data are processed exponentially to reduce the impact of data dimensions, MATLAB 2018 software measures the efficiency of agro-tourism integration in the sample range. The original data used in this paper mainly come from the “China Statistical Yearbook”, “Chinese Cultural relics and Tourism Statistical Yearbook”, “China Rural Statistical Yearbook” and other provinces and regions’ annual statistical yearbooks, tourism yearbooks and government statistical bulletin supplement.

3. Results

3.1. Analysis of the characteristics of Spatio-temporal differentiation

3.1.1. The time series evolution trend of the efficiency of agro-tourism integration

As shown in Figure 1, the overall efficiency of agro-tourism integration in China showed a relatively stable evolution trend from 2010 to 2019 and the efficiency value maintained at about 0.9. The promotion efficiency value of agriculture to tourism shows a fluctuating trend of rising at first, then decreasing and then increasing. Among them, the efficiency value of 0.768 in 2014 was the lowest and only in 2017 the efficiency value exceeded 0.85. The promotion efficiency value of tourism to agriculture is generally high. It shows a decline at first and then an upward trend, in which the efficiency value of 0.913 in 2013 is the lowest, the promotion efficiency value of most years is above 0.94 and reaches a peak of 0.960 in 2018. Overall, the promotion efficiency of tourism to agriculture is significantly higher than that of agriculture to tourism and the efficiency of agro-tourism integration is between the two. The low promotion efficiency of agriculture to tourism restricts the improvement of the integration efficiency of agriculture and tourism to a certain extent.

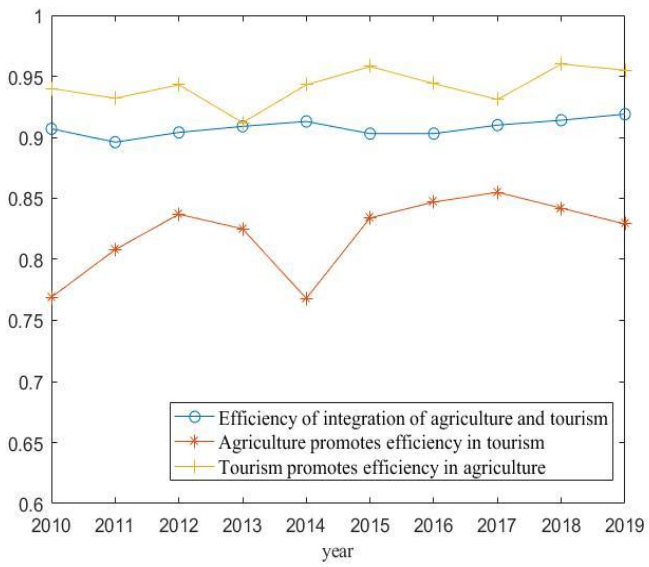

Figure 1. Trend chart of efficiency of agro-tourism integration in China from 2010 to 2019.

3.1.2. Spatial differentiation characteristics of the efficiency of agro-tourism integration

As shown in Table 2, significant spatial differences exist in the efficiency of agro-tourism integration among 31 provincial regions in China. The efficiency of agro-tourism integration in Inner Mongolia, Hubei, Shandong, Anhui and Guangdong provinces is the highest and the average value is more than 0.910. On the other hand, the five areas of Guizhou, Shanghai, Ningxia, Qinghai and Tibet showed the lowest input-output efficiency and the average value was less than 0.80. The spatial difference in mutual promotion efficiency between agriculture and tourism is also pronounced, among which the five provinces with the highest efficiency of agriculture-promoting tourism are Shandong, Hubei, Guangdong, Anhui and Beijing an average efficiency of more than 0.908. The last three regions are Qinghai, Ningxia and Xinjiang and the average efficiency is less than 0.8.

On the other hand, tourism can promote the development of agriculture and the average efficiency of tourism in the three provinces is less than 0.9. The average efficiency of Shanxi, Hebei, Guangdong, Tibet and Ningxia is more than 0.963. The standard deviation reflects the fluctuation of the efficiency value of each province over the years and the evaluation results show that the fluctuation range of efficiency is different in different regions, especially the fluctuation range of agriculture promoting tourism efficiency is the strongest. Among them, agriculture and tourism integration efficiency in Tibet, Qinghai and Shanghai changes the most.

In contrast, agriculture in Qinghai and Xinjiang changes the most and the fluctuation range of the promotion efficiency of tourism to agriculture is relatively small. The standard deviation is all less than 0.049. The efficiency of agro-tourism integration in Guangdong, Anhui and Shandong is relatively stable and the fluctuation range of the three efficiencies has been minimal over the years.

Table 2. Evaluation results of the efficiency of agro-tourism integration in 31 sample provinces of China from 2010 to 2019.

Region	The efficiency of agro-tourism integration		The efficiency of agricultural contribution to tourism		The efficiency of tourism contribution to agriculture	
	Mean	Standard deviation	Mean	Standard deviation	Mean	Standard deviation
Anhui	0.913	0.016	0.929	0.016	0.962	0.009
Beijing	0.848	0.023	0.917	0.031	0.924	0.019
Fujian	0.803	0.074	0.862	0.028	0.952	0.007
Gansu	0.841	0.045	0.872	0.042	0.945	0.011
Guangdong	0.910	0.018	0.936	0.016	0.965	0.006
Guangxi	0.860	0.068	0.894	0.055	0.955	0.017
Guizhou	0.775	0.055	0.840	0.069	0.890	0.049
Hainan	0.860	0.037	0.887	0.034	0.952	0.016
Hebei	0.894	0.043	0.901	0.043	0.966	0.007
Henan	0.879	0.040	0.904	0.028	0.954	0.012
Heilongjiang	0.855	0.030	0.906	0.030	0.947	0.007
Hubei	0.919	0.023	0.936	0.024	0.949	0.007
Hunan	0.883	0.043	0.908	0.041	0.944	0.014
Jilin	0.816	0.072	0.858	0.018	0.956	0.006
Jiangsu	0.865	0.041	0.881	0.055	0.958	0.012
Jiangxi	0.876	0.051	0.905	0.060	0.932	0.022
Liaoning	0.857	0.039	0.888	0.039	0.912	0.019
Inner Mongolia	0.936	0.024	0.889	0.053	0.895	0.033
Ningxia	0.719	0.032	0.764	0.035	0.963	0.008
Qinghai	0.680	0.110	0.788	0.178	0.956	0.017
Shandong	0.919	0.012	0.938	0.015	0.957	0.006
Shaanxi	0.894	0.025	0.851	0.044	0.936	0.008
Shanghai	0.761	0.100	0.895	0.043	0.941	0.012
Sichuan	0.856	0.023	0.818	0.087	0.929	0.030
Tianjin	0.870	0.017	0.886	0.023	0.952	0.008
Tibet	0.585	0.183	0.864	0.017	0.963	0.005
Xinjiang	0.825	0.036	0.680	0.141	0.933	0.033
Yunnan	0.839	0.047	0.877	0.036	0.938	0.026
Zhejiang	0.863	0.045	0.869	0.044	0.905	0.049
Chongqing	0.866	0.024	0.891	0.040	0.886	0.020
Shanxi	0.801	0.094	0.908	0.023	0.970	0.011

3.1.3. Spatial classification characteristics of efficiency of agro-tourism integration

Referring to the research methods of other scholars, a matrix of the distribution of agricultural and tourism integration efficiency was constructed using the mean value of agricultural and tourism integration efficiency as the vertical coordinate and the standard deviation as the horizontal coordinate. The distribution of agricultural and tourism integration efficiency was classified into four types: (1) high-efficiency stable areas with efficiency taking the value [0.85,1] and standard deviation taken as [0.01,0.05]. (2) High efficiency fluctuating areas, where the efficiency takes the value [0.85,1] and the standard deviation is [0.05,0.2]. (3) Low-efficiency stable areas, efficiency takes the value of [0.58,0.85] and standard deviation takes the value of [0.01,0.05]. (4) Low efficiency fluctuating areas, with efficiency values of [0.58,0.85] and standard deviation values of [0.05,0.2]. As shown in Figure 3, 17 provinces in the sample, including Zhejiang, Hebei and Hunan, are in high-efficiency stable areas, accounting for 54.8%; 5 provinces, including Yunnan and Gansu, are in low-efficiency stable areas, accounting for 16.13%; 7 provinces, including Tibet and Qinghai, are in low-efficiency fluctuating areas, accounting for 22.58%; and only two provinces, Guangxi and Jiangxi, are in high-efficiency fluctuating areas. Thus, more than half of the provinces in the sample have relatively high and stable efficiency in integrating agriculture and tourism. However, there are still 14 provinces with low or unstable efficiency in agro-tourism integration. So, we should focus on these regions in the future and formulate differentiated policies to promote the efficiency of agro-tourism integration.

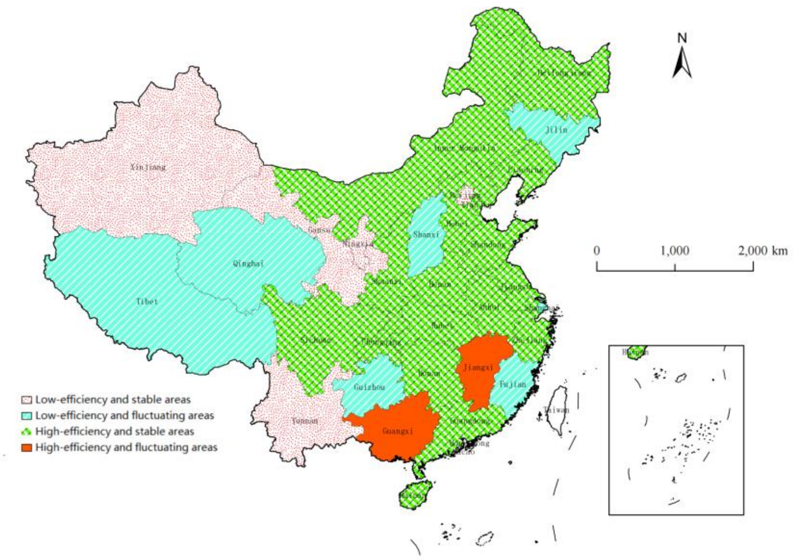

Figure 2. Spatial breakdown of agro-tourism integration's (mean) efficiency level in China.

3.1.4. Spatial structural characteristics of the efficiency of the agro-tourism integration

Using the ArcGIS cold and hotspot analysis tool, data at two-year intervals were used as analysis nodes to classify the agricultural and tourism integration efficiency values of the sample provinces into four types: cold spot, sub-cold spot, sub-hotspot and hotspot and to explore the spatial structural characteristics of the integration efficiency of the agricultural and tourism industries in China's provinces as they evolve [43,46]. This is shown in Figure 3. The range of agricultural and tourism integration efficiency hotspots in the sample provinces from 2010 to 2019 has expanded, offering the spatial evolution characteristics from dispersion to aggregation. Still, the collection tends to gradually shift from the northeast to the eastern regions such as Jiangsu and Zhejiang and the aggregation trend is becoming increasingly apparent. Except for 2015, the sub-hotspots in other years showed a year-on-year increase, showing a development trend from fragmentation to accumulation. As a result, the agglomeration area shifted from the northeast to the central and eastern regions with higher levels of economic growth, mainly in the periphery of the hotspots. In 2011, only Qinghai and Sichuan were in the sub-hotspot areas. Still, in 2013, the sub-hotspot and cold spots areas gradually expanded to the northwest. These areas have been in the sub-hotspot and cold spots areas for a more extended period, mainly because the agriculture in these areas is less efficient in promoting tourism, which leads to an increase in the number of farmers. The main reason for this is that the efficiency of agriculture in promoting tourism in these regions could be higher, resulting in a relatively low level of integration between agriculture and tourism [20,47]. The spatial analysis of the efficiency of the agro-tourism integration and the study of the cold spots suggest that the development of agro-tourism integration in China should not only focus on the construction of high-level and efficient development areas but also take advantage of the driving and diffusion effects to balance the development of the region [48].

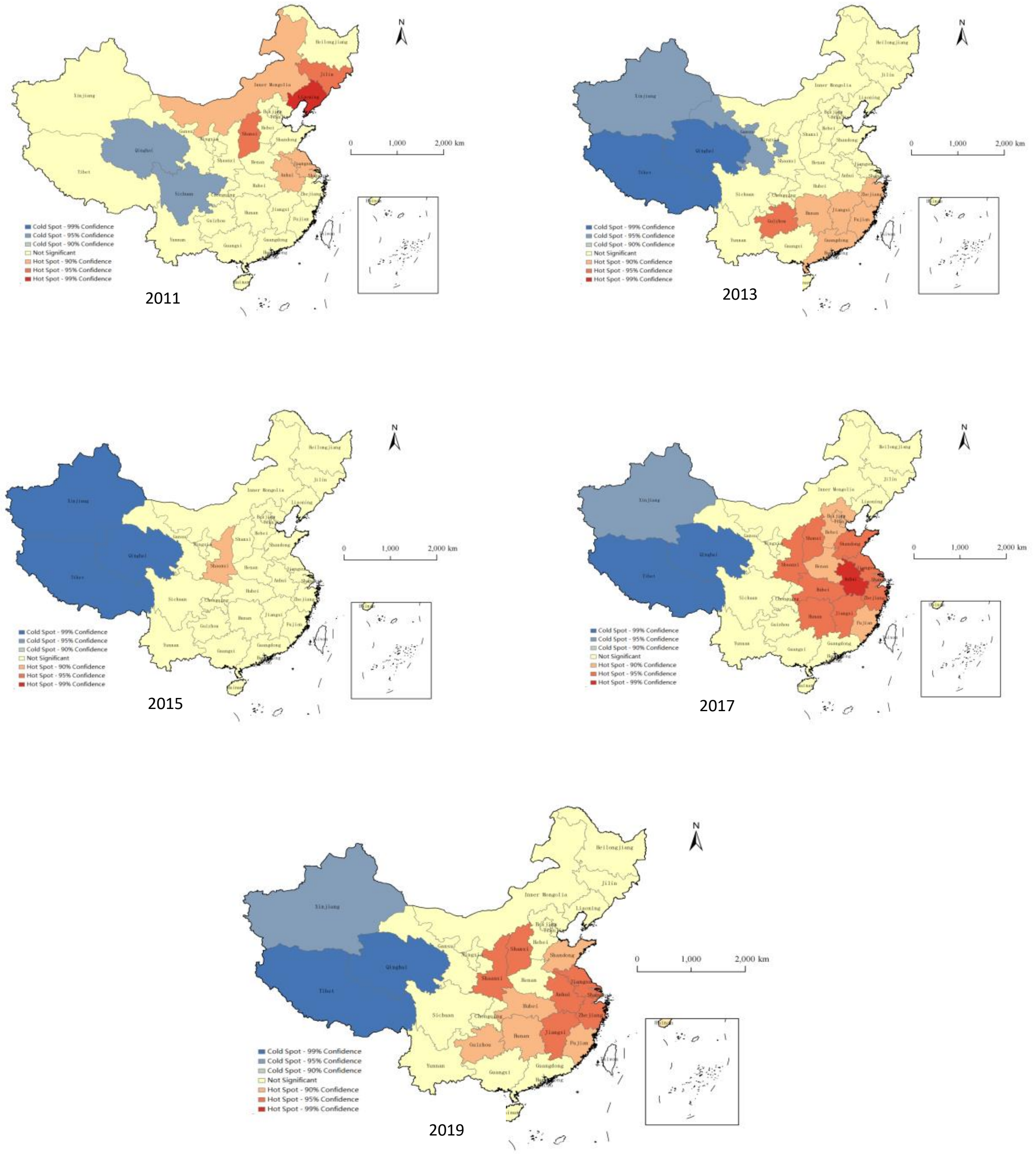

Figure 3. Cold spots and hot spots distribution of the efficiency of agro-tourism integration in China.

3.2. *Analysis of the factors influencing spatiotemporal divergence*

To investigate the mechanism of spatial variation in the efficiency of agro-tourism integration in China, seven factors (Table 3), including the level of economic development, government support, Internet development, regional innovation capability, human capital level, resident consumption level and location and transportation advantage, were selected to construct the independent variable factors of efficiency of agro-tourism integration to investigate the explanatory strength of each variable element on the spatial variation of integration efficiency of agriculture from 2010 to 2019, concerning the research methods of other scholars [49].

Table 3. Summary of factors influencing agro-tourism integration.

Primary Indicators	Secondary indicators	Variables
Economic development level	GDP per capita (10,000 CNY)	X1
Residents' consumption levels	Per capita disposable income of resident households (CNY)	X2
Government support	General fiscal public budget expenditure (CNY billion)	X3
Internet development level	Number of Internet broadband access subscribers (million)	X4
Regional innovation capacity	R&D expenditure (CNY million)	X5
Human capital levels	Percentage of the population with tertiary education and above (%)	X6
Location and transportation advantages	Road mileage (km)	X7

3.2.1. Exploration of spatial differentiation factors for the efficiency of agro-tourism integration

The results of the factor detection are shown in Table 4. As a whole, the multi-year average influence of all factors from 2011–2019 is relatively significant, except for the level of human capital X6, which does not have much explanatory power on the efficiency of agricultural and tourism integration in the sample provinces of which the level of resident consumption X2 (0.908), the level of economic development X1 (0.836), the location and transportation advantage X7 (0.639), the strength of government support X3 (0.520) and regional innovation capacity X5 (0.430) are the dominant factors influencing the spatial divergence in the efficiency of agro-tourism integration. From the perspective of each year, the leading factors influencing the spatial variation of the efficiency of agro-tourism integration are relatively stable. The top three influential factors each year are residents' consumption level, economic development and location and transportation advantages, consistent with the findings of existing studies. The higher the level of residential consumption, the more pronounced the consumption demand-led effect, resulting in very similar spatial characteristics of residential consumption and agricultural and tourism integration which may be one of the reasons for the significant influence of residential consumption level on the detection of agricultural and tourism integration efficiency factors.

From the annual change trend of the influence of various factors, the effect of the degree of Internet development on the spatial differentiation of the efficiency of agro-tourism integration is increasing year by year, the influence of regional innovation capability on the spatial differentiation of the efficiency of agro-tourism integration shows a fluctuating downward trend, the effect of government support on the spatial differentiation of the efficiency of agro-tourism integration shows a fluctuating upward trend. The influence of other factors is unchanged. Combined with the results of spatiotemporal analysis, the efficiency of agro-tourism integration in the sample provinces is increasing yearly with the popularity of the Internet and the application of the Internet facilitates the promotion of farm music and leisure villas using online platforms. Therefore, promoting the integrated development of agriculture and tourism and improving the integration efficiency is helpful. It is one of the reasons why the degree of development of the Internet has an increasing influence on the spatial differentiation of the efficiency of agro-tourism integration.

Table 4. Statistics on the q-values of the efficiency factor detection for the agro-tourism integration.

Impact factor	q-value					
	2011	2013	2015	2017	2019	Average value
X_1	0.784	0.832	0.890	0.814	0.861	0.836
X_2	0.921	0.904	0.893	0.912	0.910	0.908
X_3	0.532	0.422	0.477	0.561	0.609	0.520
X_4	0.171	0.349	0.411	0.426	0.437	0.359
X_5	0.467	0.452	0.409	0.413	0.407	0.403
X_6	0.061	0.076	0.042	0.059	0.063	0.060
X_7	0.667	0.671	0.640	0.579	0.638	0.639

3.2.2. Interaction detection of spatial differentiation in the efficiency of agro-tourism integration

The results of interaction detection are shown in Table 5. The q-values of the two-factor effects of influences on the spatial differentiation of agricultural and tourism integration in each province from 2010 to 2019 are overall more significant than the single-factor q-values and the interactions of the influencing factors show a two-factor enhancement or non-linear enhancement. In terms of interaction strength, the top three combinations of influencing factors in terms of average interaction q-values affecting the efficiency divergence of agricultural and tourism integration in China from 2010 to 2019 are residents' consumption level and regional transportation advantage, residents' consumption level and regional innovation capacity and economic development level and government support. In addition, the q-values of the interactions between the level of resident consumption and the level of economic development and other influencing factors range from 0.899-0.924 and 0.836-0.914, respectively, which are much higher than the interactions of other influencing factors. This proves the dominant role of the level of economic development and the level of resident consumption on the spatial divergence of the efficiency of agro-tourism integration.

Table 5. Interaction q-values of factors influencing the efficiency of agro-tourism integration.

Impact factor	X_1	X_2	X_3	X_4	X_5	X_6	X_7
X_1	0.836						
X_2	0.842	0.899					
X_3	0.914	0.912	0.532				
X_4	0.849	0.908	0.521	0.334			
X_5	0.846	0.919	0.446	0.412	0.421		
X_6	0.837	0.901	0.530	0.407	0.423	0.091	
X_7	0.840	0.924	0.521	0.447	0.467	0.097	0.641

4. Discussion

China is a largely agricultural country with great potential for integrating agriculture and tourism [50]. The areas with better integration and development of China's agricultural tourism are in the eastern region. However, the differences between different areas are apparent and each has its advantages [51]. Therefore, it is of great significance to evaluate and compare the efficiency of agro-tourism integration in different regions based on the analysis dimension of the overall description of internal differences to improve the efficiency of agricultural development. This study constructs an input and output index system from the perspective of industrial integration, uses the DEA cross-efficiency model to analyze the efficiency of agro-tourism integration in 31 provinces in mainland China from 2010 to 2019 and uses the geospatial analysis method to explore its spatial differentiation characteristics and causes.

First, the researchers adopted the DEA cross-efficiency model that can effectively overcome self-evaluation limitations to make the model expression more in line with the cooperative and competitive relationship between agriculture and tourism under industrial integration and development background. The efficiency evaluation results show that the overall efficiency of agro-tourism integration in mainland China is relatively stable. The average overall efficiency during the study period remained at around 0.9, increasing year by year. In 2015, the Chinese government raised relevant policies to promote the development of industrial integration at the national level and the efficiency of China's agricultural integration has maintained a relatively stable growth trend, indicating that the promotion effect of industrial policies is significant [52]. In addition, from the perspective of systematic differences in efficiency promotion, the promotion efficiency of tourism to agriculture is significantly higher than that of agriculture to tourism and the promotion efficiency of agriculture to tourism is relatively low. Therefore, in future policy formulation, more attention should be paid to the driving effect of agriculture on tourism, vigorously developing rural tourism, leisure agriculture and other agricultural tourism industries so that new agricultural subjects, new models and new industries can promote development.

Second, ArcGIS cold and hot spot analysis results show that agriculture and tourism integration efficiency between different provinces is significantly different and presents a specific fluctuation trend. The spatial differentiation characteristics are significant. Among them, agriculture and tourism integration efficiency in the eastern region is generally higher than in other areas. In all samples, 54.8% of the provinces are in high-efficiency and stable areas, 22.58% are in low-efficiency and stable regions, and the remaining 22.62% fluctuate sharply in the integration efficiency of agriculture and tourism, showing apparent path dependence in spatial differentiation. How to break through the path dependence of development and realize the deep integration and high-quality development of agriculture and tourism is a problem that needs attention in the future of the landing area. In addition, hotspots continue to gather in eastern developed regions such as Zhejiang and Jiangsu and the northwest region has long been a cold or sub-cold spot. It shows that promoting the integration of agriculture and tourism not only needs to pursue the level of efficiency but also needs to consider the balanced development between regions [53], do an excellent job in the overall regional planning and formulate differentiated policies for regional differences.

Finally, the results of geographic detector analysis show that the five driving factors, including residents' consumption level, economic development level, location and transportation advantages, government support and regional innovation capability have a significant impact on the spatial differentiation characteristics of China's efficiency of agro-tourism integration. Among them, residents' consumption level, economic development and the advantages of location and transportation are the most stable factors affecting the distribution of the efficiency of agro-tourism integration. In addition, the interaction effect of each factor is greater than the individual effect. Therefore, in promoting the integration of agriculture and tourism [54], based on fully considering the differences in residents' consumption, economic development and location advantages in various regions, the government should give full play to synergistic benefits and introduce related support policies.

5. Conclusions

Promoting the integration of agriculture and tourism is crucial to developing China's agricultural economy [55,56]. However, formulating an appropriate agricultural development strategy requires an assessment of current agricultural performance and an in-depth analysis of the causes of inefficiencies [57]. Evaluating the efficiency of agro-tourism integration is a question of resource utilization efficiency [58]. This kind of evaluation can take many forms. After considering various input and output factors, the DEA cross-efficiency model can be used as an effective evaluation tool to express better the reality of the integrated development of agriculture and tourism [28]. The findings can provide a reference for the development of agriculture and tourism under the background of industrial integration and the following main research conclusions are drawn.

First, based on the DEA cross-efficiency model, this study conducts a new comparative assessment of the efficiency of agro-tourism integration in mainland China. Overall, the efficiency of agro-tourism integration in China was stable at about 0.9 during the study period. The promotion efficiency of tourism to agriculture was higher than that of agriculture to tourism. However, the lagging level of agricultural development restricted the improvement of the efficiency of agro-tourism integration to a certain extent. Therefore, China should accelerate the high-quality growth of agriculture in the future.

Second, there are obvious differences in the efficiency of agro-tourism integration in different provinces in China. The characteristics of spatial differentiation are significant and the development trend shows obvious path dependence characteristics. The efficiency of agro-tourism integration hotspots gradually gathered in eastern developed provinces such as Zhejiang and Jiangsu. Therefore, policymakers should pay attention to the differences among regions and introduce differentiated support policies in a more targeted manner.

Third, residents' consumption level, economic development level, location and transportation advantages, government support and regional innovation capabilities significantly impact the spatial differentiation of the efficiency of agro-tourism integration. Therefore, improving the consumption level of residents, improving the level of economic development, optimizing the transportation layout, strengthening government support and increasing investment in innovation is conducive to improving the quality of agricultural tourism integration.

This study also has certain limitations. First, no spatial autocorrelation law was explored at this stage due to the research sample scale. Therefore, the spatial diffusion effect of the efficiency of agro-tourism integration in different regions could not be investigated from the core-edge theory perspective. Consequently, it is suggested that future studies further refine the research scale and explore the spatial diffusion effect of agro-tourism integration development based on the municipal or county-level scale. Second, the scale of inbound tourism and tourism revenue in China have been affected by the new crown pneumonia epidemic and geopolitical conflicts in the past three years [59,60] and the variability of tourism-related indicators is relatively large. Therefore, the data from 2020–2022 was not included in the sample observation period in this study. Finally, in the context of the rapid development of artificial intelligence and the Internet economy, new agricultural subjects, innovative agrarian production models and tourism business methods are emerging [49,61]. As a result, the boundaries between industries are becoming increasingly blurred. Therefore, measuring the input-output indicators of agriculture and tourism becomes more complex, becoming a new topic worthy of future research.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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