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Analysis and simulation of the spatiotemporal evolution pattern of tourism lands at the Natural World Heritage Site Jiuzhaigou, China

Jun Liu[a,*], Juan Wang[a], Shenghong Wang[a], Jingfan Wang[a], Guiping Deng[b]

[a] Tourism School, Sichuan University, 24 South Section 1 Ring Road No. 1, Chengdu, Sichuan, 610065, PR China
[b] Administrative Bureau of Jiuzhaigou, Sichuan, China

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ABSTRACT

This study researched the Natural World Heritage Site of Jiuzhaigou, China, which has a vulnerable ecological environment and booming tourism industry. Using satellite imaging with field calibration, we established the site's land-use databases for 2005 and 2015, analysed tourism land-use transformations, determined the driving mechanism behind land-use, and simulated the spatial patterns of tourism lands for 2025 and 2035. The results revealed that, during 2005–2015, the heritage site underwent dramatic land-use/land-cover change from tourism development. The tourism functions have been becoming more similar. Moreover, the distribution of tourism lands was determined by elevation and slope, as well as distances to transportation lands, watersheds, and existing lands. Between 2025 and 2035, the evolution of tourism lands is projected to gradually slow down, while the tourism functions of each village would still be dominated by accommodation and catering.

1. Introduction

As early as 1995, the *International Geosphere Biosphere Programme* and the *International Human Dimensions Programme on Global Environmental Change* proposed listing 'land-use/land-cover change' (LUCC) as a core research project to address global environmental changes (Gao, Niu, Wang, & Zheng, 2015). Driven by human land-use activities, the change of natural land-cover patterns affects the diversity of terrestrial ecosystems and primary production. It further alters the characteristics and processes of the regional atmospheric chemistry, leading to profound effects on local, regional, and global environments (Allan et al., 2017; Foley et al., 2005; Long, Liu, Hou, Li, & Li, 2014). In areas with vulnerable ecological environments, ecosystems have poor structural stability because of their weak ability to resist stress. Being easily disturbed by external factors, they become sensitive to environmental change, and thus, undergo retrogression and succession. Moreover, the systems have weak self-repair abilities; natural recovery takes an exceptionally long time (Zhao et al., 2006). Therefore, studies of typical ecologically vulnerable areas have become academically important (Yang, Li, Pei, Qiao, & Wu, 2018; Yu et al., 2015).

Jiuzhaigou is a Natural World Heritage Site (NWHS). It is a Biosphere Reserve approved by the United Nations Educational, Scientific, and Cultural Organization (UNESCO), as well as a Nature Reserve (NR), National Geopark, and Ramsar Site of China. It is located in an ecologically vulnerable area, where the development of the tourism industry is encouraged, even though large-scale industrialisation and urbanisation are prohibited (Li, Wu, & Cai, 2008). In fact, China's 13 NWHSs have now become world-famous tourism sites.

Rapid development of the tourism industry leads to dramatic LUCC (Xi, Zhao, Ge, Kong, & Long, 2014), as indicated by land-use change (LUC) and spatial morphology changes around scenic areas. On the one hand, LUCC has been observed within large scenic areas, with expansion into peripheral areas, where it has been occurring on a larger scale because of the development of the tourism industry (Mao, Meng, & Wang, 2014). On the other hand, stepwise tourism development is expected to varyingly affect peripheral communities (Liu, Zhu, Lin, Li, & Wu, 2017). It would significantly affect the structures and functions of the natural ecosystems of tourism sites (Davenport & Davenport, 2006).

Therefore, it is of great theoretical and practical importance to recognise and understand land-use patterns and their change processes resulting from tourism industry development in typical NWHSs. Such research could then 1) simulate and evaluate the potential effects from the tourism industry's influence on land-use, 2) optimise land-use patterns, 3) prevent ecological risks in scenic areas, and 4) promote NWHSs' undergoing sustainable development.

* Corresponding author.
E-mail address: liujun_igsnrr@126.com (J. Liu).

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2. Literature review

Despite a large number of studies on the changes of natural land-cover patterns from human land-use at a regional, national, and global scale (Foley et al., 2005; Liu et al., 2002; Pelorosso, Leone, & Boccia, 2009), our understanding of tourism-induced LUCCs and their driving mechanisms remains incomplete. This is primarily because studies on LUCC mainly rely on the interpretation of remote sensing images to obtain data on land vegetation, farmland, watersheds, and construction land (Liu, Long, Li, & Tu, 2015; Perry, 2011; Yang, Zhang, Liu, Xing, & De Sherbinin, 2017). Moreover, the lack of field surveys and calibration makes it impossible to differentiate tourism regions from other industry regions.

NWHS Jiuzhaigou is located in an ecologically vulnerable area, under the threat of natural factors (Cigna, Tapete, & Lee, 2017; Pavlova, Makarigakis, Depret, & Jomelli, 2017). The impact of tourism development on the ecosystem is particularly prominent here. Given the lack of reliable, multi-scale, and large-scale data, the top priority in studying tourism-driven land-use should be selecting a typical tourism site as the research object; conducting a microscale field survey for each piece of land based on the interpretation of remote sensing images; and establishing a tourism land-use database with multiple time-series, high-resolution, and accurate classifications (Xi et al., 2014).

Studies on LUCC typically focus on its spatiotemporal distribution and evolution, driving force, and simulation and prediction (Turner, Meyer, & Skole, 1994). Analyses of the current characteristics of LUC, as well as their spatiotemporal distribution and evolution, are prerequisites for further exploring the underlying mechanisms of change, which play a pivotal role in understanding the spatiotemporal change in LUC (Baiming, 1997). Using a number of indices (e.g. land-use dynamic (Wang, Ren-Dong, & He-Hai, 2002), land-use degree (Zhuang & Liu, 1997), and landscape pattern indexes (Peng, Liu, Li, & Wu, 2017)), a variety of analysis tools (e.g. GIS to reconstruct the land-use evolution process), and easy-to-use logistic regression models that have higher interpretability of variables (Shu, Zhang, Li, Qu, & Chen, 2014) to identify the mechanisms of LUCC in tourism regions have played a key role in the current studies on tourism land-use.

Simulation and prediction of the evolution of tourism land is of great importance for guiding the spatial optimisation of future tourism lands for sustainable development (Rawat, Kumar, & Biswas, 2013). Few studies have hitherto simulated future spatial patterns of tourism lands. Some studies have employed the cellular automata (CA) (Mitsova, Shuster, & Wang, 2011), CA–Markov (Gong, Yuan, Fan, & Stott, 2015), CLUE–S (Zhang et al., 2016), and system dynamic models (Wan et al., 2017) to simulate land-use from conventional aspects. Particularly, the CA–Markov models provide good simulation results (Azizi, Malakmohamadi, & Jafari, 2016; Halmy, Gessler, Hicke, & Salem, 2015) because of their advantage in long-time prediction and ability to simulate spatial pattern changes according to neighbourhood relations (Zhou, Shun, & Xie, 1999). Therefore, how to fully address the complexity of macro drivers in tourism-induced LUCC, address the complexity of micro-pattern evolution, and enhance the reliability of simulation models are pending problems in the simulation of tourism-induced LUCC.

3. Study area

NWHS Jiuzhaigou is in an ecologically vulnerable region, ranging from the Tibetan Plateau to the Sichuan Basin (E100°30′–104°27′, N30°35′–34°19′), with a total area of 720 km^2 and an outer conservation area of 600 km^2. With 114 lakes of different size, 17 waterfalls, and five travertine-covered shores, Jiuzhaigou is a scenic area, rare in the world, and the only one in China that attracts tourists. In the primeval forest that stretches across 300 km^2, rare animals like the giant pandas and golden monkeys are found, along with 693 invertebrates and 313 vertebrates. Moreover, Jiuzhaigou includes old Tibetan villages, forming a unique culture that attracts tourists. Given its high value for tourism and scientific popularisation, Jiuzhaigou is not only acclaimed as a rare belt comprising special geomorphological features and rich biodiversity, but praised as a ‘fairyland on Earth’ or ‘fairy world’, making it a world-famous tourism site.

Jiuzhaigou was added by UNESCO to the Natural World Heritage List in 1992, to the World Network of Man and Biosphere Reserve in 1997, and approved by China National Tourism Administration in 2007 to be an AAAAA scenic area, the highest grade for such areas in the country. From the aspect of tourism product composition, the tourism industry in Jiuzhaigou is relatively integrated, including traditional sightseeing, leisure, and vacation opportunities. Regarding the compositions of tourists, Jiuzhaigou attracts not only a large number of domestic tourists, but many foreign tourists as well, with a total of 5.09 million visits in 2015 from 1.91 million in 2005; particularly, the annual number of foreign tourists increased to about 200,000 from 184,000. Thus, the tourism industry has become an important revenue provider for the heritage site.

In 1974, UNESCO formally recommended the establishment of a buffer area for biosphere protection, and put forward the zoning mode of the core buffer area. According to *Regulations of the People's Republic of China on Nature Reserves*, a core area is a well-preserved nature–state ecosystem with a concentrated distribution of rare and endangered flora and fauna. The Chinese government enforces strict protection measures, and prohibits entry by any group or individual in such areas. Outside the core area is a buffer area restricted only to scientific research, including observation and measurement activities. Only the experimental area provides basic sightseeing services, while accommodation, catering, and the reception of tourists take place outside the nature reserve. The infrastructure for transportation, accommodation, and catering expands with the increase in tourist numbers, resulting in rapid expansion of land-use. Given that the heritage site is ecologically vulnerable, and the environment is sensitive to human tourism activities, weak tourism development would lead to an irreversible effect on the environment. Therefore, we chose Zhangzha, Pengfeng, Longkang, Congya, and Yazha villages—areas most influenced by tourism activities—as our research objects in order to investigate the LUCC process in the heritage site (Fig. 1).

4. Materials and methodology

4.1. Data

We interpreted land-use data using artificial visual interpretation, and obtained basic classification maps based on QuickBird images from 14 July 2005 and Google Earth images from 21 October 2015, which are four-band multispectral images[1] with a spatial resolution of 0.7 m and true-colour visible spectrum images (400–700 nm wavelengths) with 0.6 m spatial resolution, respectively. Next, using Participatory Rural Appraisal (Jianchao, Zhao, & Guansheng, 2011), eight surveyors confirmed the function of each piece of land in the Zhangzha, Pengfeng, Longkang, Congya, and Yazha villages from 25 May to 3 June 2017, and further confirmed the spatial patterns of tourism lands during 2005–2015 by interviewing local management and residents. This enabled us to verify and classify the land-use distribution map, and obtain two high-resolution tourism land distribution datasets.

Digital elevation mode (DEM) data with a spatial resolution of 30 m originally produced by NASA were derived from Google Earth using ‘91 Weitu’, while ArcGIS was used to provide slope information. Land-use data on major transportation lands, watersheds, and single-type lands were extracted from the vector land-use map of the studied areas established through artificial visual interpretation in conjunction with

[1] Blue [B: 450–520 nm], green [G: 520–600 nm], red [R: 630–690 nm], and near-infrared [NIR: 760–900 nm].

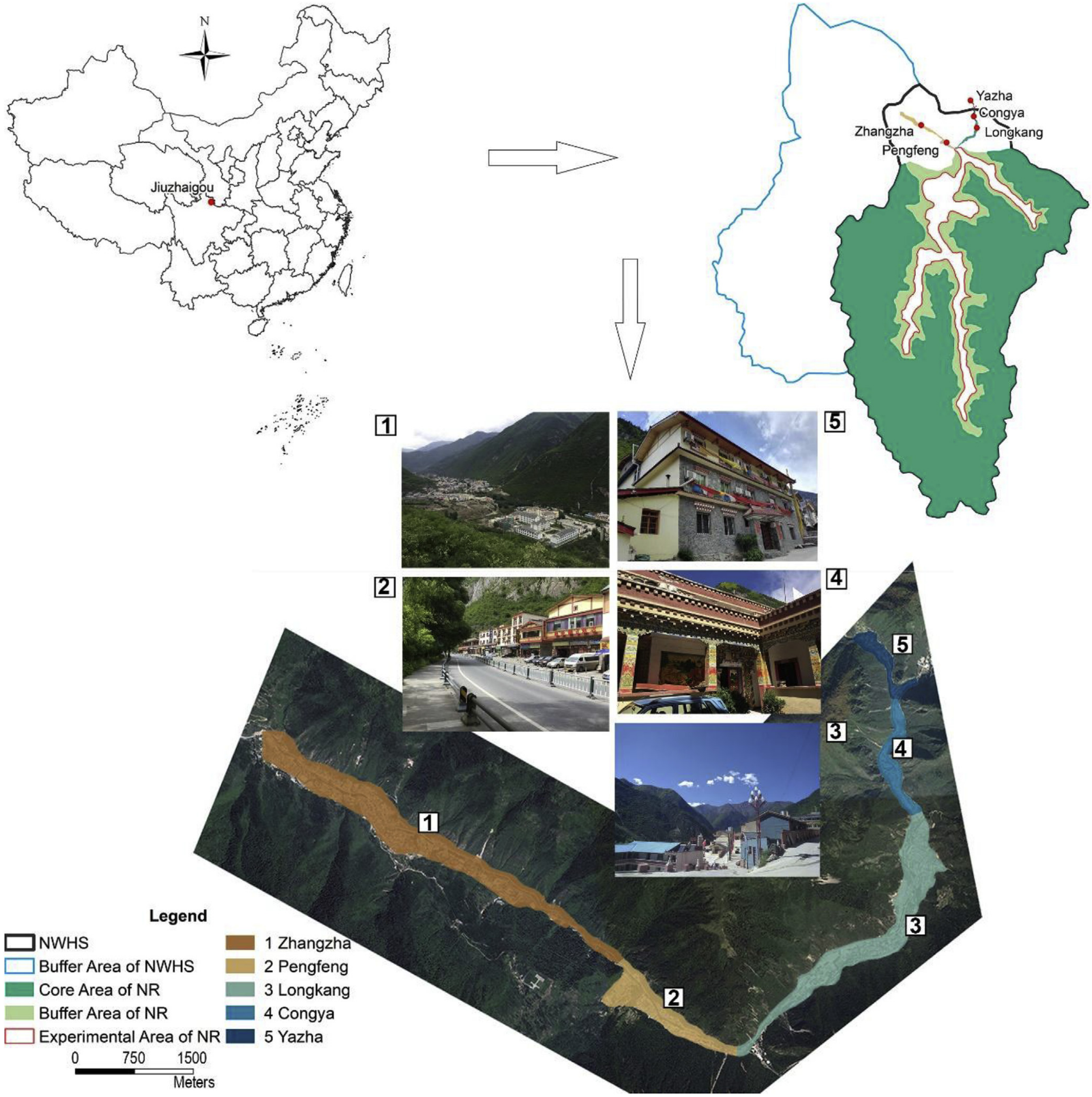


Fig. 1. Location of study area and distribution of the five villages.

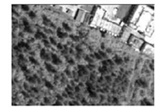
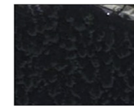
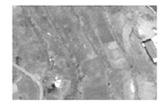
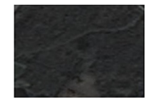
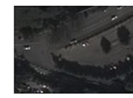
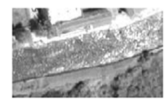
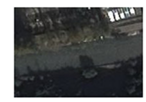
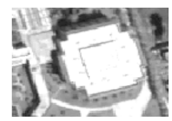
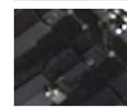
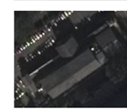
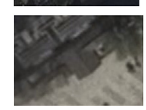
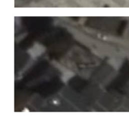
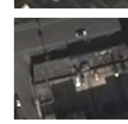
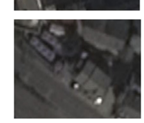
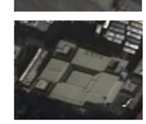
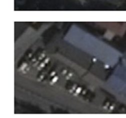
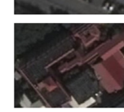
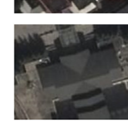
field calibration. This was followed by spatial analysis with the ArcGIS built-in command Distance to provide a corresponding distance map. The resolution of grid data was set at 5 m. Ecological protection data were aggregated from the *Comprehensive Planning of 'Total Watershed Jiuzhai' As a World-Class Leisure and Vocation Tourism Site* report provided by the Tourism Bureau of Jiuzhaigou County. This report details the coverage of the water source protection belt, mountain forest reserve, and nature reserve with a scale of 1:10,000. We designated them as restrictive construction areas to simulate the future tourism land-use map.

4.2. Methodology

4.2.1. Land-use classification

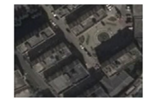
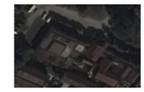
As per tourism land functions, tourism land-use is typically classified according to catering, accommodation, transportation, sightseeing, shopping, and entertainment (Xi et al., 2013). However, the field surveys revealed that, in the studied area, a high degree of tourism activities existed. The tourism industry was operated in a centralised and comprehensive mode to a significant extent. In accordance with China's land-use classification criteria (GB/T 21010–2007), the lands in the studied area were classified as forest-lands, grasslands, tourism transportation lands, watersheds and water resource infrastructure lands, commercial lands, public management and service lands, residential lands, unused lands, and others. Next, according to the ratio of tourism function-providing land areas to the total construction areas, commercial and residential lands were grouped into a single-type (with a ratio of 1), a dominant type (with a ratio of ≥ 3/5), and a balanced-type (with a ratio of ~ 1/2). Finally, the lands in the studied area were classified into 20 types (Table 1), with

Table 1
Land-use classification and definition in the studied area.

No	Land-use types	Definitions	Tourism land-use	Typical land feature images, 2005	Typical land feature images, 2015
1	Forestlands	Lands where trees and shrubs grow	No		
2	Grasslands	Lands where herbaceous plants dominate	No		
3	Tourism transportation lands	Land used for tourism transportation, such as surface route and stations, including road lands and street lands	Yes		
4	Watersheds and water resource infrastructure lands	Such as river surface, lake surface, pond surface, ditches, and hydraulic construction lands	No		
5	Catering lands	Entire buildings that provide tourists with catering	Yes		
6	Balanced-type catering-shopping lands	Tourism catering versus shopping occupies nearly 1/2 of the total construction area	Yes		
7	Catering-dominant lands	Tourism catering occupies ≥3/5 of the total construction area	Yes		
8	Balanced-type catering-accommodation lands	Tourism catering versus tourism accommodation occupies nearly 1/2 of the total construction area	Yes		
9	Balanced-type catering-residential lands	Tourism catering versus residential use occupies nearly 1/2 of the total construction area	Yes		
10	Shopping lands	The entire buildings are used for tourism shopping	Yes		
11	Balanced-type shopping-residential lands	Tourism shopping versus residential use occupies nearly 1/2 of the total construction area	Yes		
12	Entertainment lands	The entire buildings are used for entertainment	Yes		
13	Entertainment-dominant lands	Tourism entertainment occupies ≥3/5 of the total construction area	Yes	/	
14	Accommodation lands	The whole buildings are used for accommodation	Yes		
15	Accommodation-dominant lands	Tourism accommodation occupies ≥3/5 of the total construction area	Yes		

(*continued on next page*)

Table 1 (*continued*)

No	Land-use types	Definitions	Tourism land-use	Typical land feature images, 2005	Typical land feature images, 2015
16	Residential lands	The entire buildings are used for residence	No		
17	Residence-dominant lands	Residential land use occupies ≥3/5 of the total construction area	No		
18	Public management and service lands	Lands used for governmental, social, scientific, educational, cultural, and medical organizations; public facilities; as well as parks and green fields	No		
19	Unused lands	Lands that are not yet used and whose functions are unclear	No		
20	Other lands	Lands other than the above types	No		

lands showing the ratio of ≥1/2 classified as tourism land-use or non-tourism land-use otherwise.

4.2.2. Land-use process analysis

We first introduced the 'land-use transfer flow' index (Caihong, Ren, & Xiaoyan, 2013) (Eqs. (1) and (2)) and the utilisation of the social network analysis tool UCINET to visualise the index, so it is possible to straightforwardly explore the transfer relations among different types of land-use, and then, analyse the land-use processes. Thus,

$$L_f = L_{out} + L_{in} \tag{1}$$

and

$$L_{nf} = L_{in} - L_{out}, \tag{2}$$

where L_f is the land-use transfer flow, L_{out} is the outflow, L_{in} is the inflow, and L_{nf} is the net land-use transfer flow.

4.2.3. Dynamic degree of single-type land-use

A dynamic degree of single-type land-use is defined as the quantity of transferred lands for a given land-use type during a given time period, presenting a LUC rate as shown by Eq. (3):

$$\mathrm{k} = \left(A_{t_2} - A_{t_1}\right)/A_{t_1}/\Delta t \times 100\%, \tag{3}$$

where k is a dynamic degree of single-type land-use, and A_{t_1} and A_{t_2} stand for the area of a type of land-use at time t_1 and t_2, respectively, with Δt being the time change. Δt is expressed in years, thus presenting an annual change rate.

4.2.4. Activity degree of land-use

An activity degree of land-use presents the degree of change for a given land-use with respect to its existing distribution, namely, the ratios of the sum of inflows plus outflows to the total existing area:

$$L_a = \frac{(L_{out} + L_{in})}{A_0}/\Delta t \times 100\% = L_f/A_0/\Delta t \times 100\%, \tag{4}$$

where L_a is an activity degree of land-use and A_0 is the initial area of a given land-use.

4.2.5. Dominant change index

During the studied period, a given type of land-use with a varying area may undergo spatial replacement. This means that the land-use in a region is converted to another type of land-use, while other land-uses may be converted to the first type of land-use in another region (Pontius, Shusas, & Mceachern, 2004). Such replacements are called swap changes (see Eq. (5)). The sum of the swap and net changes represents the total LUC. The dominant change index (C_D) evaluates whether the change of a given type of land-use during a given period is dominated by quantitative change or spatial replacement. $C_D > 50\%$ refers to dominance of quantitative change, and of spatial exchange otherwise, as shown by the following equations:

$$C_E = 2*\min(L_{in}, L_{out}), \tag{5}$$

$$C_D = |L_{in} - L_{out}|/L_f \times 100\% = |L_{nf}|/L_f \times 100\%, \tag{6}$$

Where C_E is the land-use type swap change and C_D the dominant change index.

4.2.6. Analysis model of the driving mechanism

Logistic regression models have been widely employed in LUC analysis, including the analyses of land retrogression, farmland change, and ecological land-use evolution. Binary logistic regression models are models of binary dependent variables, as described below:

$$\log \frac{P_i}{1 - P_i} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots \cdots \beta_n X_n, \tag{7}$$

where P_i is the probability of each grid showing land-use type I, and X_n is the driver. Logistic stepwise regression determines the effect of the drivers on single-type land-use, and the quantitative relation between them identifies the determinants of land-use patterns. Exp(β) is an exponential function of the regression function coefficient, with the natural index as the base to evaluate the effect of the independent variable on the dependent variables. It thus presents the change in the land-use type occurrence rate when the drivers are increased by a unit, where the land-use type occurrence rate is defined as the ratio of event occurrence frequency to event non-occurrence frequency. When Exp(β) < 1, the occurrence rate decreases; when Exp(β) = 1, the occurrence rate does not change; and when Exp(β) > 1, the occurrence rate increases.

The regression results were verified with the receiver operating characteristic curve (ROC) proposed by Pontius and Schneider (2001). ROC values are in the range of 0.5–1. When 0.5 < ROC < 0.7, the prediction accuracy is low; when 0.7 < ROC < 0.9, the prediction accuracy is acceptable to some extent; when ROC > 0.9, the prediction accuracy is high. When ROC = 0.5, the prediction results are useless, while the scenario of ROC < 0.5 is not empirically feasible, as it does not reflect the true conditions. When the ROC value is closer to 1, the prediction results are expected to be more suitable.

4.2.7. Simulation models for future land-use patterns

CA models are grid dynamic models in which time, space, and state are dispersed, and that can simulate spatiotemporal evolution processes (Santé, García, Miranda, & Crecente, 2010), with the core part of CA models defining the transformation rules. Markov models can predict the change at a future time point by utilising the quantity of LUC and probability of land-use transfer. As such, they are advantageous for long-term predictions, but do not possess spatial features. In conclusion, both types of models have some limitations.

CA–Markov models introduce spatial features to the prediction results of long time-series Markov models, thus integrating the capabilities of CA models to simulate complex-system spatial changes (Azizi et al., 2016). They provide a better simulation of LUCs from both temporal and spatial aspects.

We employed logistic regression models to generate a map of spatial probability distribution for land-use types. According to the map, we defined transformation rules in CA models, combining the rules with CA–Markov models to form a logistic–CA–Markov coupling model. We used the IDRISI Selva software to perform the simulation and prediction of tourism-driven LUCs of the heritage site for 2025 and 2035.

The research framework is shown in Fig. 2 below.

5. Results

5.1. LUCC during 2005–2015

In 2005, the largest lands were forestlands, public management and service lands, and grasslands with respective areas of 885,075 m^2, 477,075 m^2, and 475,375 m^2. In 2015, the largest lands were forestlands (1,139,475 m^2), other lands (806,000 m^2), and tourism transportation lands (443,675 m^2).

During 2005–2015, the area of tourism lands increased from 606,775 m^2 to 806,050 m^2, that is, from 17.21% to 22.86% of the total land area. Although the activity degree of tourism lands was 7.72%—a value lower than the 8.70% for all lands on average—the activity degree of tourism housing land-use was as high as 11.74% (Table 2), and its area increased from 207,150 m^2 to 362,375 m^2. Over the entire period, accommodation land-use accounted for the largest areas, followed by accommodation-dominant and catering land-uses.

All 20 types of land-use underwent complex conversions during the studied period, showing 183 types of land transfer relations (Fig. 3). The other lands, forestlands, accommodation lands, tourism transportation lands, and residence-dominant lands showed the largest net inflows with values of 335,075 m^2, 254,400 m^2, 844,00 m^2, 44,050 m^2, and 39,300 m^2, respectively. The grasslands, unused lands, public

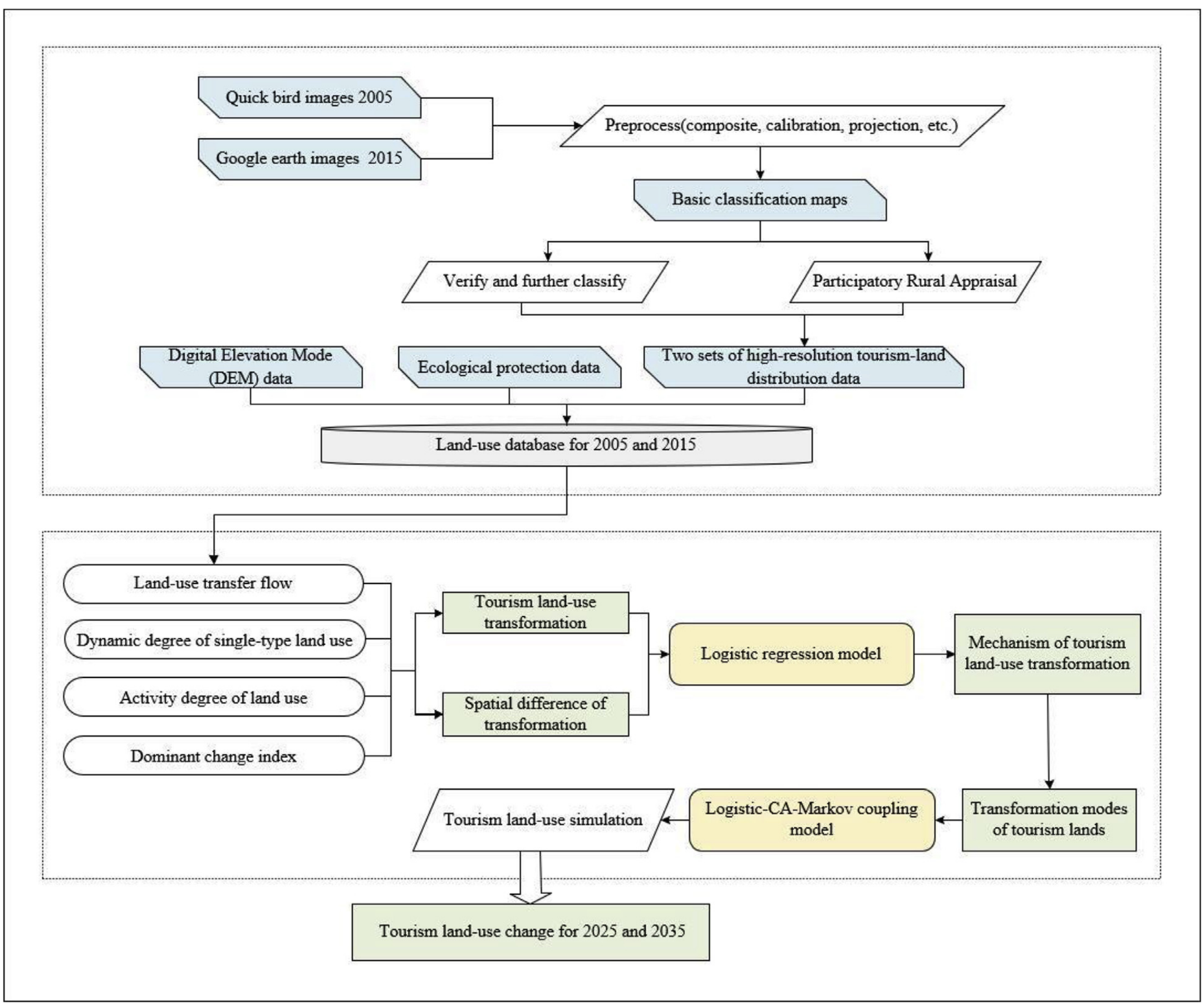


Fig. 2. The framework of the research.

Table 2
The activity degree and dominant change index of tourism lands from 2005 to 2015.

Land-use types	Study area		Zhangzha		Pengfeng		Longkang		Congya		Yazha	
	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%
Tourism lands	7.72	42.52	9.07	58.37	7.26	37.17	6.48	23.20	6.27	33.59	16.96	71.14
Tourism housing lands	11.74	63.82	12.67	67.74	15.29	73.02	6.92	38.98	1224.08	98.37	78.41	85.34
All	8.70	–	9.08	–	6.32	–	8.98	–	8.56	–	10.53	–

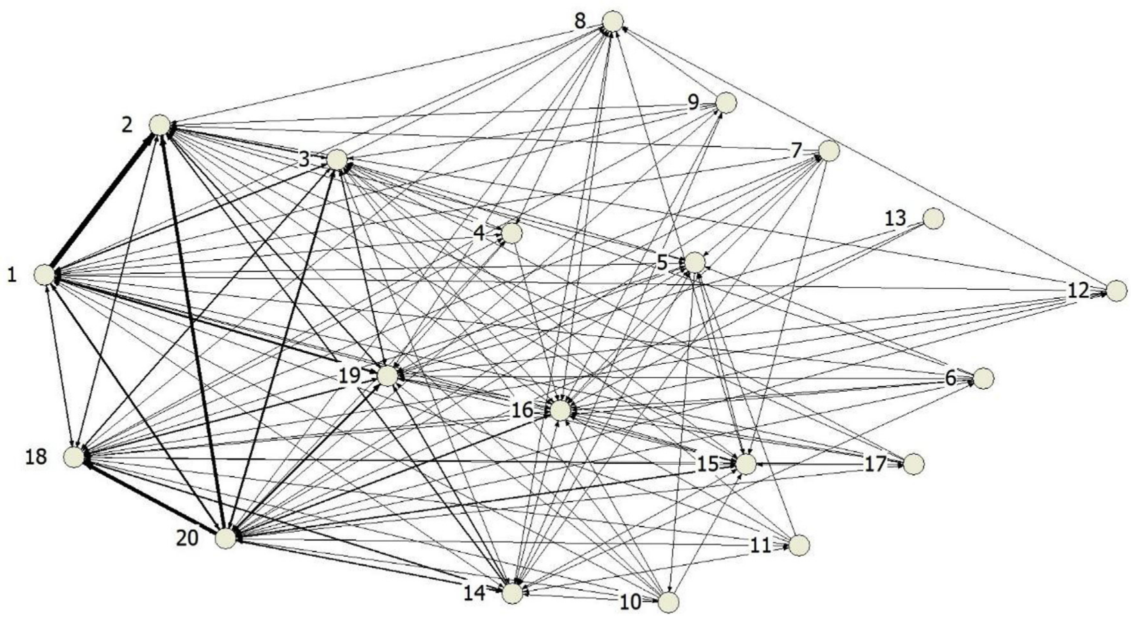


Fig. 3. Land-use transfer flows for 2005–2015.1, forestlands; 2, grasslands; 3, tourism transportation lands; 4, watersheds and water resource infrastructure lands; 5, catering lands; 6, balanced-type catering-shopping lands; 7, catering-dominant lands; 8, balanced-type catering-accommodation lands; 9, balanced-type catering-residential lands; 10, shopping lands; 11, balanced-type shopping-residential lands; 12, entertainment lands; 13, entertainment-dominant lands; 14, accommodation lands; 15, accommodation-dominant lands; 16, residential lands; 17, residence-dominant lands; 18, public management and service lands; 19, unused lands; 20, other lands.

management and service lands, residential lands, and watersheds and water resource infrastructure lands were the primary lands that showed positive net outflows of 445,025 m^2, 196,375 m^2, 107,650 m^2, 39,700 m^2, and 6350 m^2, respectively. Balanced-type catering–residential, balanced-type catering–shopping, balanced-type shopping–residential, and entertainment-dominant lands accounted for a small portion of the inflows and outflows.

As shown by the dominant change index, different types of land-use had different transfer modes. Forestlands, tourism transportation lands, watersheds and water resource infrastructure lands, balanced-type catering–accommodation lands, residential lands, and public management and service lands were dominated by swap changes, that is, their changes primarily took place in the form of spatial replacements. The remaining lands were mainly characterised by changes in their quantities, with entertainment-dominant land showing the most significant change (Table 3).

5.2. Tourism land-use transformation during 2005–2015

Twelve types of tourism lands showed an increasing trend. Tourism transportation, tourism accommodation, and accommodation-dominant lands accounted for the most tourism land-use. Compared with 2005, 2015 saw an increase by 11.02%, 89.67%, and 58.81% for the three types of lands above, respectively.

Although each type of tourism land-use continued to increase, they showed different activity degrees. Shopping, balanced-type catering–shopping, and balanced-type catering–residential lands showed the highest, second highest, and third highest activity degrees, respectively. The above three types of land-use showed the highest annual change rates, k, of 39.46%, 29.09%, and 15.15%, respectively. All the rates showed an increasing trend over time. For these types of land-use, L_a was 48.65%, 35.45%, and 16.97%, respectively. However, entertainment, tourism transportation, and balanced-type catering–accommodation land-uses were the least active, with L_a of 5.1%, 5.64%, and 6.36%, respectively.

As indicated by the dominant change index, except for the tourism transportation and balanced-typed catering–accommodation lands primarily characterised by swap change, the other types of tourism lands, such as catering-dominant, balanced-type catering–accommodation, and entertainment-dominant lands, were primarily characterised by a change in their quantities (Table 3).

5.3. Spatial difference of tourism land-use transformation among villages

Regarding the tourism function, all five villages provided accommodation—tourism accommodation lands accounted for the largest part of the total area of tourism housing lands (Figs. 4 and 5). During 2005–2015, the housing land areas related to tourism accommodation land-use increased from 170,425 m^2 to 294,500 m^2. Moreover, in terms of the area of tourism housing lands, the catering function was the second most important after the accommodation function, with the land-use area of tourism catering increasing from 33,450 m^2 in 2005 to 56,075 m^2 in 2015.

Although the five villages showed similar functions, there was a

Table 3
Land-use analysis indicators from 2005 to 2015.

Land-use types	Area/m^2		Land-use transfer flow/m^2		Analysis index		
	2005	2015	L_f/m^2	L_{nf}/m^2	k/%	L_a/%	C_D/%
Forestlands	885075	1,139,475	529550	254400	2.87	5.98	48.04
Grasslands	475375	30350	485875	−445025	−9.36	10.22	91.59
Tourism transportation lands	399625	443675	225400	44050	1.10	5.64	19.5
Watersheds and water resource infrastructure lands	198025	191675	48150	−6350	−0.32	2.43	13.19
Catering lands	14375	26925	20800	12550	8.73	14.47	60.34
Balanced-type catering-shopping lands	550	2150	1950	1600	29.09	35.45	82.05
Catering-dominant lands	7400	13000	6200	5600	7.57	8.38	90.32
Balanced-type catering-accommodation lands	9475	9850	6025	375	0.40	6.36	6.22
Balanced-type catering-residential lands	1650	4150	2800	2500	15.15	16.97	89.29
Shopping lands	925	4575	4500	3650	39.46	48.65	81.11
Balanced-type shopping-residential lands	750	1250	700	500	6.67	9.33	71.43
Entertainment lands	11075	15125	5650	4050	3.66	5.10	71.68
Entertainment -dominant lands	0	700	700	700	/	/	100.00
Accommodation lands	94125	178525	131500	84400	8.97	13.97	64.18
Accommodation-dominant lands	66825	106125	62400	39300	5.88	9.34	62.98
Residential lands	124175	84475	145800	−39700	−3.20	11.74	27.23
Residence-dominant lands	1400	7750	7350	6350	45.36	52.50	86.39
Public management and service lands	477075	369425	403650	−107650	−2.26	8.46	26.67
Unused lands	287800	91425	321175	−196375	−6.82	11.16	61.14
Other lands	470925	806000	657075	335075	7.12	13.95	50.99

significant difference in the activity degree and transformation mode of tourism land-use between them. Pengfeng, Longkang, and Congya showed a tourism land activity degree of 7.26%, 6.48%, and 6.27%, respectively—all lower than the mean activity degree of all the tourism lands in the entire region. The tourism lands of Zhangzha and Yazha were relatively active, showing an activity degree of 9.07% and 16.96%, respectively. Further analysis of the activity degree of tourism housing lands indicated that only the tourism housing land of Longkang was relatively inactive at 6.92%. Conversely, the tourism housing lands of Congya and Yazha were very active, particularly the former, with an activity degree of 1224.08%.

As indicated by the dominant change index, there were significant differences in tourism land transfer modes between the five villages. On average, the dominant change indices of tourism housing lands in the entire region were above 50%, indicating that they were primarily characterised by a change in their quantities. However, between the five villages, Longkang showed a dominant change index of 38.98% for its tourism housing land, indicating that its tourism land transfer was primarily characterised by spatial replacement (Table 2).

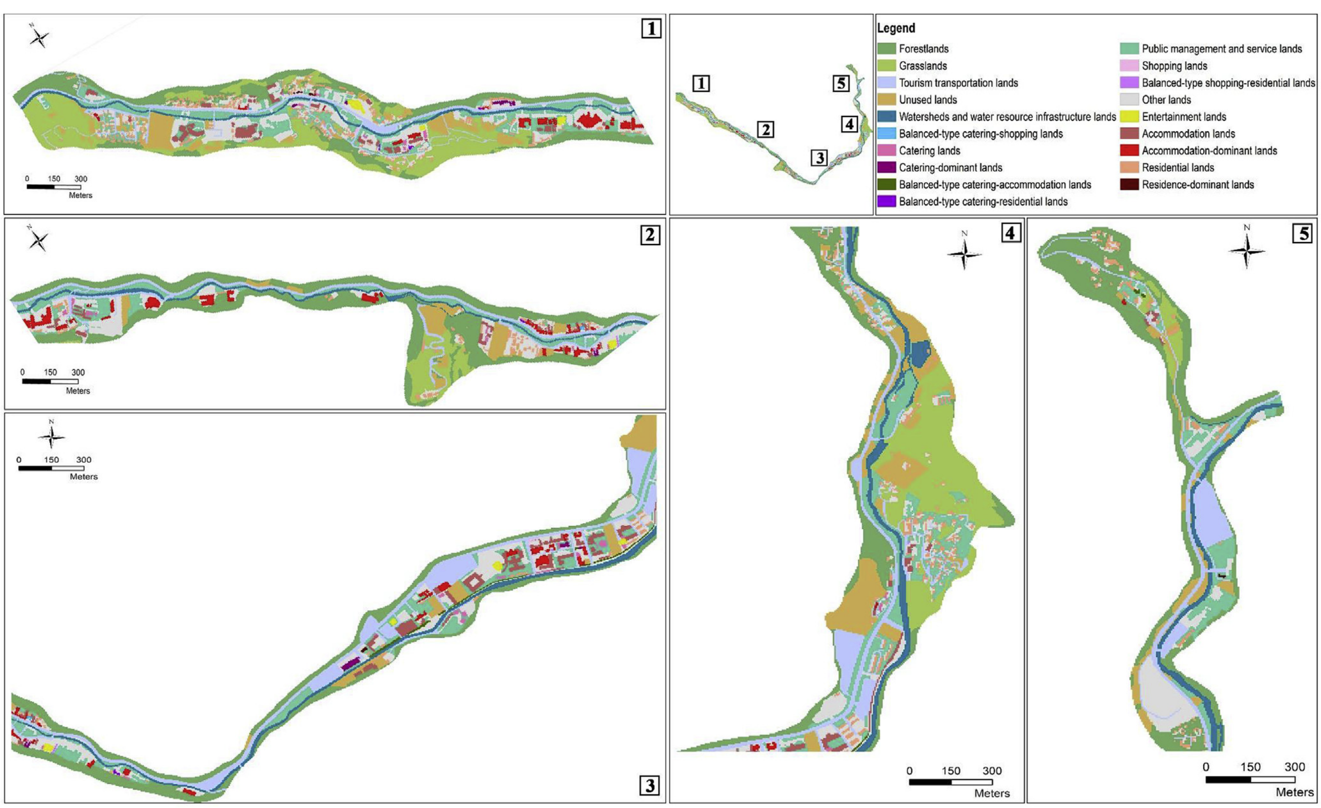


Fig. 4. Land-use distribution in 2005.

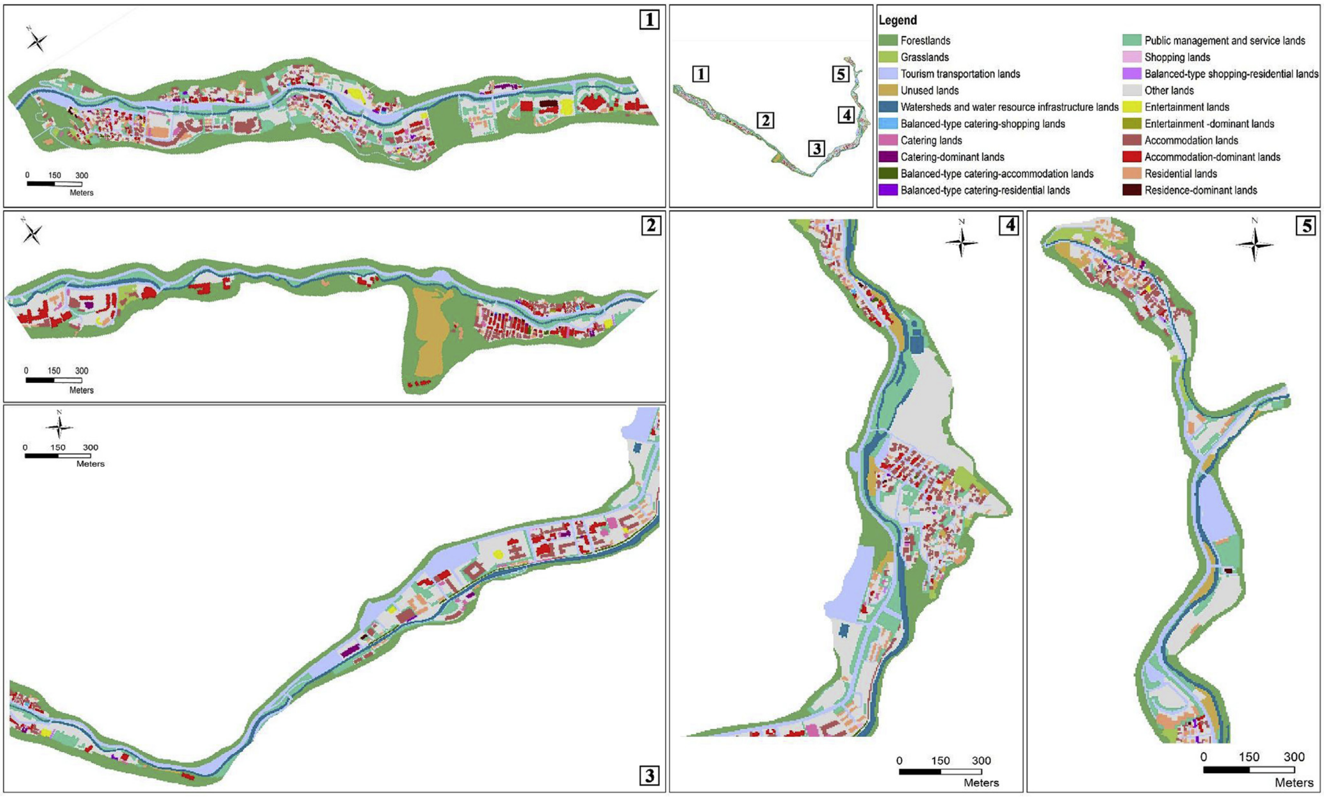


Fig. 5. Land-use distribution in 2015.

5.4. Mechanism of tourism land-use transformation

Logistic regression analysis indicated that the distribution of each type of land was primarily determined by its elevation, slope, and distance to major transportation lands, watersheds, and existing lands. Subsequently, we use the tourism accommodation and catering lands—associated with two most important tourism functions in the studied area—as examples.

The distribution of accommodation and catering land-use positively correlated with the elevation and distance to major transportation lands, with higher elevation or longer distance giving rise to a higher distribution probability. However, it negatively correlated with the slope and distance to watersheds and existing lands, indicating that accommodation and catering tended to be situated in flat areas—it was more likely to have new accommodation and catering lands around existing ones. Moreover, with a shorter distance to watersheds, the two types of land-use were more likely to appear, indicating that accommodation and catering lands were relatively close to rivers.

Accommodation-dominant land-use positively correlated with the elevation and distance to major transportation lands and watersheds. Such land-use was found in high-elevation areas and had a weak dependence on transportation lands and watersheds. Accommodation-dominant lands tended to be found in flat areas, and showed an evident trend of placement around existing accommodation-dominant lands (Table 4).

5.5. Tourism land-use simulation for 2025 and 2035

The logistic–CA–Markov coupling model was used to simulate the land-use pattern in 2015. The simulation results were compared with the actual results obtained via map interpretation. A Kappa coefficient of 0.7463 showed good reliability of the prediction results (Zhang, Zhou, Renqiang, Zhou, & Zhang, 2010), with the model showing satisfactory prediction efficacy. When predicting the land-use distribution map for 2025 and 2035, we considered the effect of tourism on the ecological environment, and designated forestlands, grasslands, and watersheds as restrictive construction areas by referring to the natural conservancy layout planned in the *Comprehensive Planning of 'Total Watershed Jiuzhai' As a World-Class Leisure and Vocation Tourism Site*. Moreover, transportation lands were set as restrictive construction areas to protect existing transportation infrastructure.

The simulation revealed that, during 2025–2035, each type of tourism land-use would increase. The tourism transportation, tourism accommodation, and accommodation-dominant lands would still be the most important tourism lands (Figs. 6 and 7). Compared to 2015, the tourism lands in 2025 and 2035 would increase by 119,800 m^2 and 272,250 m^2, respectively, and the tourism housing lands would increase by 103,350 m^2 and 253,300 m^2, respectively (Table 5). According to Tables 6 and 7, the increase in tourism land from rapid development of the tourism industry would stem primarily from land-use for public management and services, unused lands, and other lands. Accommodation and catering remain the most important types of tourism operations. Their ratios relative to other types of tourism operations are projected to continue increasing.

During 2025–2035, the activity degree of tourism lands is expected to gradually decrease. For 2005–2015, the activity degree of tourism lands was 7.72%, but will drop to 2.15% during 2015–2025, and 2.45% during 2025–2035. Meanwhile, the activity degree of tourism housing lands showed a gradual decrease, with a value of 11.74% for 2005–2015, but only 4.34% for 2015–2025 and 4.82% for 2025–2035.

The tourism land-use transfer during 2005–2015 was dominated by spatial replacement, with a dominant change index of 42.52% for tourism land-use. However, for 2015–2025 and 2025–2035, the transfer turned to be dominated by a change in land quantities, showing a dominant change index of 68.97% and 67.22%, respectively. The transfer of tourism housing land-use was dominated by a change of quantities over all periods, with a dominant change index of 63.82%, 65.72%, and 66.85% for 2005–2015, 2015–2025, and 2025–2035,

Table 4
Exp(β) and ROC values of the logistic regression models.

Land-use types	DEM	Slope	Dist_r	Dist_w	Dist_1	Dist_2	Dist_3	Dist_4	Dist_5	Dist_6	Dist_7	ROC
1	1.0094	1.1418	0.9996	1.0034	0.9898							0.9898
2	1.0030	0.9979	1.0054	0.9985		0.9993						0.9708
3	1.0043	0.9901		0.9997			0.9436					0.9806
4	1.0044	0.9949	1.0029					0.9420				0.9657
5	1.0045	0.9155	1.0060	0.9963					0.9975			0.9671
6	1.0049	0.9802	0.9829	0.9995						0.9994		0.9839
7	1.0045	0.9531	0.9962	0.9961							0.9984	0.9715
Land-use types	DEM	Slope	Dist_r	Dist_w	Dist_8	Dist_9	Dist_10	Dist_11	Dist_12	Dist_13	Dist_14	ROC
8	1.0083	0.9311	1.0177	0.9754	0.9996							0.9737
9	1.0038	0.9848	0.9978	0.9960		1.0000						0.9664
10	1.0054	0.8824	1.0005	1.0013			0.9998					0.9688
11	1.0045	1.0479	0.9859	0.9962				0.9978				0.9418
12	1.0060	0.9647	1.0026	0.9999					0.9921			0.9735
13	1.0108	0.7135	0.9650	1.0125								0.9932
14	1.0038	0.9843	1.0035	0.9989							0.9956	0.9655
Land-use types	DEM	Slope	Dist_r	Dist_w	Dist_15	Dist_16	Dist_17	Dist_18	Dist_19	Dist_20		ROC
15	1.0041	0.9645	1.0030	1.0012	0.9938							0.9673
16	1.0042	0.9882	0.9998	0.9998		0.9616						0.9850
17	1.0058	0.8233	1.0088	0.9894			0.9999					0.9845
18	1.0044	0.9704	0.9996	0.9953				0.9667				0.9789
19	1.0034	0.9529	1.0055	1.0033					0.9845			0.9721
20	1.0041	0.9348	1.0032	1.0000						0.9743		0.9768

Note: ① Land-use types in rows 1–20 refer to Table 1 and Dist_1–20 is the distance to existing lands in 2005; ② Dist_r and Dist_w are the distances to major transportation lands and to watersheds, respectively.

respectively.

Over 2015–2025 and 2025–2035, the activity degree of tourism lands in the five tourism regions is expected to drop dramatically compared to 2005–2015. The activity degrees of the tourism lands in Pengfeng, Longkang, Congya, and Yazha would be lower than the mean activity degree of the entire region. Tourism land-use in Zhangzha is projected to be more active than in other regions at 4.55% and 3.62% for 2015–2025 and 2025–2035, respectively. As indicated by the dominant change index, the tourism land-use transfer in the five regions would be dominated by quantity change, except for Yazha, which

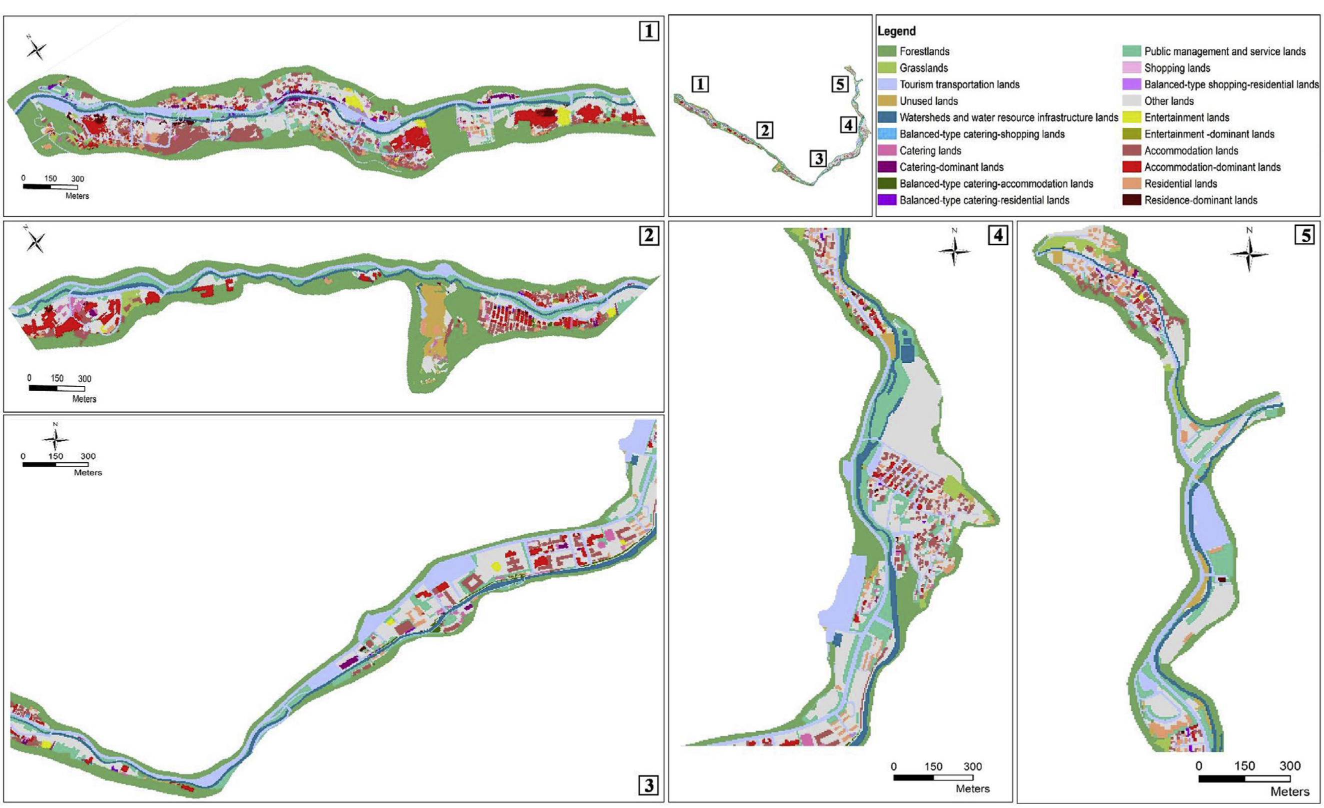


Fig. 6. The simulated results of land-use pattern for 2025.

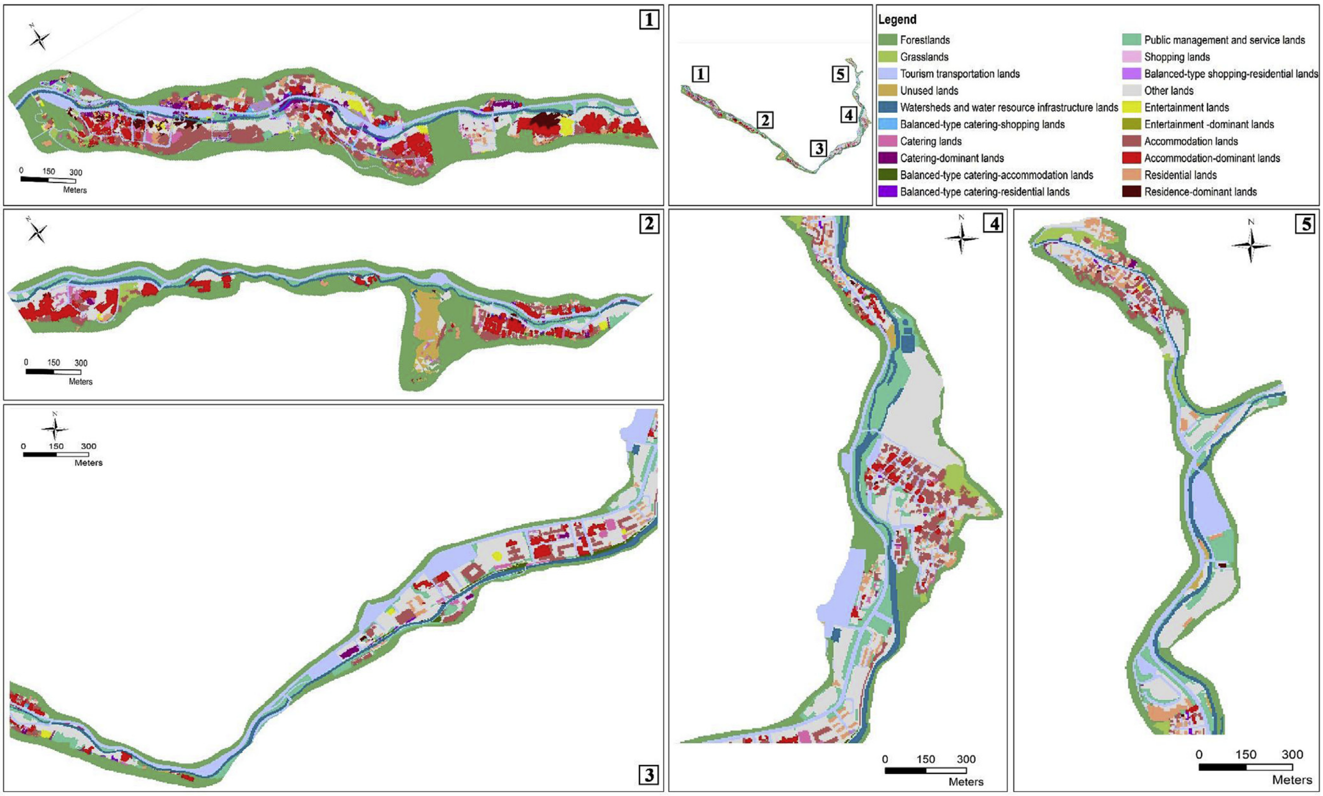


Fig. 7. The simulated results of land-use pattern for 2035.

showed a transfer dominated by spatial transfer for 2015–2025, with a dominant change index of 44.44% (Table 8).

6. Conclusion and discussion

6.1. Conclusion

During 2005–2015, tourism development drove the LUC of the studied area to undergo dramatic changes. Each type of land-use showed an active change—transportation, accommodation, and catering especially drove the tourism lands to expand continually. The tourism functions in the studied regions have been gradually becoming more similar, with tourism housing primarily providing accommodation and catering. On a village scale, the activity degrees and transformation modes of tourism lands varied with each village. The distribution of tourism lands was thus primarily determined by the elevation, slope, and distance to major transportation lands, watersheds, and existing lands. Over 2025–2035, the evolution of tourism lands is projected to gradually slow down, but the major tourism functions in each village would still be dominated by accommodation

Table 5
Analysis indicators of the simulation results.

Land-use types	Area/m^2		2015–2025			2025–2035		
	2025	2035	L_f/m^2	L_{nf}/m^2	k/%	L_f/m^2	L_{nf}/m^2	k/%
Forestlands	1,156,200	1,160,125	16725	16725	0.15	3925	3925	0.03
Grasslands	32800	38550	3500	2450	0.81	7900	5750	1.75
Tourism transportation lands	460125	462625	16450	16450	0.37	2500	2500	0.05
Watersheds and water resource infrastructure lands	194300	194725	2625	2625	0.14	425	425	0.02
Catering lands	34225	47800	13050	7300	2.71	16925	13575	3.97
Balanced-type catering-shopping lands	3625	5975	1625	1475	6.86	3700	2350	6.48
Catering-dominant lands	18750	27475	6950	5750	4.42	10775	8725	4.65
Balanced-type catering-accommodation lands	9525	11150	5575	−325	−0.33	5075	1625	1.71
Balanced-type catering-residential lands	7225	15000	3875	3075	7.41	9725	7775	10.76
Shopping lands	8025	13550	5700	3450	7.54	6225	5525	6.88
Balanced-type shopping-residential lands	1450	5000	750	200	1.60	3650	3550	24.48
Entertainment lands	18325	23925	3500	3200	2.12	6250	5600	3.06
Entertainment-dominant lands	1200	2500	500	500	7.14	1300	1300	10.83
Accommodation lands	218025	256400	64150	39500	2.21	80775	38375	1.76
Accommodation-dominant lands	145350	206900	51575	39225	3.70	79900	61550	4.23
Residential lands	79650	84600	46575	−4825	−0.57	33250	4950	0.62
Residence-dominant lands	14700	28675	8200	6950	8.97	17125	13975	9.51
Public management and service lands	308725	237075	107700	−60700	−1.64	80950	−71650	−2.32
Unused lands	50700	41025	47625	−40725	−4.45	16525	−9675	−1.91
Other lands	763700	663550	198500	−42300	−0.52	188850	−100150	−1.31

Table 6
Transition matrix for 2015–2025 (m^2).

Land-use types		2025																				2015 total
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
2015	1	1,139,475	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1,139,475
	2	525	29825	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	30350
	3	0	0	443675	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	443675
	4	0	0	0	191675	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	191675
	5	25	0	0	0	24050	0	350	0	50	25	0	0	0	625	75	125	75	75	0	1450	26925
	6	0	0	0	0	0	2075	25	0	0	0	0	0	0	0	25	0	0	0	0	25	2150
	7	0	0	0	0	350	0	12400	0	0	0	0	0	0	25	75	0	25	0	0	125	13000
	8	0	0	0	0	325	25	25	6900	500	0	0	0	0	0	50	500	25	400	0	1100	9850
	9	0	0	0	0	0	0	0	0	3750	0	0	0	0	100	275	0	0	0	0	25	4150
	10	0	0	0	0	25	0	0	0	0	3450	0	0	0	350	75	0	25	0	0	650	4575
	11	0	0	0	0	0	0	0	0	0	0	975	0	0	200	0	0	0	0	0	75	1250
	12	0	0	0	0	0	0	0	0	0	0	0	14975	0	0	0	0	0	0	0	150	15125
	13	0	0	0	0	0	0	0	0	0	0	0	0	700	0	0	0	0	0	0	0	700
	14	225	0	0	0	1125	0	225	0	300	100	0	0	0	166200	5200	725	600	275	0	3450	178425
	15	850	225	0	50	150	0	325	0	0	50	0	0	0	225	99950	550	1100	50	150	2450	106125
	16	500	0	0	0	1300	75	675	500	275	75	0	150	0	6975	2725	58775	100	1050	525	10625	84325
	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	525	0	7125	0	0	100	7750
	18	1975	400	0	1050	2075	525	2050	300	1350	775	75	550	25	11650	8200	4525	2075	285225	1600	40450	364875
	19	3925	475	0	600	1400	0	75	150	25	125	0	0	0	2625	325	3450	150	8500	47250	17425	86500
	20	8700	1875	0	925	3425	925	2600	1675	975	3425	400	2650	475	29050	27850	11000	3400	13150	1175	685600	799275
2025 total		1,156,200	32800	443675	194300	34225	3625	18750	9525	7225	8025	1450	18325	1200	218025	145350	79650	14700	308725	50700	763700	3,510,175

Note: 1, forestlands; 2, grasslands; 3, tourism transportation lands; 4, watersheds and water resource infrastructure lands; 5, catering lands; 6, balanced-type catering-shopping lands; 7, catering-dominant lands; 8, balanced-type catering-accommodation lands; 9, balanced-type catering-residential lands; 10, shopping lands; 11, balanced-type shopping-residential lands; 12, entertainment lands; 13, entertainment-dominant lands; 14, accommodation lands; 15, accommodation-dominant lands; 16, residential lands; 17, residence-dominant lands; 18, public management and service lands; 19, unused lands; 20, other lands.

Table 7
Transition matrix for 2025–2035 (m^2).

Land-use types		2035																				2025 total
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	
2025	1	1,156,200	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1,156,200
	2	1075	31725	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32800
	3	0	0	460125	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	460125
	4	0	0	0	194300	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	194300
	5	0	0	0	0	32550	75	25	0	175	25	0	0	0	350	175	75	50	25	0	700	34225
	6	0	0	25	0	25	2950	200	0	0	0	0	0	100	0	200	0	75	0	0	50	3625
	7	0	0	0	0	600	0	17725	25	75	0	0	0	0	0	200	0	125	0	0	0	18750
	8	0	0	0	0	325	0	0	7800	425	0	0	0	0	0	150	200	0	75	0	550	9525
	9	0	0	25	0	50	0	0	0	6250	0	0	0	0	25	875	0	0	0	0	0	7225
	10	0	0	0	0	0	0	50	0	0	7675	0	0	0	75	125	0	50	0	0	50	8025
	11	0	0	0	0	0	0	0	0	0	0	1400	0	0	50	0	0	0	0	0	0	1450
	12	0	0	0	0	0	0	50	0	0	0	0	18000	0	0	0	0	0	0	0	275	18325
	13	0	0	0	0	0	0	0	0	0	0	0	0	1200	0	0	0	0	0	0	0	1200
	14	100	375	175	0	1900	0	450	0	175	375	75	225	0	196825	12375	750	1875	25	0	2325	218025
	15	475	750	100	0	575	50	775	50	0	0	325	125	0	400	136175	750	3200	25	0	1575	145350
	16	225	25	0	0	1750	0	725	225	150	50	25	175	0	6075	2325	65500	175	75	550	1600	79650
	17	0	0	0	0	25	0	100	0	0	0	0	50	0	50	1050	0	13125	0	0	300	14700
	18	225	1000	550	75	2650	1050	2125	275	4100	775	550	975	225	13750	9725	4725	3150	232425	200	30175	308725
	19	350	875	300	100	325	0	0	0	75	0	550	125	50	775	125	1725	50	925	37600	6750	50700
	20	1475	3800	1325	250	7025	1850	5250	2775	3575	4650	2075	4250	925	38025	43400	10875	6800	3500	2675	619200	763700
2035 total		1,160,125	38550	462625	194725	47800	5975	27475	11150	15000	13550	5000	23925	2500	256400	206900	84600	28675	237075	41025	663550	3,526,625

Note: 1, forestlands; 2, grasslands; 3, tourism transportation lands; 4, watersheds and water resource infrastructure lands; 5, catering lands; 6, balanced-type catering-shopping lands; 7, catering-dominant lands; 8, balanced-type catering-accommodation lands; 9, balanced-type catering-residential lands; 10, shopping lands; 11, balanced-type shopping-residential lands; 12, entertainment lands; 13, entertainment-dominant lands; 14, accommodation lands; 15, accommodation-dominant lands; 16, residential lands; 17, residence-dominant lands; 18, public management and service lands; 19, unused lands; 20, other lands.

Table 8
Activity degree and dominant change index of tourism lands from 2015 to 2035.

Periods	Land-use types	Study area		Zhangzha		Pengfeng		Longkang		Congya		Yazha	
		L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%	L_a/%	C_D/%
2015–2025	Tourism lands	2.15	68.97	4.55	69.01	1.34	71.00	0.33	64.05	0.03	66.67	0.45	82.14
	Tourism housing lands	4.34	65.72	7.94	67.21	1.47	52.94	0.67	51.20	0.02	100.00	0.31	44.44
	All	1.72	–	2.91	–	1.41	–	0.48	–	0.36	–	0.82	–
2025–2035	Tourism lands	2.45	67.22	3.62	62.84	2.32	62.29	1.36	83.32	0.54	92.31	0.93	85.12
	Tourism housing lands	4.82	66.85	5.64	62.32	4.22	62.29	3.67	83.30	2.64	91.67	2.01	85.00
	All	1.63	–	2.45	–	0.99	–	1.10	–	0.35	–	0.69	–

and catering, with lower activity degree of tourism lands than that during 2005–2015.

6.2. Discussion

Monitoring and evaluating LUCC in relation to the socioeconomic development of a heritage site is of critical importance for sustainable land-use at the studied site. Given that the heritage site is highly dependent on tourism development, tourism has become the main driver of the site's LUCC. As such, an adequate approach to solving the data deficiency problem in monitoring tourism land-use must be urgently addressed by tourism research scholars.

This study verified the possibility of differentiating tourism lands from other construction lands to establish an accurate land-use database using high-resolution remote sensing images and field calibration of each land's land-use. As a result, the tourism lands only accounted for 50–70% of the total construction lands. Therefore, the effect of tourism on LUCC may be overestimated in the absence of a field survey for each land (Boavida-Portugal, Rocha, & Ferreira, 2016). However, such field surveys are very time-consuming and costly. They require governments to propose ambitious tourism land-use research programs (such as the ‘Census of Geographical Conditions’, a program already in progress (Deren, Lin, & Shao, 2016)) in order to comprehensively survey and study tourism lands in typical and ecologically vulnerable regions, and then, develop adequate policies and strategies for sustainable land use.

The development of the tourism industry requires a variety of functional spaces, such as transportation, accommodation, catering, sightseeing, shopping, and entertainment. This study revealed significant differences in the area, activity degree, and transfer mode of lands with different tourism purposes. It indicated that the major factors that influence different types of tourism land-use may be different as well. For an in-depth study on the effect of tourism development on LUCC, it is necessary to further analyse the different effects of different tourism functions on land-use. This requires tourism land-use to be included in the current land-use classification criteria. It further requires construction lands to be classified into sub-types according to their major tourism functions. Moreover, we also expect regional differences in the transformation trend of tourism land-use. Therefore, for a comprehensive and integrated understanding of the effect of tourism development on land-use in heritage sites, it is necessary to conduct a comparative study of different NWHSs.

Simulation studies would make it possible to predict the quantity and spatial distribution pattern of future tourism lands, which may have high value for governments (Tian & Qiao, 2014) or for heritage site management. For instance, governments can ascertain the types of tourism lands that would be needed in the future, especially regarding the allocation of construction lands and their distribution for different tourism functions.

As mentioned in the *Introduction*, for China to successfully prevent large-scale urbanisation in ecologically vulnerable NWHSs, it must restrict natural ecosystems, such as forestlands and grasslands, from being converted into construction lands (Verburg, Veldkamp, & Fresco, 1999). While the Chinese government has been delineating the safety borders of ecologically vulnerable regions (Liu et al., 2015), simulation results such as ours may help policymakers judge the likelihood of future tourism development expanding beyond these delineated borders. This would allow the government to intervene in the scale and mode of development. However, the current tourism land-use simulation models still have some limitations because of the high precision of land-use classification, an issue that should be addressed in further studies.

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