Research Article

Wang Song, Zhao Yunlin, Xu Zhenggang*, Yang Guiyan, Huang Tian, and Ma Nan

Landscape pattern and economic factors' effect on prediction accuracy of cellular automata-Markov chain model on county scale

https://doi.org/10.1515/geo-2020-0162
received October 06, 2019; accepted May 26, 2020

Abstract: Understanding and modeling of land use change is of great significance to environmental protection and land use planning. The cellular automata-Markov chain (CA-Markov) model is a powerful tool to predict the change of land use, and the prediction accuracy is limited by many factors. To explore the impact of land use and socio-economic factors on the prediction of CA-Markov model on county scale, this paper uses the CA-Markov model to simulate the land use of Anren County in 2016, based on the land use of 1996 and 2006. Then, the correlation between the land use, socio-economic data and the prediction accuracy was analyzed. The results show that Shannon's evenness index and population density having an important impact on the accuracy of model predictions, negatively correlate with kappa coefficient. The research not only provides a reference for correct use of the model but also helps us to understand the driving mechanism of landscape changes.

*** Corresponding author: Xu Zhenggang,** Key Laboratory of Forestry Remote Sensing Based Big Data & Ecological Security for Hunan Province, Central South University of Forestry and Technology, Changsha 410004, Hunan, P. R. China; College of Forestry, Northwest A & F University, Yangling 712100, Shaanxi, P. R. China, e-mail: rssq198677@163.com
Wang Song: Key Laboratory of Forestry Remote Sensing Based Big Data & Ecological Security for Hunan Province, Central South University of Forestry and Technology, Changsha 410004, Hunan, P. R. China; Hunan Urban and Rural Ecological Planning and Restoration Engineering Research Center, Hunan City University, Yiyang 413000, Hunan, P. R. China
Zhao Yunlin, Yang Guiyan: Key Laboratory of Forestry Remote Sensing Based Big Data & Ecological Security for Hunan Province, Central South University of Forestry and Technology, Changsha 410004, Hunan, P. R. China
Huang Tian, Ma Nan: Hunan Urban and Rural Ecological Planning and Restoration Engineering Research Center, Hunan City University, Yiyang 413000, Hunan, P. R. China

Keywords: county scale, CA-Markov model, landscape indices, correlation analysis

1 Introduction

Land is one of the indispensable basic resources in human life and production. Land use is a process in which people use and renovate land by selecting different natural attributes to meet people's needs for life and society. The land carries human activities in different time and space, thus creating an extremely complex and varied land use pattern. The pattern of land use, in turn, will have a positive or negative impact on human activities.

The land-use/land-cover (LULC) change may affect climate, ecosystem processes and biodiversity [1]. Therefore, understanding and modeling of LULC change is of great significance to environmental protection and land use planning [2]. A full understanding of the interaction between the driving forces of LULC change and a complete simulation is a prerequisite for accurately predicting future land use changes.

The driving force problem has always been a dominant aspect in the land use study [3]. There are many factors that can drive changes in land use, including natural, economic, political, social, cultural, etc. [4]. All the above factors are often divided into two categories: natural factors and socio-economic factors by the essential attributes [5,6]. Natural factors mainly include local climate, geological features and vegetation. The social and economic factors mainly include population change, economic development, policy and planning [7]. Identifying the primary causes and estimating the processes are crucial for land use planning, utilization of regional resources and environment management [8].

Previous studies on the driving factors were mostly concentrated in the field of topographic [9], climate changes [10], population growth [11], urbanization [12,13], changes in the direction of economic development [14], borderline effect [15] and other fields. However, there are few studies associating natural and socio-economic factors. On the other hand, the common points of the above studies are large-scale, liking watershed or city, which emphasizes a macro perspective of the land use change. It lacks small-scale research, such as county scale.

To understand the process of LULC changes, LULC-change models are inevitable [16]. In recent years, many models have been used to simulate and predict land use change, such as conversion of land use and its effects on small regional extent (CLUE-S) model [17,18], which is one of the most widely used land-use models, Markov model [19], multiagent systems (MAS) model [20,21], cellular automata (CA) model [22,23] and other models [24,25]. In most cases, these models showed relatively good results. However, in fact, land use changes are always caused by complex factors. The neighborhood scale, conversion rules, and simulation mechanisms would influence the CA's accuracy of the simulation [22]. Markov models are susceptible to location factors and decision-making processes. These models are all limited to theories and methods [26]. So, there is a need to integrate these models to improve the effect of simulating land use, like CA-Markov model.

Landscape prediction is the basis of urban planning. The simulation results can help to understand the current urban development trends and related land use issues and to examine the consequences of urban evolution [27,28]. At present, there are some studies on the prediction of land use types at the county level [29,30]. Cellular automata-Markov model is an important prediction model, but there is no study on the affected factors at the county level. To explore the impact of land use and socio-economic factors on the prediction of CA-Markov model on county scale, the paper uses the CA-Markov model to simulate the land use of Anren County, China, and analyzes the prediction accuracy of the model.

2 Methods

2.1 Study area

Anren County is located in the south-east of Hunan Province (113° 05′ to 113° 36′ E, 26° 17′ to 26° 50′ N), China. It consists of 17 rural communities, such as Yongle River Town, Anping Town, etc. (Table 1). Yongle River Town is the political, economic and cultural center of Anren County. The total area coverage of the study area is 1,461 km^2, and the elevation is descending from south-east to north-west. The annual precipitation average is 1,430 mm, and the annual temperature average is 17.7°C. Anren County has convenient transportation adjacent to eight counties and cities. In 2013, Anren County had a total population of 4,47,800 and per capita income is 5,448 yuan.

Table 1: Population and economic situation of towns and townships in Anren County in 2013

Towns and townships	Population (person)	Population density (person/km^2)	Per capita income (yuan/person)
Yongle River Town	1,39,178	397	9,530
Anping Town	41,197	812	4,914
Pingshang Township	16,336	226	3,111
Yangji Township	17,268	326	3,420
Pailou Township	33,433	401	3,823
Zhushan Township	14,502	447	3,188
Huawang Township	19,908	321	3,097
Longhai Town	19,267	272	4,880
Xinzhou Township	8,063	152	2,880
Dukou Township	22,994	432	2,889
Chengping Township	17,972	503	3,038
Longshi Township	15,650	222	2,969
Yangnao Township	9,918	97	3,206
Lingguan Town	22,372	324	3,882
Haoshan Township	12,319	93	3,387
Guanwang Town	16,147	128	3,306
Pingbei Township	21,271	471	3,147
Total	4,47,795	306	5,448

2.2 Cellular automata-Markov chain prediction

Cellular automata was originally proposed by Ulam and Neumann in the 1940s, aiming to provide a formal framework for studying the behavior of complex, self-reproducible systems [31]. It is a dynamic system that evolves in discrete space-time dimensions and has the ability to simulate the spatiotemporal evolution of complex systems. The cellular automaton consists of the following four parts: cell, lattice, neighborhoods, and rule. It should also include cell states and discrete time. As a kind of grid dynamics model that can be used to process a large number of variables, the core feature of the CA model is the generation of complex global patterns by predefining a set of simple transformation rules [32,33]. Cellular automata is a suitable method to simulate and predict the temporal and spatial evolution of complex geographical processes [34,35]. It is widely used in physical science, geography, ecology and mathematics [36].

The Markov chain model is a spatial probability model based on the grid data using the Markov chain, which takes advantage of the evolution from $t - 1$ to t to the probability of future $t + 1$ land use change; it is a suitable tool to simulate the future LULC dynamics [1,37]. It can show the direction and extent of future land use change in the region [38]. The model is widely applied to the prediction of geographical features, which lacks after-effect events; it has also been an important prediction technique for the study of geography [39].

The Markov chain and cellular automata analysis model is a hybrid of the CA and Markov models [16]; it is suitable for the detection and simulation of land use change [1,40]. In the CA-Markov model, the Markov chain process controls temporal dynamics among the land use types through the transition matrices [1,40]. Cellular automata model controls spatial dynamics through the local rules considering either neighborhood configuration and transition probabilities [37,41,42]. Geographic information system (GIS) and remotely sensed data can be used to define initial conditions, parameterize the CA-Markov model, calculate transition probabilities, and determine the neighborhood rules [43].

In this study, TerrSet software is used to simulate the land use of the CA-Markov area. One of the functional modules of TerrSet is the land cover change simulation model, which provides the user with the CA-Markov model. The most characteristic is that CA-Markov model can define the transformation rules between land use types through multicriteria evaluation system and multiobjective decision support system [44]. The TerrSet CA-Markov model strengthens the simulation ability of the spatial pattern based on the accurate prediction of the number structure of land use in the future with Markov chain. Therefore, we can effectively predict the quantity and spatial distribution of land use structure. The CA-Markov model has greater accuracy advantage than GIS-based technology in the simulation of land use change [45].

2.3 Analysis process

This study firstly used ENVI 5.0 [46] for remote sensing images of Anren County in 1996, 2006 and 2016, included geometric correction, atmospheric correction, image cropping, etc. The above images belonged to Landsat Thematic Mapper (TM) or Operational Land Imager (OLI) and downloaded from Geospatial Data Cloud (http://www.gscloud.cn/). Then, land use raster data maps were extracted by the supervised classification method. The land use map was analyzed by ArcGIS [47,48], and the area and proportion of land use types in Anren County were calculated. The landscape metrics were reported by Fragstates [49]. A total of seven representative landscape metrics belonging to class level and landscape level were selected in the study: number of patches (NP), landscape shape index (LSI), largest patch index (LPI), patch density (PD), patches percentage of landscape (PLAND), Shannon's evenness index (SHEI) and perimeter-area fractal dimension (PAFRAC). Then, we simulated the land use in 2016 by TerrSet software with CA-Markov model based on the 1996 and 2006 land use raster maps reported in ref. [50] and compared with the actual land use in 2016 to get the kappa coefficient. Finally, the factors affecting land use simulation were analyzed by drawing scatter plots and correlation analysis through R version 3.5.1 [51] to analyze the correlation between kappa coefficient, landscape metrics and socio-economic data. The "ggplot2" and "Hmisc" of R packages were used to make scatter plots and to calculate Pearson correlation coefficient (Figure 1). The core data, including the land use map of Anren in 1996, 2006, 2016 and simulated land use in 2016, were reposited in Dryad (https://datadryad.org) and could be accessed by doi: 10.5061/dryad.s1rn8pk4g.

3 Result and analysis

3.1 Distribution of land use and the change

The land use type was classified into built-up land, cultivated land, barren land, forest land and water (Table 2). Thirty years from 1996 to 2006 and 2016, cultivated land and forest land have always been the main types of land use in Anren County, consistently accounting for more than 90% of the total area. In addition, significantly changed area was observed in forest land (from 712.73 km^2 to 844.68 km^2 and 693.46 km^2) compared with cultivated land (from 664.14 km^2 to 576.47 km^2 and 677.87 km^2). In contrast, the area of barren land has always been the smallest and a tendency toward lower was seen from 1996 to 2016 (from 3.58 km^2 to 3.02 km^2 and 2.85 km^2). The area of water was unstable, it was reduced by 55% from 1996 to 2016 (from 54.67 km^2 to 18.82 km^2 and 23.53 km^2). Built-up land remained at a relatively low level, although a trend was witnessed for the increase in 30 years (from 27.74 km^2 to 19.87 km^2 and 65.15 km^2).

Table 2: Area statistics of different land types in 1996, 2006 and 2016 (km^2)

year Land use type	1996	2006	2016
Built-up land	27.74	19.87	65.15
Cultivated land	664.14	576.47	677.87
Barren land	3.58	3.02	2.85
Forest land	712.73	844.68	693.46
Water	54.67	18.82	23.53

3.2 Distribution of landscape and the change

As shown in Table 3, the values of NP in Yongle River Town were 9,455, 10,273 and 7,582 in 1996, 2006 and 2016, far more than other townships in Anren County. During the period from 1996 to 2016, the NP in Anren County decreased (from 42,830 to 29,008) and most of the towns also decreased. It reflects that the reduction of the fragmentation of the landscape in Anren County. Largest patch index is the percentage of the total landscape area occupied by the largest patch and a representation of the degree of landscape dominance. The largest patch of Haoshan Township was accounting

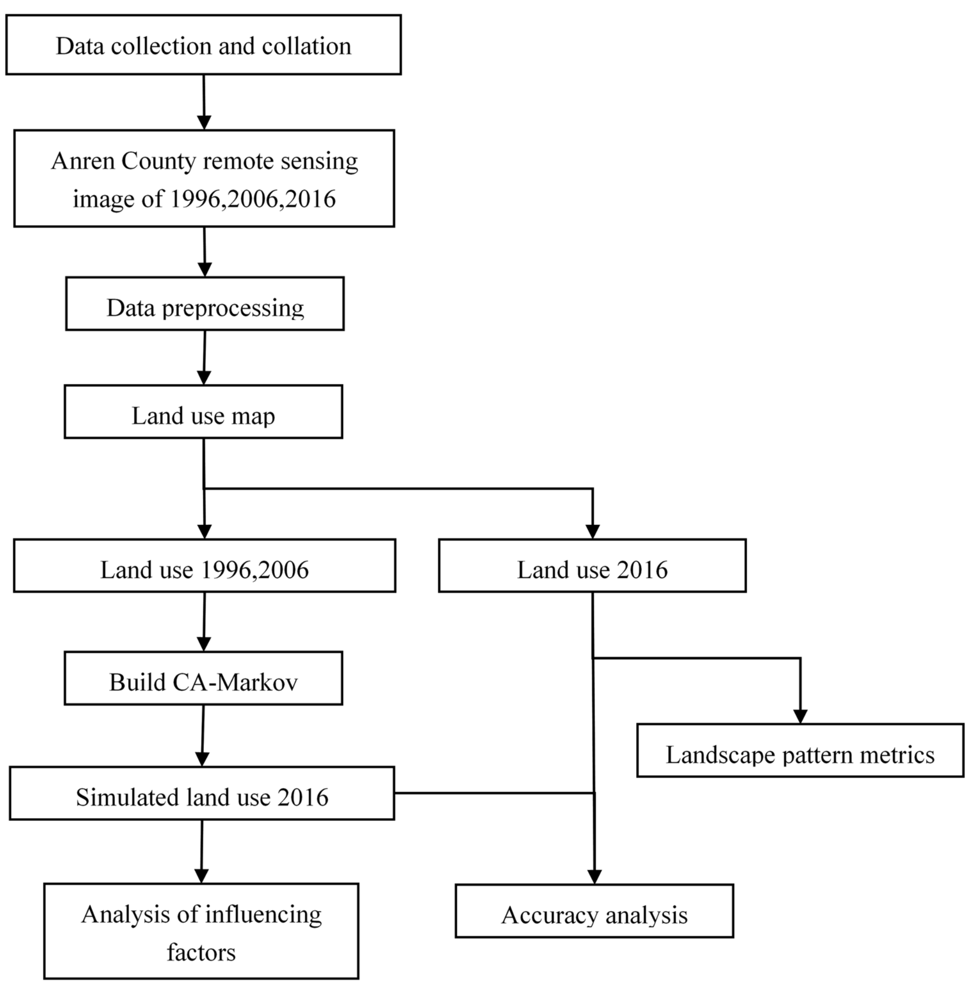

Figure 1: Data processing flow of the research.

Table 3: Landscape metrics analysis on county scale

Landscape metrics	2016					2006					1996				
	NP	LPI	LSI	PAFRAC	SHEI	NP	LPI	LSI	PAFRAC	SHEI	NP	LPI	LSI	PAFRAC	SHEI
Anren County	29,008	35.17	102.82	1.45	0.58	38,445	26.75	113.49	1.53	0.51	42,830	40.80	98.08	1.49	0.58
Anping Town	1,560	75.78	22.77	1.48	0.40	1,955	86.01	17.75	1.49	0.31	1,520	87.69	14.56	1.46	0.26
Chengping Township	1,152	68.90	22.36	1.48	0.55	1,597	32.25	28.99	1.57	0.54	1,888	60.62	25.19	1.52	0.58
Dukou Township	1,598	50.08	21.09	1.45	0.54	2,446	74.88	29.71	1.54	0.49	2,308	56.87	24.52	1.51	0.49
Guanwang Town	1,744	27.98	28.07	1.49	0.52	3,071	56.50	27.26	1.54	0.39	3,924	53.54	28.50	1.53	0.50
Haoshan Township	1,021	85.04	14.71	1.44	0.32	547	95.91	6.85	1.48	0.12	1,245	91.01	10.77	1.45	0.24
Huawang Township	1,321	51.99	27.52	1.44	0.54	1,388	33.07	28.32	1.52	0.46	1,487	54.08	24.54	1.44	0.50
Lingguan Town	1,617	54.72	29.33	1.42	0.59	1,789	45.39	32.49	1.53	0.50	1,881	58.59	25.75	1.43	0.52
Longhai Town	1,767	62.03	28.63	1.42	0.53	2,233	46.54	40.14	1.55	0.50	2,201	50.86	27.94	1.44	0.64
Longshi Township	1,295	48.27	19.18	1.44	0.54	1,196	58.64	18.11	1.51	0.40	1,430	54.36	15.93	1.46	0.51
Pailou Township	1,762	33.29	23.33	1.46	0.61	2,318	36.97	22.93	1.51	0.56	1,627	38.79	16.76	1.46	0.55
Pingbei Township	1,170	66.87	22.18	1.44	0.55	1,452	57.43	26.76	1.53	0.50	1,350	66.11	19.69	1.45	0.54
Pingshang Township	1,840	52.62	34.12	1.48	0.54	2,744	34.29	43.69	1.59	0.48	4,139	43.59	39.09	1.53	0.68
Xinzhou Township	1,228	29.70	27.99	1.49	0.51	2,376	50.74	34.07	1.57	0.45	2,791	32.41	31.36	1.53	0.65
Yangji Township	988	45.68	22.87	1.43	0.53	1,291	40.68	26.94	1.54	0.48	1,318	51.57	22.80	1.47	0.51
Yangnao Township	1,635	26.71	27.20	1.49	0.42	2,019	87.43	20.35	1.56	0.28	3,769	45.32	31.06	1.54	0.47
Yongle River Town	7,582	25.46	52.22	1.45	0.62	10,273	21.34	61.51	1.52	0.55	9,455	48.55	47.62	1.48	0.60
Zhushan Township	1,201	72.30	22.43	1.49	0.50	1,320	58.81	27.06	1.57	0.48	2,043	69.10	25.70	1.54	0.52

NP: number of patches; LPI: largest patch index; LSI: landscape shape index; PAFRAC: perimeter-area fractal dimension; SHEI: Shannon's evenness index.

for a large proportion compared with other townships (from 91.01% to 95.91% and 85.04%). The LPI values in Anren County and other most townships were declined from 1996 to 2016. In terms of LSI, the patches' shape of Yongle River Town and Pingshang Township is more complicated than other townships. The LSI values of various towns in Anren County were increased during the study period, showing that the overall landscape shape of Anren County is very complicated. In PAFRAC, the values of towns in 2016 were all below 1.50. It indicates that the patches' shape of Anren County is getting simpler. Shannon's evenness index can compare the diversity of landscapes in different periods and describe the distribution uniformity of various landscape types. The overall SHEI of Anren County remained unchanged, and the SHEI of each township increased or decreased. It means the landscape heterogeneity characteristics were obvious.

Landscape metrics were analyzed at the class level in 2016 (Table 4). In terms of the NP, the number of built-up land patches was the largest (10,484) and barren land was the least (840). In the PLAND, the proportions of forest land and cultivated land were accounting for 47.31% and 46%, respectively. In the PD, the density of the built-up land was the largest (7.17), indicating that the degree of fragmentation is high, which is mainly caused by human activities. The density of patch in barren land was the smallest (0.57). The LPI values of cultivated land and forest land were higher than other land use types, indicating that the cultivated land and forest land were dominant in Anren County. The size of the PAFRAC value reflects the complexity of the shape of the landscape. The value of water was the smallest (1.38), which shows that the shape of water is relatively simple and is greatly disturbed by human beings.

Table 4: Landscape metrics analysis at the class level in 2016

Land use type	NP	PLAND	PD	LPI	PAFRAC
Built-up land	10,484	4.80	7.17	0.48	1.48
Cultivated land	8,121	46.00	5.55	35.17	1.48
Barren land	840	0.21	0.57	0.02	1.48
Forest land	5,962	47.31	4.08	12.46	1.43
Water	3,601	1.68	2.46	0.30	1.38

NP: number of patches; PLAND: patches percentage of landscape; PD: patch density; LPI: largest patch index; PAFRAC: perimeter–area fractal dimension.

3.3 Land use predicted by CA-Markov model

In the simulated land use types of Anren County in 2016 (Figure 2), the area of forest land was the largest with 857.25 km^2, occupied 58.60% of the total land use area of Anren County. Followed by cultivated land, with cultivated land area of 568.71 km^2, accounting for 38.87% of the total area. The area of the built-up land was 20.50 km^2 and the proportion was 1.40%. The area of water was 12.96 km^2, accounting for 0.89%. The area of barren land was the smallest, only 3.55 km^2 (Figure 2a).

By comparing the land use of Anren County in 2016 and the simulated land use in the same year, the overall kappa coefficient is 0.8048. It shows that the simulation land use of Anren County in 2016 is highly similar to the land use of Anren County in 2016. There were six townships with kappa coefficient above 0.8, including Anping Town, Guanwang Town, Haoshan Township, Pailou Township, Yangnao Township and Yongle River Town. Among them, Haoshan Township has the highest kappa coefficient of 0.8797. In others, the kappa coefficients of Longhai Town and Pingbei Township are relatively low, 0.6968 and 0.6510, respectively.

3.4 Relationship between kappa coefficient and landscape, population, income, respectively

The correlation between all calculated landscape indices and kappa coefficients is quite different (Figure 3). The r^2 (goodness-of-fit) of the SHEI and kappa coefficient is 0.201, 0.316, 0.189 in 1996, 2006, 2016, respectively. It shows significant differences than others. There is an obvious correlation between kappa coefficient and SHEI with the trend being the same for different years. The correlation analysis results also prove that there is a significant correlation between kappa coefficient and SHEI (r = −0.562, p = 0.0151). Although the trends between NP and kappa coefficient of different years were same, the result is obviously affected by the outliers. Correlation analysis also indicates that there is no correlation among them. The relationship trends between other landscape indices and kappa coefficient of different years are inconsistent. Scatter plots of kappa coefficient and population and population density and per capita income were also marked (Figure 4). It can be found that population density has a more significant correlation with kappa coefficient than population and income (r = −0.269, p = 0.2812).

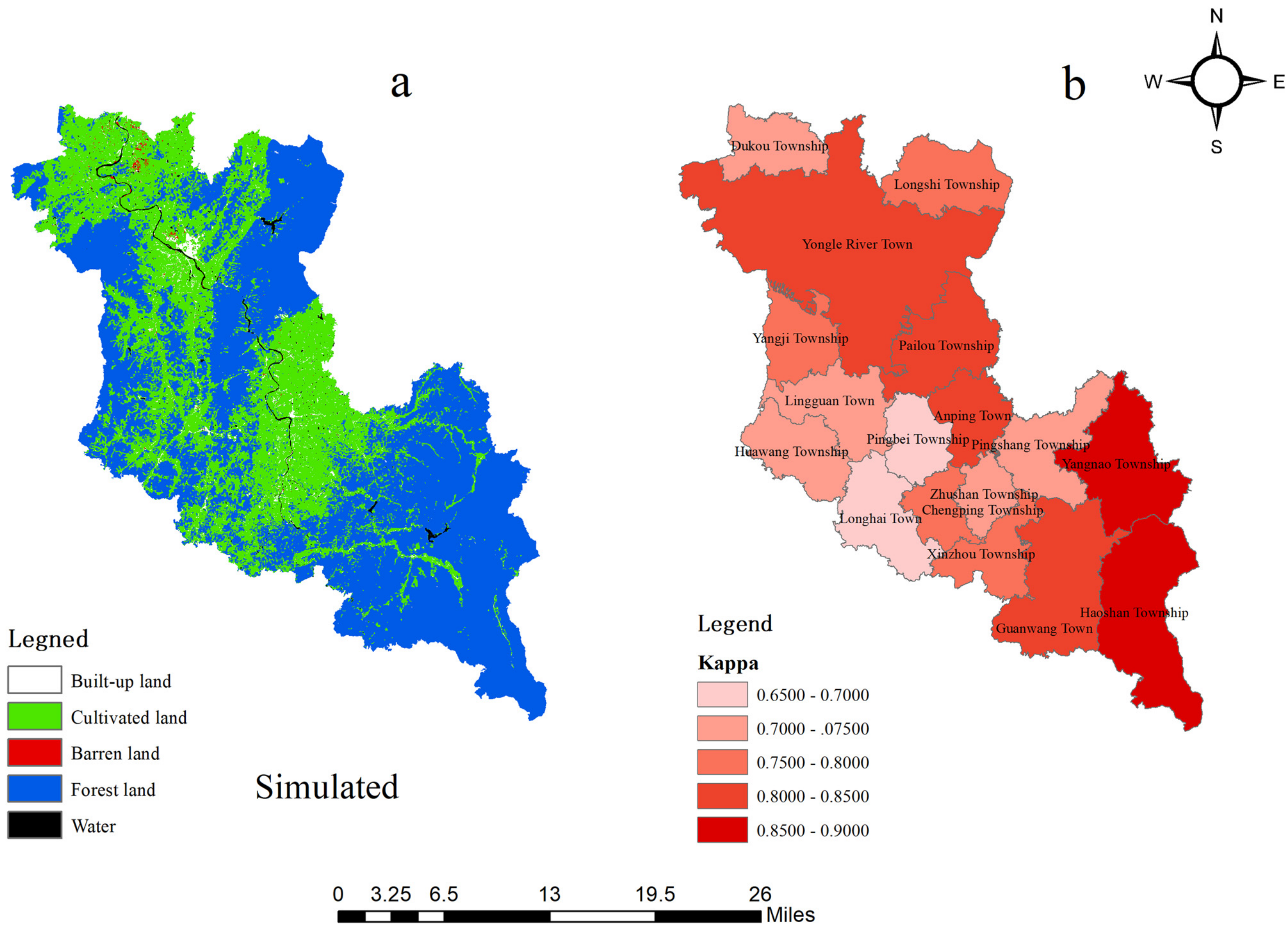

Figure 2: Simulated LULC of 2016 of Anren County (a: Land use simulation of Anren County. b: accuracy of land use simulation of Anren County).

4 Discussion

In recent years, many studies have used Markov and CA models to simulate land use. Gong et al. (2015) analyzed spatial and temporal changes of land use in Harbin from 1989 to 2007 and then to predict future trends by using CA-Markov model [52]. Hyandye and Martz (2017) simulated Usangu Catchment's LULC of 2020 based on LULC of 2000, 2006 and 2013 using Markov chain and CA analysis and analyzed the importance of social, edaphic, climatic and landscape geomorphology factors to LULC change [16]. The simulation model of land use be affected by various factors. Spatial accessibility factors [53,54], topography, people density, housing density, land price, etc., have been investigated in previous records [22,45,55–57]. Especially, socio-economic data have a confirmatory impact to the simulation of the CA-Markov model [58]. However, little information has been focused on landscape metrics. This study analyzed the change and simulation of land use in Anren County. The relationship between simulation accuracy and landscape metrics and socio-economic factors is studied. The timescale of this study is short and human factors play a major role, so the impact of landscape metrics and socio-economic factors on simulation accuracy was analyzed. By plotting the scatter plots, it was found that SHEI and population density have obvious correlation with the kappa coefficient of land use in the simulations of Anren County. Correlation analysis also confirmed that they were negatively correlated. Shannon's evenness index is a landscape metric that describes the distribution uniformity of different landscape types and can reflect the landscape diversity of the study area. The more complex the land use in the study area, the more difficult it is to simulate land use based on the land use simulation principle, and the lower the accuracy. The population factor is one of the most important factors affecting land use and landscape pattern in human factors [57]. The increase in population has led to raising in demand for food, housing, industrial

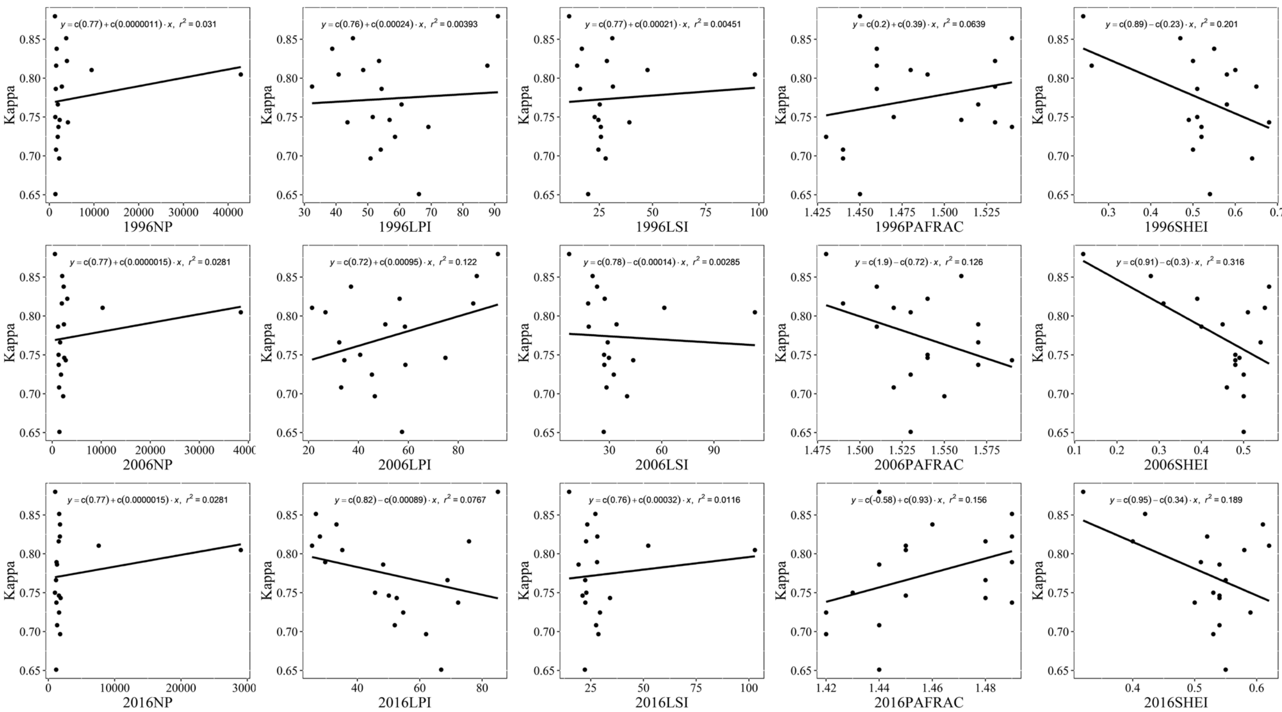

Figure 3: Relationship between kappa coefficient and landscape metrics of 1996, 2006, 2016.

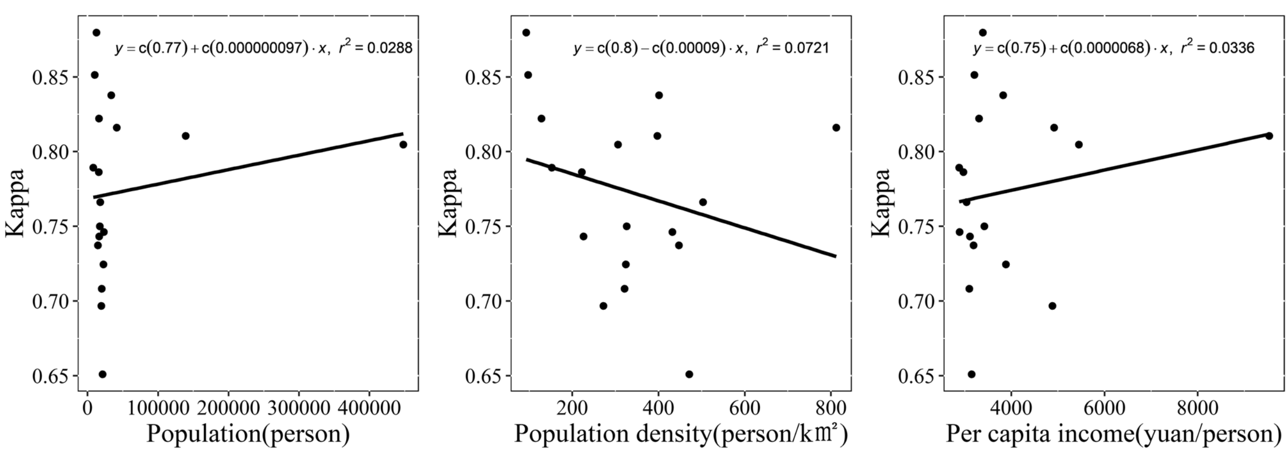

Figure 4: Relationship between kappa coefficient and population, population density, per capita income.

output, etc. Causing changes in the structure and mode of land use further affects the diversity of land use. The greater the population density, the more complicated the land use. The population density is also a significant factor affecting simulation in many studies [22,55,56,59]. Therefore, both population density and kappa coefficient have a correlation that cannot be ignored. On the other hand, the weak correlation between kappa coefficient, landscape pattern and economic factors enhanced that the CA-Markov model is a powerful tool to predict the change of land use on county scale.

5 Conclusion

Over the past 30 years, land use types in Anren County have changed. The forest land and cultivated land were the dominant land types during this period. The area of forest land was slightly reduced. Changes in land use types have led to changes in landscape patterns, including patch and class levels. The CA-Markov model is a powerful tool to predict the change of land use on county scale. The relationship between simulation accuracy, landscape metrics and socio-economic factors is studied shows that SHEI and population density having an important impact on the accuracy of model predictions were negatively correlated with kappa coefficient. Through this study, we have found that it is difficult to understand how focused factors affect prediction accuracy of CA-Markov model, because the correlation analysis cannot reflect causality. In further studies, we should focus on the mechanism of external factors affecting the model.

Acknowledgement: This research was supported by Science and Technology Project of Yiyang City (2017JZ07), Key Technology R&D Program of Hunan Province (2016TP2007, 2017TP2006) and Major Science and Technology Program of Hunan Province (2017NK1014).

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