



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search

<http://ageconsearch.umn.edu>

aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.

Dynamic Simulation of Land Use in the Southern Loess Plateau

Bin GUO *

College of Geomatics, Xi'an University of Science and Technology, Xi'an 710054, China

Abstract To study the dynamic changes of land use and predict the future land use scenarios based on the current land use, this paper uses Cellular Automata – Markov (CA – Markov) model to simulate the landscape pattern in 2030. The results show that in the study area during the period 1980 – 2005, grassland and construction land increased, and woodland increased slightly; waters and unused land decreased, and arable land underwent dramatic changes. The simulation precision of CA – Markov model is 87.28% , indicating that the use of it for simulation is reliable. The land use of the study area will be changed greatly in the future. This method provides a reference for the regions to carry out land prediction , and the research results can provide a basis for the study of optimization of land.

Key words Landscape pattern, CA – Markov, RS, GIS, Southern region of the Loess Plateau

The full understanding and complete simulation of the interaction between the driving forces of LUCC is the premise of accurately predicting the land cover change in the future^[1–6]. The major models for the land use change and simulation in the current academic world include system dynamics model, Clue-s model, CA model, multi-agent model and Markov model^[7–12]. There are some problems in the above models in terms of applicability and simulation precision. The efficiency of CLUE-s is low, needing to be assisted by other softwares. Markov model can only predict the dynamic changes of landscape pattern number, and fails to predict the spatial distribution of landscape^[22]. Cellular Automata model can predict the spatial distribution of landscape pattern, but it can not predict the changes of number^[23]. A number of practical studies show that the current dynamic simulation of land use is gradu-

ally shifted from the simulation using the single method to the simulation using a variety of methods^[9]. CA – Markov coupling model not only has the spatial and temporal dynamic simulation function of Cellular Automata model, but also has the long – term forecast advantages of Markov model, with strong scientificity and practicality^[25]. In this paper, GIS and CA – Markov model were used to predict the land use scenarios in 2030, and explore the characteristics of land use change, in order to provide a decision – making basis for the scientific and rational use of land resources.

1 Data sources and methods

1.1 Data sources In this paper, the southern Loess Plateau is selected as the study area, and the main sources of data are shown in Table 1.

Table 1 Data sources

Data types	Acquisition time	Resolution	Data sources
Remote sensing image	1980, 1992, 2005	30 m, 15 m	http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp
DLG	1988	1:1 000 000	http://www.data.ac.cn/zrzy/shi3.htm
DEM(ASTER GDEM, SRTM)	2009	30 m, 90 m, 1:250000	http://srtm.datamirror.csdn.cn/
Soil type map	1980	1:500 000	http://www.geodata.cn
Landform type map	1996	1:4 000 000	1:4000000 geomorphological map compiled by Li Bingyuan
NDVI	August 21, 2007	1 km	http://westdc.westgis.ac.cn
Land use map	1980, 1990, 2000, 2005	1:2 500 000, 1:100 000	http://www.geodata.cn
Land use zoning map	1996	1:1 000 000	http://www.geodata.cn
Fieldwork data	2008 – 2011	–	Land type

1.2 Research methods

1.2.1 Land use transition matrix. Land use transition matrix stems from the quantitative description of system state and state transition in the system analysis.

A is the transition matrix of the original land use change; A_{ij} is the area of land use type j in period $k + 1$ transformed from land use type i in period k ; row represents land use type i in period k ; column represents land use type j in period $k + 1$; B_{ij} is transfer rate; C_{ij} is contribution rate^[25].

$$B_{ij} = A_{ij} \times 100 / \sum_{j=1}^8 A_{ij} \tag{1}$$

$$C_{ij} = A_{ij} \times 100 / \sum_{i=1}^8 A_{ij} \tag{2}$$

1.2.2 Simulation precision test. Based on the land use data in 1980 and 1992, CA – Markov model is used to predict the land use in 2005, and the difference between forecast results in 2005 and

Received: December 30, 2013 Accepted: February 25, 2014
Supported by National Natural Science Foundation of China (41271159) ;
Engagement Fund of Xi'an University of Science and Technology (201103) ;
Doctor Startup Fund of Xi'an University of Science and Technology
(2011QDJ036) ; College Students' Innovation and Entrepreneurship Training
Program of XUST (S13018).
* Corresponding author. E-mail: woshiguobinzi@163.com

image interpretation results is calculated. If the prediction is correct, the difference is 0. ARCGIS10 is used to gather statistics on the regions with the difference of 0, and the precision is calculated.

1.2.3 Predictive simulation of landscape pattern. The technical route is shown in Fig. 1.

2 Results and analysis

2.1 Landscape pattern transition matrix From Table 2, we find that the land use change was remarkable from 1985 to 2005, and the arable land underwent the most obvious change. Only 2.176 9 km² of arable land was transformed into unused land; 262.494 3 km² of arable land was transformed into waters; 303.093 5

km² of arable land was transformed into woodland; 852.927 9 km² of arable land was transformed into grassland; 1 123.804 0 km² of arable land was transformed into construction land; 1 443.22 km² of arable land was transformed into other types. And 97 460.29 km² of arable land was not transformed.

2.2 Prediction precision test Based on the land use data in 1980 and 1992, the land use map in 2005 is obtained by the prediction in CA – Markov, and the prediction results and remote sensing interpretation results are used for map operation. In ARCGIS10, the proportion of number of grid with the property value of 0 to total number of grid after map operation is obtained, and the simulation precision is calculated at 87.28%.

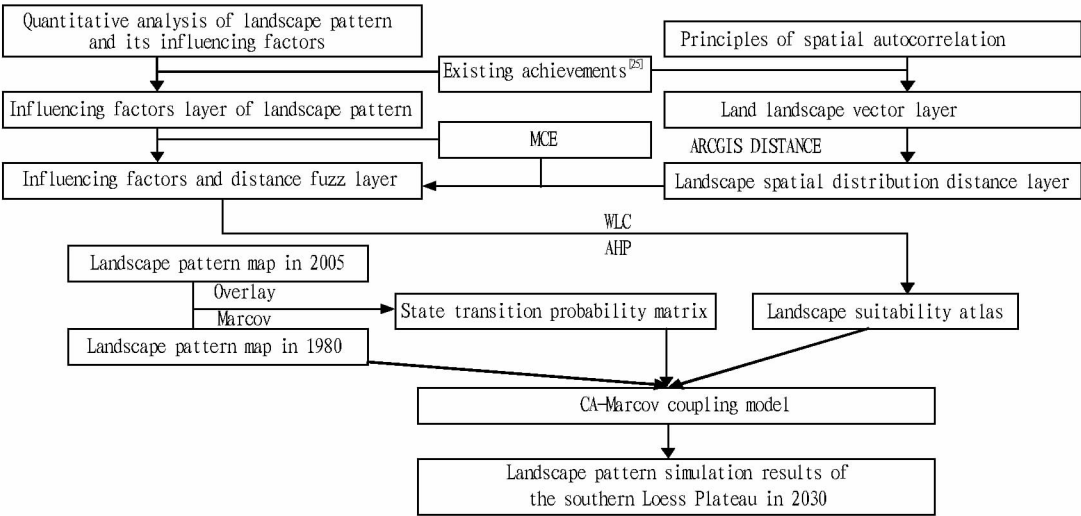


Fig.1 The technical route of landscape pattern prediction and simulation
Table 2 Land use transition matrix in the period 1985 – 2005

	Arable land	Woodland	Grassland	Waters	Construction land	Unused land	1980 total (share//%)
Arable land A transfer-out rate(%)	97460.29	303.09	852.93	262.49	1123.80	2.18	100004.79
B transfer-in rate(%) C	97.46	0.30	0.85	0.26	1.12	0	
	98.88	0.59	1.28	10.78	23.44	1.59	44.69
Woodland A transfer-out rate(%)	50.72	50407.66	501.31	19.71	30.92	0.99	51011.31
B transfer-in rate(%) C	0.10	98.82	0.98	0.04	0.06	0	
	0.05	98.71	0.75	0.81	0.64	0.72	22.80
Grassland A transfer-out rate(%)	737.29	317.93	65373.05	82.63	79.76	1.19	66591.84
B transfer-in rate(%) C	1.11	0.48	98.17	0.12	0.12	0	
	0.75	0.62	97.92	3.39	1.66	0.87	29.76
Waters A transfer-out rate(%)	307.93	1.33	31.42	2069.92	8.11	0	2418.71
B transfer-in rate(%) C	12.73	0.06	1.30	85.58	0.34	0	
	0.31	0	0.05	84.98	0.17	0	1.08
Construction land A transfer-out rate(%)	2.90	0.01	0.83	0.56	3551.68	0	3555.99
B transfer-in rate(%) C	0.08	0.00	0.02	0.02	99.88	0	
	0.00	0.00	0.00	0.02	74.08	0	1.59
Unused land A transfer-out rate(%)	2.44	36.77	3.19	0.34	0	132.89	175.62
B transfer-in rate(%) C	1.39	20.93	1.82	0.19	0	75.67	
	0	0.07	0	0.01	0	96.83	0.08
2005 total (share//%)	98561.57	51066.79	66762.73	2435.65	4794.28	137.24	223758.26
	44.05	22.82	29.84	1.09	2.14	0.06	100

This precision basically meets the requirements of landscape pattern prediction and simulation, indicating that using CA – Markov model for landscape pattern prediction and simulation is

credible.
2.3 CA – Markov model result analysis Using CA – Markov, the land use map in 2030 is simulated according to the techni-

cal route in Fig. 1, as shown in Fig. 2. The area of various types of landscape and the proportion in 2030, and the landscape pattern change and simulation results in the period 2005–2030 are shown in Table 3. From Fig. 2 and Table 3, it is found that in the future period of time, the land use will still experience great changes in

Table 3 The prediction results in 2030 (proportion//%; area//km²)

Land use type	Area in 2005	Area proportion in 2005	Area in 2030	Area proportion in 2030	Area change in the period 2005–2030	Area proportion change in the period 2005–2030
Construction land	4 794.28	1.59	6091.15	2.722 201	1 296.87	1.132 201
Unused land	137.24	0.08	128.85	0.057 584	–8.39	–0.022 416
Woodland	51 066.56	22.80	51 341.58	22.945 11	275.02	0.145 11
Waters	2 435.65	1.08	2 218.99	0.991692	–216.66	–0.088 308
Arable land	98 561.51	44.69	97 898.06	43.751 7	–663.45	–0.938 3
Grassland	66 762.55	29.76	66 079.63	29.531 7	–682.92	–0.228 3
Total	223 758.26	100	223 758.26	100	0	0

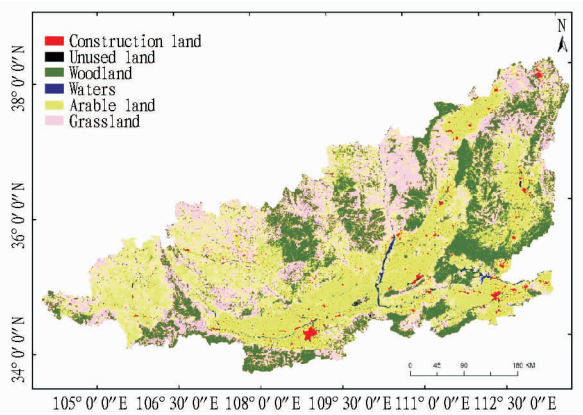


Fig. 2 The landscape pattern prediction and simulation map of the southern Loess Plateau in 2030

3 Discussions

Land use change study is always the focus of recent research of farming–pastoral ecotone of China. This article carries out land use change and simulation studies, which is of important theoretical and practical value to scientific and rational use of land resources in the study area. GIS and remote sensing provide technical support for carrying out regional-scale land use change studies, but the research results of land use change are affected by the data quality and interpretation precision of remote sensing images and other factors. Due to the impact of the spatial resolution of remote sensing images in this article, only the first-level land use type is currently determined when conducting remote sensing image interpretation, and the second-level land use type is not yet divided, so it is necessary to further reduce the scale in the future studies. In addition, the natural factors and human factors are the main driving factors for land use change, and in the short time scale, human factors play a major role. Due to the time factor, this article only carries out the research of land use change, and it is necessary to carry out research on the land use change drivers in the future. The prediction of land use change is a complex system problem, and there is a need to set the transition rules in the prediction and simulation of land use change, using Cellular Automata-

the study area, and the construction land will continue to increase, still spatially distributed in the plains; the distribution pattern changes from piece form to surface form and belt form; arable land, waters, grassland and unused land will be reduced, and arable land is reduced obviously.

ta model. The transition rules are set based on the land suitability evaluation results in this article, and the setting of transition rules needs to be further studied.

4 Conclusions

(i) From 1980 to 2005, the land changes showed that the land use structure was basically stable in the study area, and the sequencing of area proportion of land use type was not changed; arable land, grassland and woodland are the main land types in the study area.

(ii) From 1980 to 2005, the spatial variation of land types showed that the areas with increased construction land were mainly concentrated in Guanzhong Basin, and Fen River Valley; there were significant regional differences in the conversion of land use types, due to the impact of different natural factors and human factors.

(iii) Cellular Automata and Markov coupling model are used for the prediction and simulation of landscape pattern, and the precision is 87.28%, indicating that using CA–Markov model for the prediction and simulation of landscape pattern is feasible.

(iv) In the future period of time, the land use will still experience great changes in the study area, and the construction land will continue to increase, still spatially distributed in the plains; the distribution pattern changes from piece form to surface form and belt form; arable land, waters, grassland and unused land will be reduced, and arable land is reduced obviously.

References

- [1] KE CQ, OUYANG XY. The advances in modeling urban spatial change based on cellular automata[J]. Journal of Nanjing University(Natural Sciences), 2006, 42(1): 103–110. (in Chinese).
- [2] ZHANG XF, CUI WH. Integrating GIS with cellular automaton model to establish a new approach for spatio-temporal process simulation and prediction [J]. Acta Geodaetica et Cartographica Sinica, 2001, 30(2): 148–155. (in Chinese).
- [3] CAI YM, LIU YS, YU ZR, *et al.* Progress in spatial simulation of land use change CLUE-S model and its application [J]. Progress in Geography, 2004, 23(4): 63–71. (in Chinese).

The agricultural land is requisitioned in the process of urban expansion, so part of the land added value income should be used for increasing arable land, in order to maintain national consumption of food crops under existing agricultural technical conditions. However, it is uncertain about whether the new arable land developed through land reclamation has the productivity of previously requisitioned arable land.

In a nutshell, the amount of arable land in terms of quantity is not equal to efficiency of arable land in terms of quality. In the distribution of land added value, sacrificing the interests of some people in exchange for the interests of other people is the policy bias, and the injustice to the landowners. So the land added value income should establish a special account, and it is necessary to establish authorized investment projects and distribution projects to achieve the distributive justice under land ownership by the whole people.

References

- [1] "Yihuang Toushu" represent the rationality of abusing public power[N]. Economic Information Daily, 2010-10-15. (in Chinese).
- [2] The Central People's Government of the People's Republic of China, Laws and Regulations, PRC Law on Land Management[DB/OL]. http://www.gov.cn/banshi/2005-05/26/content_989_2.htm, 2013-11-16. (in Chinese).
- [3] You-tien Hsing, The great urban transformation: politics of land and property in China[M]. Oxford: Oxford University Press, 2010: 182.
- [4] WU J. Investigation on land acquisition—Based on the investigation of land rights and interests in 17 regions in the year of 2011 [J]. The World of Survey and Research, 2012(11): 27-30. (in Chinese).
- [5] HAN J. Investigation on Chinese cultivated land[M]. Shanghai: Shanghai Far East Publishers, 2009: 73. (in Chinese).
- [6] WU J. Investigation on land acquisition—Based on the investigation of land rights and interests in 17 regions in the year of 2011 [J]. The World of Survey and Research, 2012(11): 27-30. (in Chinese).
- [7] WANG QG, ZHANG ZL. Rural land price for compulsory acquisition appraisal and resolving approaches[J]. Dong Yue Tribune, 2009, 30(1): 57-62. (in Chinese).
- [8] "Zaocheng" deficiency fire should cure[N]. People's Daily, 2013-8-28. (in Chinese).
- [9] LUBU XX (Japan). Constitution III human rights[M]. Beijing: Peking University Press, 1981: 318-319, 325-327. (in Chinese).
- [10] China's Land Policy Reform Group. Chinese land policy reform: A framework of general measures[J]. Land & Resources, 2006(9): 34-37. (in Chinese).
- [11] "Yihuang Toushu" represent the rationality of abusing public power[N]. Economic Information Daily, 2010-10-15. (in Chinese).
- [12] Village official's crime of "land transaction" occurred frequently, alarms start to guarantee farmers'land rights and interests[N]. Press Digest, 2008-11-12. (in Chinese).
- [13] LI X, YE JA. Neural-network-based cellular automata for realistic and idealized urban simulation[J]. Acta Geographica Sinica, 2002, 57(2): 159-166. (in Chinese).
- [14] LI X, YE JA. Cellular automata for simulating complex land use systems using neural networks[J]. Geographical Research, 2005, 24(1): 19-27. (in Chinese).
- [15] LI X, YE JA, LIU XP. Geographical simulation systems: Cellular automata and multi-agent systems[M]. Beijing: Science Press, 2007. (in Chinese).
- [16] LONG Y, HAN HY, MAO QZ. Establishing urban growth boundaries using constrained CA[J]. Acta Geographica Sinica, 2009, 64(8): 999-1008. (in Chinese).
- [17] YANG Y, REN ZY. A comparative study on LUCC of Guangdong area based on GIS[J]. Journal of Arid Land Resources and Environment, 2013, 27(5): 40-45. (in Chinese).
- [18] HOU ZH, MA YJ, GE H. The vegetation cover change in Fen River basin[J]. Journal of Arid Land Resources and Environment, 2013, 27(2): 162-166. (in Chinese).
- [19] ZHAO GW, CHEN YB, CHEN JF, et al. Spatial scale sensitivity of CA-Markov model[J]. Scientia Geographica Sinica, 2011, 31(8): 897-902. (in Chinese).
- [20] LI Z, LIU WZ, ZHENG FL. Land use change in Heihe catchment on loess tableland based on CA-Markov model[J]. Transactions of the Chinese Society of Agricultural Engineering, 2010, 26(1): 346-352. (in Chinese).
- [21] LIU XH, Andersson C. Assessing the impact of temporal dynamics on land-use change modeling[J]. Computers, Environment and Urban Systems, 2004, 28(1/2): 107-124.
- [22] WEI W, SHI PJ, ZHOU JJ. Landscape pattern evolution in Shiyang River basin based on GIS[J]. Journal of Arid Land Resources and Environment, 2013, 27(2): 156-161. (in Chinese).
- [23] GUO HH, LI B, HOU Y, et al. Cellular automata model and multi-agent model for the simulation of land use change: A review[J]. Progress in Geography, 2011, 30(11): 1336-1344. (in Chinese).
- [24] LI YC, HE CY. Scenario simulation and forecast of land use/cover change in Northern China[J]. Chinese Science Bulletin, 2008, 53(6): 713-723. (in Chinese).
- [25] GUO B. Landscape dynamic and optimization of South Loess Plateau based on GIS[D]. Shaanxi Normal University, 2011. (in Chinese).
- [26] LIU G, HE XF. Practice course of GIS[M]. Beijing: Tsinghua University Press, 2003. (in Chinese).

(From page 54)

[4] ZHANG YM, ZHAO SD, P. H. Verburg. CLUE-S and its application for simulating temporal and spatial change of land use in Naiman Banner[J]. Journal of Natural Resources, 2003, 18(3): 310-318. (in Chinese).

[5] CAI YL. A study on land use/cover change; the need for a new integrated approach[J]. Geographical Research, 2001, 20(6): 645-652. (in Chinese).

[6] TANG HJ, WU WB, YANG P, et al. Recent progresses of land use and land cover change(LUCC) models[J]. Acta Geographica Sinica, 2009, 64(4): 456-468. (in Chinese).

[7] DUAN ZQ, P. H. Verburg, ZHANG FR, et al. Construction of a land-use change simulation model and its application in Haidian District, Beijing[J]. Acta Geographica Sinica, 2004, 59(6): 1037-1047. (in Chinese).

[8] WANG LP, JIN XB, DU XD, et al. Land use scenarios simulation of Foshan city based on gray model and cellular automata model[J]. Transactions of the Chinese Society of Agricultural Engineering, 2012, 28(3): 237-242. (in Chinese).

[9] XIAO M, WU JQ, CHEN QB, et al. Dynamic change of land use in Changhua downstream watershed based on CA-Markov model[J]. Transactions of the Chinese Society of Agricultural Engineering, 2012, 28(10): 231-238. (in Chinese).

[10] YANG QS, LI X. Calibrating urban cellular automata using genetic algorithms[J]. Geographical Research, 2007, 26(2): 229-237. (in Chinese).

[11] QIN XH, DUAN XJ, LI H, et al. Urban land expansion simulation model based on SD and CA—a case study of Nantong City[J]. Scientia Geographica Sinica, 2009, 29(3): 439-444. (in Chinese).

[12] HOU XY, CHANG B, YU XF. Land use change in Hexi corridor based on CA-Markov methods[J]. Transactions of the Chinese Society of Agricultural Engineering, 2004, 20(5): 286-291. (in Chinese).

[13] LI X, YE JA. Neural-network-based cellular automata for realistic and idealized urban simulation[J]. Acta Geographica Sinica, 2002, 57(2): 159-166. (in Chinese).

[14] LI X, YE JA. Cellular automata for simulating complex land use systems using neural networks[J]. Geographical Research, 2005, 24(1): 19-27.