Environ Monit Assess (2010) 164:133–142
DOI 10.1007/s10661-009-0880-2

Land-use change simulation and assessment of driving factors in the loess hilly region—a case study as Pengyang County

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Received: 15 May 2008 / Accepted: 10 March 2009 / Published online: 28 March 2009

Abstract The main objective of this study is to evaluate the land-use change and its relationship with its driving factors in the loess hilly region. In this study, a case study was carried out in Pengyang County. We set two land-use demand scenarios (a baseline scenario (scenario 1) and a real land-use requirement scenario (scenario 2)) during year 2001–2005 via assuming the effect of driving factors on land-use change keeps stable from 1993 to 2005. Two simulated land-use patterns of 2005 are therefore achieved accordingly by use of the conversion of land use and its effects model at small regional extent. Kappa analyses are conducted to compare each simulated land-use pattern with the reality. Results show that (1) the associated kappa values were decreased from 0.83 in 1993–2000 to 0.27 (in scenario 1) and 0.23 (in scenario 2) in 2001–2005 and (2) forest and grassland were the land-use types with highest commission errors, which implies that conversion of both the land-use types mentioned above is the main determinant of change of kappa values. Our study indicates the land-use change was driven by the synthetic multiply factors including natural and social–economic factors (e.g., slope, aspect, elevation, distance to road, soil types, and population dense) in 1993–2000 until "Grain for Green Project" was implemented and has become the dominant factor in 2001–2005.

Keywords CLUE-S model · Land-use change · Driving factor · Loess hilly region

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Introductions

Land-use change models are usually used to illustrate land-use change and its relationship with driving forces. Even so, it is complicated to assess driving forces of land-use change (Verburg et al. 2002). Policies have an important influence on land-use patterns. Omitting policy variables might cause an incomplete assessment. In many studies, they are not given explicit attention because they are difficult to include in a quantitative assessment (Verburg et al. 2004b). Few researchers managed to incorporated land-use change models into investigations on policy-dominated driving forces and assess the policy-dominated area quantitatively. Castella et al. integrated the conversion of land use and its effects model at small regional extent (CLUE-S) model and other models to assess driving forces of the policy-dominated area in Northern Vietnam and implied the drawback of heavy requirements in data (Castella et al. 2007; Castella and Verburg 2007). Hence, it is crucial to develop convenient approaches to assess the policy-dominated driving area quantitatively.

The loess hilly region is a representative deteriorated landscape with low vegetation cover and fragmented and complex topography, in which severe eco-environmental issues exist (Fu et al. 2006). In-depth analysis of land-use change and its relation with driving forces is helpful in addressing the eco-environmental issues and for land-use management and planning in the loess hilly region.

In this study, we tend to develop a quantitative approach by employing the CLUE-S model to assess land-use change and the driving factors of the loess hilly region in period of 1993–2005, taking Pengyang County as case study. Land-use scenarios that differ with respect to land-use requirements are analyzed to reveal the temporal change of driving factors of the study region.

Study area

The study area, Pengyang County, is a typical county with a semiarid climate and hilly loess landscape on the Loess Plateau (Fig. 1). It is situated between 35°41′–36°17′ N and 106°32′–106°58′ E and covers an area of 2,528.7 km^2. The climate shows clear seasonal variations. The mean annual precipitation is about 520 mm, ranging from 350 to 550 mm. The mean annual temperature is 7.2°C, and the frost-free duration is 170 days per year. There are floods in summer and droughts in other seasons. The land surfaces, mostly at 1,248–2,483 m asl, are highly dissected by deeply incised gullies. Severe ecological issues such as soil erosion are threatening rural ecosystems and constrain crop–pastoral activities at local and landscape scales. To realize ecological agriculture targets, some progress has been made in the last 20 years in soil and water conservation by using small catchments as the base unit and the implementation of the national Grain for Green Project. Environmental pressure is thus gradually decreasing.

Methods and materials

Data collection

The data employed in this study include land-use maps of 1993, 2000, and 2005, a soil type map made in 1987, digital elevation model data and social–economic documents. The land-use map of 1993 is at the scale of 1:50,000. The land-use maps of 2000 and 2005 are derived respectively from the interpretation of ETM+ image of year 2000 at pixel of 15 m and SPOT5 image of year 2005 at pixel of 5 m. Through reclassification of land-use types of the above three phases of land-use maps, four land-use types are obtained as forest, grassland (unutilized land included), cropland, and others (water, residential land included). Furthermore, residential land, rivers, and roads are extracted respectively from the associated maps to form driving force maps to represent the corresponding driving factors. Slopes, aspects, and elevation are derived from the digital elevation model at resolution of 10 × 10 m and also used to represent driving factors. The Pengyang County soil type map of 1987, at a scale of 1:200,000, is used to represent another driving factor. Population density data, derived from the Pengyang statistics annual book from 1993 to 2005, is used as another driving factor after it was mapped. All analyses are made on the Geographical Information System software platform ArcGIS 9.1 (ESRI Inc. 2004) using pixels of 100 × 100 m as unit of observation.

Land-use change modeling

The CLUE-S model was developed to simulate land-use change by quantifying empirical relationships between land use and its driving factors by Peter H. Verburg in Wageningen University (Pontius and Schneider 2001; Verburg et al. 2002). It has been extensively implemented in China, Philippine, Central America, The Netherlands, etc. and proves an excellent grid-based, multi-scale, and spatially explicit land-use change model (Verburg et al. 2002, 2004a; Chen et al. 2008).

The CLUE-S model is made up of none spatial module and spatial module. The nonspatial module in the CLUE-s model calculates the aggregate

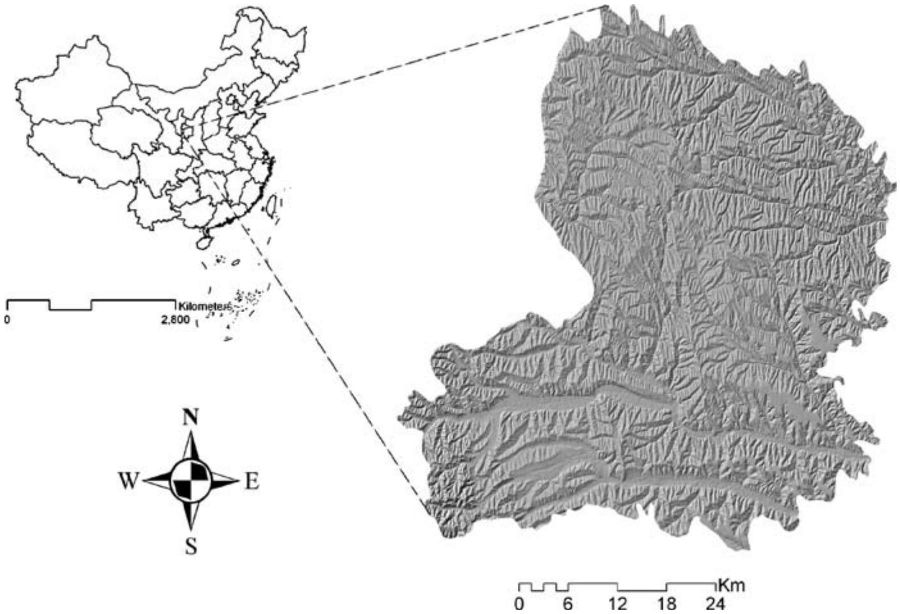


Fig. 1 Location of study area

area of change for all land-use types, and the spatial module translates these demands into land-use changes at various locations within a study region (Verburg et al. 2002). Allocation of each land-use type is based on a combination of empirical and spatial analyses and dynamic modeling (Verburg et al. 2002). Empirical analysis is applied to determine the relationships between spatial distribution of land use and a number of proximate factors that are driving or constraining land-use change. Based on the competitive advantage of each land use at a location, the competition among land uses for a particular location is simulated. The schematic representation of the procedure to allocate change in land use in CLUE-S model is in Fig. 2 (Verburg et al. 2002).

Land demands and scenarios

For the land demand module, different alternative model specifications are possible, ranging from simple trend extrapolations, scenario approach, to complex economic models (Verburg et al. 2002). In this study, two scenarios are set to simulate the land-use pattern of 2005 based on land use of 2000.

Scenario 1 Assuming the effect of driving factors on land-use change keeps stable in 1993–2005 and land-use requirement of 2001–2005 keeps the linear change on base of the trend in the period of 1993–2000: In this situation, the annual area of land-use types of

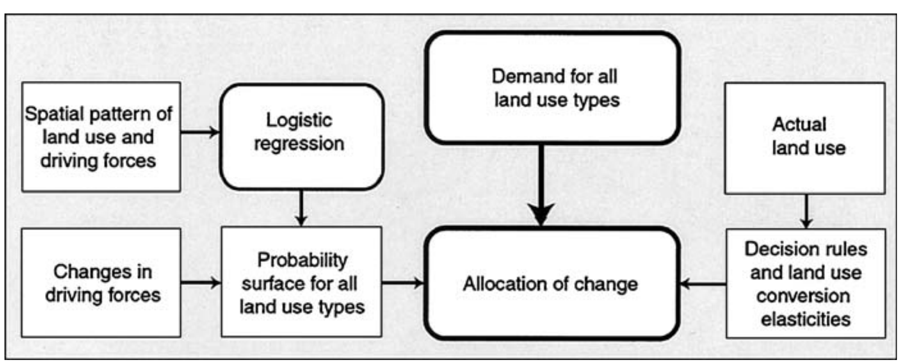


Fig. 2 Schematic representation of the procedure to allocate changes in land use in CLUE-S model (Verburg et al. 2002)

2001–2005, in one hand, could be extrapolated from the annual land-use area in the period 1993–2000. In the other hand, the land-use pattern of 2005 could be achieved through simulation of land-use change based on the land-use pattern of 2000 on the platform of the CLUE-S model.

Scenario 2 Assuming the effect of driving factors on land-use change keeps stable in 1993–2005 and land-use requirement of 2001–2005 is as the reality: In this situation, the annual area of various land-use types of 2001–2005 is determined by quadratic smooth methods on base of the reality. The land-use pattern of 2005 obtained through simulation of land-use change on the CLUE-S model is also based on land-use pattern of 2000.

Definition of land-use conversion elasticity

The CLUE-S model allows the stability of various land-use type addressed by setting the ELAS coefficient according to the expert knowledge on the historic and recent situation for specified land-use type. The ELAS coefficient, between 0 and 1, increases in value with a decrease of probability for land-use conversion. If the ELAS coefficient is 0, it means a conversion of land use with no barrier. If the ELAS coefficient is 1, it means no conversion allowed. In this study, the ELAS coefficients of cropland, forest, grassland, and others are set to be 0.6, 0.7, 0.2, and 0.9, respectively, after the local condition and need of model are taken into account.

Driving forces and binary logistic regression

Eight driving factors, chosen to contribute to the CLUE-S modeling, are distance to residential land, distance to river, distance to road, population density, slopes, aspects, elevation, and soil types.

The logistic regression is designed to estimate the parameters of a multivariate explanatory model in situations where the dependent variable is dichotomous, and the independent variables are continuous or categorical. Binary logistic regression analysis is employed to construct the relation between each of the four land-use types and relevant driving factors. First, the spatial data of four types of land use and the eight driving factors of 1993 are transformed to ASCéò format and incorporated into a single text file by means of FILE-CONVERTER module of the CLUE-S model. Second, binary logistic regression analysis is conducted on the statistical software SPSS 13.0 (SPSS Inc. 2004) using stepwise option after the text file was imported and the coefficient of each factor for specific land-use types can be thereafter achieved. These coefficients are interpreted as weights in an algorithm that generates a map depicting the probability of a specific category of land-use change for all sampling units. Positive values of the parameter estimate indicate that larger values of the explanatory variable will increase the likelihood of the occurrence of the event. Likewise, negative values of the parameter estimate indicate that larger values of the explanatory variable will decrease the likelihood of the occurrence of the event (Serneels and Lambin 2001). The regression confidence degree is equal to or larger than 99% (i.e., $A = 0.01$) and the coefficients that do not satisfy the condition are excluded. The achieved coefficients are part of the parameters of spatial module of the CLUE-S model. Finally, a relative operating characteristic (ROC) curve method is implemented to validate the prediction accuracy of the regression.

Validation of modeling accuracy

The goodness of fit of the logistic regression model is measured by the ROC (Pontius and Schneider 2001). The ROC is based on a curve relating the true-positive proportion and the false-positive proportion for a range of cutoff values in classifying the probability. The ROC statistic measures the area beneath this curve and varies between 0.5 (completely random) and 1 (perfect discrimination).

Land-use change simulation

Input the parameters achieved above and run the CLUE-S model to simulate the land-use change based on the land-use pattern of 1993. The simulated land-use pattern of 2000 is obtained. Compare the simulated map and the reality of 2000 by use of kappa analysis. The obtained kappa coefficient is then used to address the simulation precision. When the simulation precision is satisfied, the parameters of scenario 1 and 2 may be input to run the CLUE-S model respectively to gain the simulated land-use pattern of 2005 based on 2000 to assess the land-use change and associated driving factors.

Land-use change assessment

Kappa analysis yields a statistic, K, which is an estimate of kappa. It is a measure of agreement or accuracy between the remote sensing-derived classification map and the reference data as indicated by (a) the major diagonal and (b) the chance agreement, which is indicated by the row and column totals (Rosenfield and Fitzpatrick-Lins 1986; Congalton 1991; Paine and Kiser 2003). In this study, kappa coefficient is used to measure the agreement between the simulated land-use pattern and the reality. K values >0.8 (i.e., $>80\%$) represent strong agreement or accuracy between the classification map (simulated land-use pattern) and the ground reference information (reality). K values between 0.60 and 0.80 (i.e., 60% to 80%) represent high agreement. K values between 0.40 and 0.60 (i.e., 40% to 60%) represent moderate agreement. K values <0.40 (i.e., $<40\%$) represent poor agreement (Landis and Koch 1977).

The CLUE-S model helps to reveal the causality between land-use changes and driving factors (Verburg et al. 2002, 2004c). If the factors that drive land-use change are appropriately chosen, the simulation leads to a high agreement between the simulated land-use pattern and the reality. On the contrary, a high agreement may also demonstrate the strong capability of driving factors in explaining land-use change. In this study, kappa analysis is therefore used to represent the agreement between the simulated land use and the reality and explain the causality and consequence between land-use changes and driving factors. K values increase with an increase of explanatory capability.

Analyze the agreements between each of the scenarios and the reality of 2005 with kappa coefficients and commission errors. Remote sensing software ENVI 4.1 (ITT 2004) is employed to run confusion matrix analysis in which kappa coefficients and commission errors are achieved. Instead of kappa analysis for agreements between land-use patterns as a whole, the commission errors unravel the spatial difference for specific land-use types between each of the simulated land-use patterns and the reality of 2005. In addition, by incorporating the social–economic supplements, changes of land-use and the driving factors in the period of 2001–2005 from 1993–2000 may be evaluated quantitatively.

Table 1 Estimated coefficients of binary logistic regression for land-use patterns in 1993

Driving factor	Cropland	Forest	Grassland	Others
Dark loessial style soil			0.276	
Erosive gully		0.537		
Erosive dark loessial soil		−0.577		0.326
Shallow dark loessial soil	−0.358			0.406
Gray-cinnamon soil		0.584		
Cultivated dark loessial soil				0.192
Elevation		0.005	0.002	−0.002
Slope		0.002	0.001	−0.001
Aspect	−0.052	0.048	0.049	0.009
Population density	0.004	0.008	−0.014	0.002
Distance to river	0.0003		−0.00027	−0.00007
Distance to road	0.00006		0.00004	−0.00008
Distance to residential land	0.00017		0.00016	−0.00023
ROC	0.804	0.789	0.783	0.807

Results analysis

Binary logistic regression analysis in SPSS

Table 1 gives the estimated coefficients for the logistic regression, describing the land-use pattern for the main land-use types in 1993. The ROC values indicate that the spatial pattern of all four land-use types can be reasonably explained by the independent variables.

Land demands and scenarios

Table 2 lists the land demand areas from 1993 to 2000 conducted by quadratic smooth method according to the *Pengyang County statistics yearbooks (1993–2000)* and relevant land-use documents. Assuming land use in 2001–2005 changes linearly based on the trend from 1993 to 2000, the land demand areas in 2001–2005 for scenario 1 will be obtained by conducting linear fitting (see Table 3). Table 4 lists the reality land demand areas conducted by quadratic smooth method for scenario 2.

Land-use change simulation

Model accuracy validation

Input the land-use requirement areas from 1993 to 2000 (see Table 1) into the CLUE-S model and make a run. The land-use pattern of 2000 (Fig. 3c) is achieved based on the land-use pattern of 1993 (Fig. 3a). Kappa analysis is subsequently conducted for comparison between the simulated land use (Fig. 3c) and the reality (Fig. 3b). Kappa value obtained is 0.84 and represents a strong agreement, which indicate the chosen driving factors could explain the land-use change well.

Table 2 Areas for various land types in 1993–2000

Year	Cropland	Forest	Grassland	Others
1993	130,964	14,892	92,790	9,155
1994	127,350	15,644	95,596	9,211
1995	124,736	16,396	97,402	9,267
1996	122,122	17,148	99,208	9,323
1997	119,508	17,900	101,014	9,379
1998	118,894	18,652	100,820	9,435
1999	117,280	19,410	101,626	9,485
2000	116,684	20,156	101,414	9,547

Table 3 Demand areas for various land-use types in 2000–2005 (in scenario 1)

Year	Cropland	Forest	Grassland	Others
2001	113,062	20,908	104,228	247,801
2002	111,033	21,660	105,449	247,801
2003	109,004	22,412	106,670	247,801
2004	106,975	23,164	107,891	247,801
2005	104,946	23,916	109,112	247,801

Scenarios analysis

Scenario 1 Input the land-use requirement areas in 2001–2005 for scenario 1 (see Table 3) into the CLUE-S model and run it. On base of land-use map of year 2000, the simulated land-use pattern for 2005 (see Fig. 4b) is obtained. Conduct a kappa analysis between the simulated land-use pattern and reality (Fig. 4a) and K value is 0.27, which represents a poor agreement between them.

Scenario 2 Input the land-use requirement areas in 2001–2005 for scenario 2 (see Table 4) into the CLUE-S model and run it. On base of land-use map of year 2000, the simulated land-use pattern for 2005 (see Fig. 4c) is obtained. Conduct a kappa analysis between the simulated land-use pattern and the reality (Fig. 4a) and the resulting K value is 0.23, which also represents a poor agreement between them.

Table 4 Demand areas for various land-use types in 2000–2005 (in scenario 2)

Year	Cropland	Forest	Grassland	Others
2001	95,460	23,908	118,830	9,603
2002	88,897	28,660	120,285	9,959
2003	82,334	37,412	117,840	10,215
2004	75,771	45,164	116,269	10,597
2005	69,208	51,373	116,347	10,873

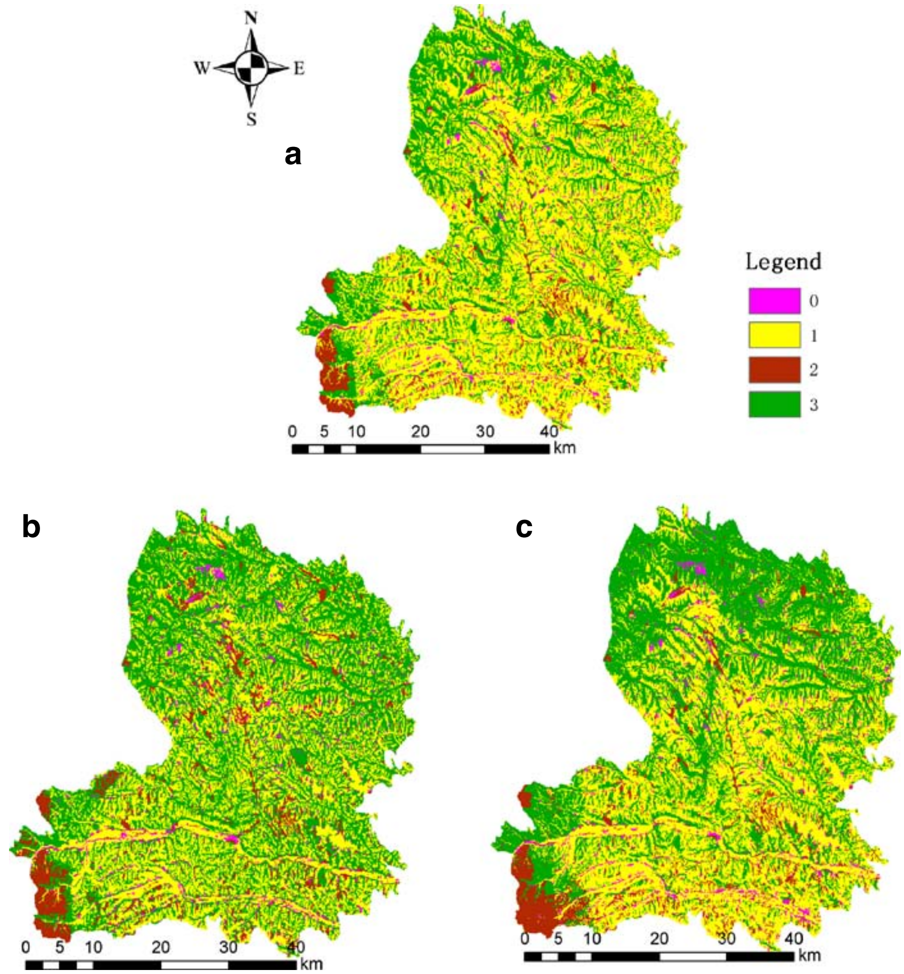


Fig. 3 **a** Reality map of year 1993, **b** reality map of 2000, and **c** simulated map of year 2000. *Legend* *1* cropland, *2* forest, *3* grassland, and *0* others

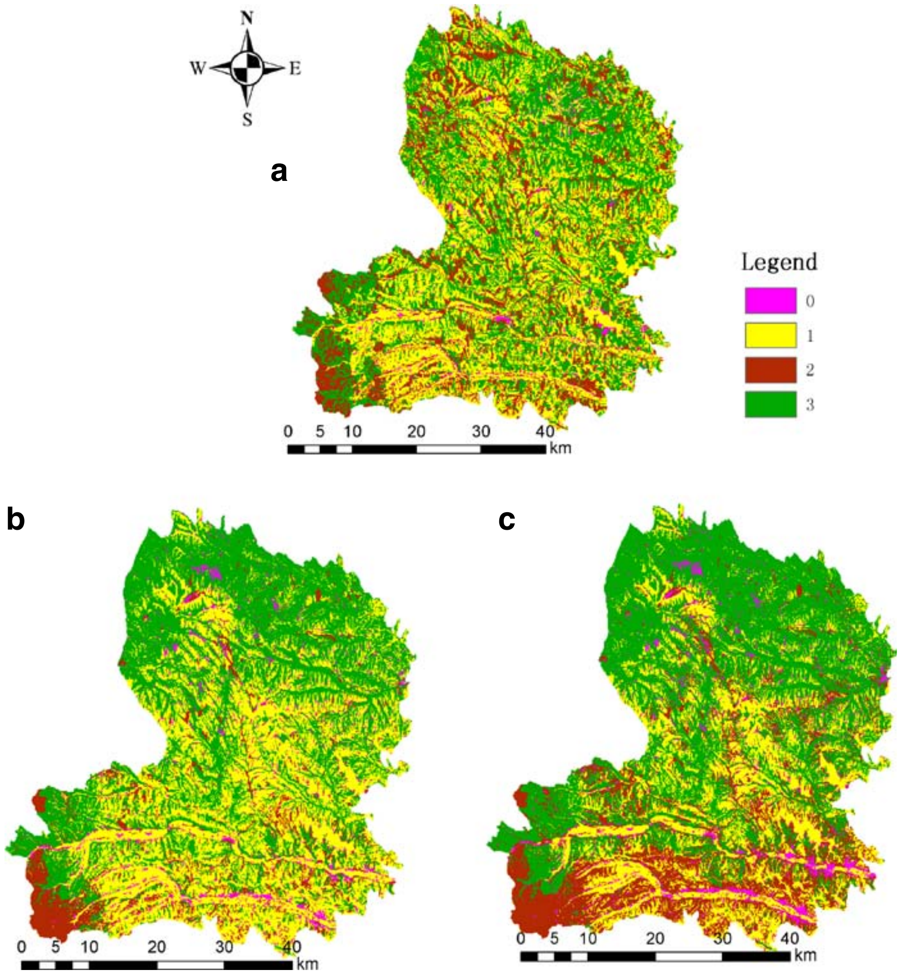
The fact that K values of scenario 1 and scenario 2 is 0.27 and 0.23, respectively, indicates poor agreements between both the simulated land-use patterns and the reality of 2005. The change of kappa coefficients in the whole period of 1993–2005 is thereafter analyzed. As the parameters of the CLUE-S model keep unchanged, the land-use simulation produce a strong agreement in the period 1993–2000 ($K = 0.84$) but poor agreements in the period 2001–2005 ($K = 0.27$ or 0.23). For a model validation has been carried out and proves a strong accuracy by means of kappa analysis as described above, the facts like the changes of kappa values in the whole period 1993–2005 and the poor agreement results in 2001–2005 may imply that the driving factors in 2001–2005 could have changed from those in 1993–2000.

Land-use change and driving factors assessment

Land-use change assessment

The analyses of commission errors, focusing on the main land-use types, are performed to compare the simulated land-use patterns in scenario 1 or 2 with the reality of 2005. The results are listed in Table 5 and indicate that as the percents of commission error concerned, the land-use types in both scenarios satisfy others < cropland < grassland < forest. The commission errors of forest in scenario 1 and scenario 2 are 55.9% and 69.2%, respectively. Both values are larger than 50% and the highest in all four land-use types. The commission errors of grassland in scenarios 1 and 2 are 48.6% and 50.2%, only less than of

Fig. 4 **a** Reality map of 2005, **b** simulated map of 2005 for scenario 1, and **c** simulated map of 2005 for scenario 2. *Legend 1* cropland, *2* forest, *3* grassland, and *0* others



forest. Grassland and forest are the land-use types with commission errors significantly larger than cropland and others.

The land-use patterns in scenario 1 (Fig. 4b) and scenario 2 (Fig. 4c) are subsequently analyzed from a spatial perspective. In the south of Pengyang County, where soil quality is better and water is relatively better supplied, the dominating conversion of land use is from cropland to forest and cropland appears as larger and constant parcels. Meanwhile, in north of Pengyang County where soil is poor and water supply is insufficient, the area of grassland is increased and croplands come to disappear. In short, soil type and water contribute seemly to determine land-use distribution in both scenarios. However, the real land-use pattern (Fig. 4a) is significantly different. In the poor qualified Northern Pengyang County, a larger area of forest is distributed evenly while the increase of forest is not noticeable. In the central or southern region, there are not new significantly larger parcels of grassland or cropland appeared and cropland is still the dominating land-use type.

Table 5 Commission errors for various scenarios (percent)

Land-use type	Scenario 1	Scenario 2
Cropland	40.1	36.84
Forest	55.87	69.22
Grassland	48.65	50.2
Others	32.19	33.29

Briefly, the mismatches of land-use types between both the scenarios and the reality of 2005 also imply the poor agreements between these simulated patterns and the reality. As the historical information is added to taken into account, the change of land-use driving factors, especially the factors that drive forest and grassland convert in 2001–2005 from 1993–2000, might be conformed the cause of those mismatches.

Driving factor analysis

The “Grain for Green Project” policy has been implemented in loess hilly region, southern Ningxia since 2000. The Pengyang County is included. As the “Grain for Green Project” policy announces, the croplands with slopes over 25° ought to be converted to grassland or forest, and grassland and forest, in the other location, might be the priority in suitable locations as long as enough qualified cropland is maintained. In the period 2001–2005, this county had tried improving the environment by implementing the land-use distribution strategy of the “Grain for Green Project” policy. Area of cropland decreased and grassland and forest expanded. Slope lands above 25° were completely covered by grassland or forest till 2005. In addition, farmers have been encouraged to relocate in developed areas from relatively poor conditions with severe eco-environmental issues like soil erosion. Pressures from population have been thereafter well mitigated. Comparing the period before 2000, the land-use pattern was thus better optimized.

In summary, social–economic documents unravel that in the period 2001–2005, it was due to the implement of the “Grain for Green Project” policy that the dominating land-use conversion of Pengyang County was a conversion from cropland to forest or grassland. The involvement of human-activity-driving policy made the driving factors in 2001–2005 distinguished from in 1993–2000. The fact that this judgment, derived from social–economic documents, matches the analyses described above conforms that the “Grain for Green Project” policy is the dominating factor that drives land-use change in 2001–2005.

Conclusions and discussion

In this study, we set two land-use demand scenarios like a baseline scenario (scenario 1) and a real land-use requirement scenario (scenario 2) for 2001 to 2005. Two simulated land-use patterns of 2005 are thereafter achieved accordingly in support of the CLUE-S model and kappa analyses between each of the simulated land-use patterns and the reality are conducted. The results indicate that the associated kappa values were decreased from 0.83 in 1993–2000 to 0.27 (in scenario 1) and 0.23 (in scenario 2) in 2001–2005 and that forest and grassland are the land-use types with highest commission errors, which implies that the conversion of both of these land-use types is the main determinant of change of kappa values. The results implies explicitly that the land-use change was driven by the synthetic multiply factors including natural and social–economic forces likely slope, aspect, elevation, distance to road, soil types, population dense, etc. in 1993–2000 until “Grain for Green Project” was implemented and has become the dominant factor in 2001–2005.

Whereas the CLUE-S model unravels a spatial causal relation between land-use allocation and driving factors (Verburg et al. 2002, 2004c; Zhang et al. 2007), we develop an integrated approach to explore the temporal change of driving factors by means of the CLUE-S model quantitatively. Through land-use simulation using the CLUE-S model and kappa analysis, we propose that the temporal change of kappa values demonstrate the temporal change of driving factors from 1993–2000 to 2001–2005. By assessing the agreements for specific land-use types between each of the simulated land-use patterns and the reality of 2005, commission error analyses reveal the potential driving factors furthermore. As the social–economic information is taken into account, we conform that the “Grain for Green Project” policy is the dominating driving factor in 2001–2005. The integrated approach may be appropriate for application in other loess hilly regions even other policy-dominated areas. We provide a case study for bridging the knowledge gaps in application of the CLUE-S model into policy-dominated areas.

Some researchers argued that due to the stability and resilience of land-use system, disturbances and external influence will, mostly, not directly change the landscape structure (Conway 1985; Verburg et al. 2002). Whereas impact the “Grain for Green Project” on the environment is a constant long-term immense program from human being, the policy might not be included in the situation. On the contrary, our case study around the "Grain for Green Project" proves the vast strong impacts of this policy on changes of land-use pattern. In addition, we provide a reference for the CLUE-S model or other similar land-use change models to address the issues how these models apply in the policy-dominated areas.

Acknowledgements The project was supported by the National Natural Science Foundation of China (contract no. 40571091).

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