Environmental Management (2009) 43:899–907
DOI 10.1007/s00267-008-9263-7

Land Use and Land Cover Change Analysis and Prediction in the Upper Reaches of the Minjiang River, China

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Received: 9 December 2007 / Accepted: 17 December 2008 / Published online: 17 March 2009

Abstract Scientists have aimed at exploring land use and land cover change (LUCC) and modeling future landscape pattern in order to improve our understanding of the causes and consequences of these phenomena. This study addresses LUCC in the upper reaches of Minjiang River, China, from 1974 to 2000. Based on remotely sensed images, LUCC and landscape pattern change were assessed using cross-tabulation and landscape metrics. Then, using the CLUE-S model, changes in area of four types of land cover were predicted for two scenarios considering forest polices over the next 20 years. Results showed that forestland decreased from 1974 to 2000 due to continuous deforestation, while grassland and shrubland increased correspondingly. At the same time, the farmland and settlement land increased dramatically. Landscape fragmentation in the study area accompanied these changes. Forestland, grassland, and farmland take opposite trajectories in the two scenarios, as does landscape fragmentation. LUCC has led to ecological consequences, such as biodiversity loss and lowering of ecological carrying capacity.

Keywords Land use and land cover change (LUCC) · CLUE-S · Minjiang River · Upper reaches

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Land use and land cover change (LUCC) encompass some of the most important human alterations affecting the surface of the earth (Lambin and others 2001). The study of causes, processes, and consequences of LUCC is one of the main research topics of landscape ecology (Wu and Hobbs 2002). Landscapes can be seen as the contingent and historically variable outcome of this interplay between socioeconomic and biophysical forces (Wrbka and others 2004). Understanding the processes of LUCC is important for both scientific and public policy (David and others 2001).

The patterns, causes, and consequences of spatial heterogeneity with respect to ecosystem function are recognized as a current research frontier in both landscape and ecosystem ecology (Lovett and others 2005). While many ecosystem processes are difficult to observe directly, landscape pattern can be derived from mapping as well as from remotely sensed data. Satellite imagery, in conjunction with geographic information systems (GIS), has been widely applied and is recognized as a powerful and effective tool in detecting LUCC (Ehlers and others 1990; Treitz and others 1992; Harris and Ventura 1995; Yeh and Li 1999).

Many researchers with different disciplinary backgrounds have focused on understanding and modeling the factors determining the location of land use changes at different spatial and temporal scales (Brown and others 2000; Schneider and Pontius 2001; Thompson and others 2002). This work has provided knowledge of the factors responsible for the spatial allocation of land use changes in a series of case studies (Geist and Lambin 2002). Furthermore, a range of methods and models to simulate land use change (Angelsen and Kaimowitz 1999; Miller and others 1999; Verburg and others 2004; Parker and others 2003), and to assess the impact of land use change on ecosystem functioning (Wear and Bolstad 1998; Crews-Meyer 2002), has been developed.

The land use change model utilized in this study is based on the CLUE-S model (Conversion of Land Use and its Effects at a Small regional extent [Verburg and others 2002]), which aims at a better understanding of land use change complexity and allows for the exploration of future land use management options and their effects on environment and ecosystems.

LUCC has primarily been studied in cases where it leads to severe environmental problems. For example, there is a long tradition of interdisciplinary work focusing on the causes of land degradation and soil erosion (Blaikie 1985; Blaikie and Brookfield 1987; Adams 1990). Many studies have found that human activities have become a dominant factor shaping most cultivated landscapes of the Earth (Goudie and Viles 1997). Understanding the causes and consequences of LUCC is helpful to policy makers for better policy.

The upper reaches of the Minjiang River in southwestern China form one of the most important sources of the Yangtze River. The study area is one of the most important forest regions in China. The region has suffered from continuous forest harvesting over the last several decades. The upper Minjiang is a hotspot area of biodiversity and situated at the intersection of many biogeographic divisions (Hu 2002). Unfortunately, continuous deforestation had led to a series of ecological problems, such as a decline in ecological carrying capacity, biodiversity loss, and accelerated soil erosion.

This study was designed to examine the LUCC and landscape pattern change in the upper Minjiang and explore the short-term land cover changes and ecological consequences. The research also assessed the driving factors and social consequences of improving our understanding of LUCC. Such a case study in a forest region may be helpful for policymakers seeking to ensure sustainable local forest and land uses.

Materials and Methods

Study Area

The study area is located in the upper reaches of Minjiang River, on the eastern edge of the Qinghai-Tibet Plateau (102°59′–104°14′E, 31°26′–33°16′N) (Fig. 1). It is regarded as the ecological 'fence' enclosing the Chengdu plain, and is a typical mountainous region with upland ecosystem vulnerability and sensitivity. The study area is about 22,564 km^2 and includes five counties: Songpan, Heishui, Mao, Li, and Wenchuan. The area population was ~380,000 in 2000. The study area is represented in a GIS by 618,545 pixels of 4 ha (200 × 200 m) each.

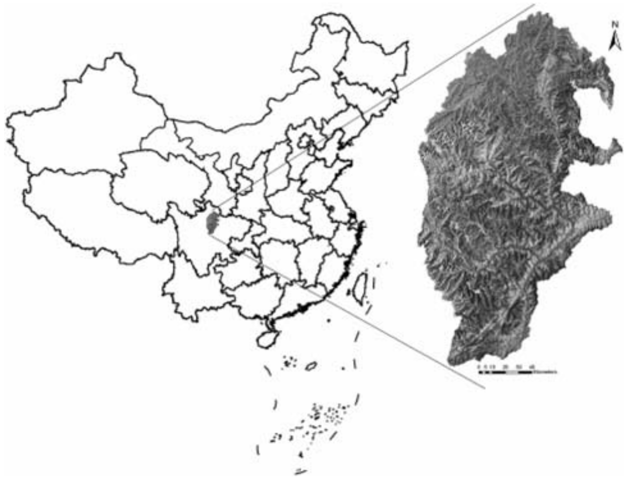

Fig. 1 Location of the study area

The topography of the area is characterized by a complex distribution of hills and vallies. Elevation ranges from 700 to 6260 m, with an average of about 3000 m. The Wolong natural reserve for the giant panda (*Ailuropoda melanoleuca*) lies in the southern part of the area.

Data Preparation

Satellite images in 1974 (Landsat MSS), 1986, 1996, and 2000 (Landsat TM) were used to derive thematic land use maps based on seven categories: forestland, shrubland, grassland, farmland, settlement, water area, and bare rock. The images were geometrically corrected and geocoded to the Transverse Mercator coordinate system, using topographic maps of 1:10,000. Approximately 65 evenly distributed ground control points were selected from each image. These were used to spatially resample the images, using a nearest neighbor algorithm, which selects the value of the pixel in the input image closest to the computed coordinate. Land use types were determined by a combination of supervised classification and manual interpretation of satellite images, supplemented with secondary information on climate and geomorphology, vegetation maps, and ground truth data (Kilic and others 2006). To determine the accuracy of the image classification, the stratified random sampling method (Jensen 1996) was used to generate 140 reference points for each of the classified images. One hundred forty reference points were located in the field with the help of a global positioning system (GPS) with ±5 m error for ground-truthing. The kappa accuracy index (Congalton 1991) was 85.2% in 1974, 87.5% in 1986, 90.3% in 1995, and 92.2% in 2000. We used both ERDAS Imagine 9.0 and ARCGIS9.0 to integrate the data using standard GIS features. Due to the different resolutions of remotely sensed images (MSS, 79 × 79 m; TM, 30 × 30 m), all results of classification were resampled at 80 × 80 m for further analysis.

The socioeconomic data used for the study include the following.

1. The statistical yearbooks of the five counties in the study area from 1982 to 2000. Consumption data were obtained both from per-family average consumption data recorded in statistical yearbooks and from 50 questionnaires randomly distributed to local residents within the study area.
2. Data on the area's forest resources were obtained from the forestry bureaus of Songpan, Heishui, Mao, Li, and Wenchuan counties.

Research Methods

The analysis of LUCC consisted of three parts.

1. The landscape area changes for different land use types were summed.
2. The conversion among main land use types in different years were studied based on the cross-tabulation matrix method of Pontius and others (2004). The cross-tabulation matrix is a fundamental starting point in analysis of land change, illustrating the conversion between seven land use/cover types (Pontius and others 2004). The cross-tabulation analysis was conducted in ERSI ARCGIS9.0.
3. Landscape fragmentation was analyzed for the period 1974–2000 using the following landscape metrics: number of patches, size (patch density), shape (landscape shape index [LSI]), distribution (aggregation index), and diversity (Shannon's diversity index [SDI]). All vector land use maps in 1974, 1986, 1995, and 2000 (coverage file in ARCGIS) were converted to raster files at a cell resolution of 80 × 80 m. Landscape metrics were then calculated using Fragstats 3.3 (Mcgarigal and Marks 1995).

Future land use/cover was predicted with the CLUE-S model. This is a land use change prediction model that has been used and validated in a wide range of applications (Veldkamp and others 2001; Verburg and Veldkamp 2004). The model is especially useful for assessing changes in complex spatial patterns of shifting land uses because of the explicit attention given to linkages between the temporal and the spatial dynamics of land use change. Land use change is determined by both macroscale factors (such as economy and climate) and microscale factors (such as location characteristics). The interplay between these two types of factors results in land use changes at the microscale that may, through feedback, affect macroscale conditions, e.g., through changes in the supply-demand characteristics of an agricultural product. At the same time, a land use change at a particular location can also affect ecological characteristics of the location itself, e.g., through erosion or nutrient depletion. These processes will affect future land use options at that location.

A short overview of the CLUE-S model is presented here; a more detailed description of the model is given by Verburg and others (2002). Special attention is devoted to the implementation of temporal dynamics that are specific for different land use types and to the feedback between the land use history and the allocation of land use change.

Configuration of the Model

The simulation resolution was 200 × 200 m,including 1345 rows and 810 columns. We set 10 test scenarios under resolution from 1000 to 100 m, with a step of 100 m. The results showed that the greatest resolution in the CLUE-S model reaches 200 m in the study area.

In our study, two scenarios were tested over the period 2001–2020: an historic trend (HT) scenario and a natural forest protection (NFP) scenario. 'Natural forest protection' was initiated in 2000, when the deforesting of natural forest lands was prohibited. Meanwhile, 'grain for green' was carried out, which ruled that the farmland in steep areas (slope, >25°) must be returned to forest. Thus, the NFP scenario reflects the actual situation in the area, while the HT scenario provides a hypothetical comparison. The latter was formulated based on historical changes from 1974 to 2000. In HT scenario, land use area demand was predicted via the ARIMA approach, which is a time series analysis approach based on the historic land use area. Except for land use area in 1974, 1986, 1994, and 2000, the land use data in other years from 1974 to 2000 were obtained from statistical yearbooks for the five counties in the study area. All the results reached the 0.05 significance level tested by Pearson test. The NFP scenario was assumed under the "natural forest protection" and "grain for green" policies. The areas of land use type demand in the NFP scenario were adjusted based on the results in the HT scenario with natural forest protection planning, which stipulated the area of afforested land each year. The predicted land use areas under the two scenarios are shown in Fig. 2.

We focus on land cover change in the near-future. The aforementioned seven land use/cover types were integrated into five categories for modeling: forestland, shrubland, grassland, farmland, and other.

Location characteristics determine the relative suitability of a location for the different land use types. The relative probability of finding a land use type at a particular

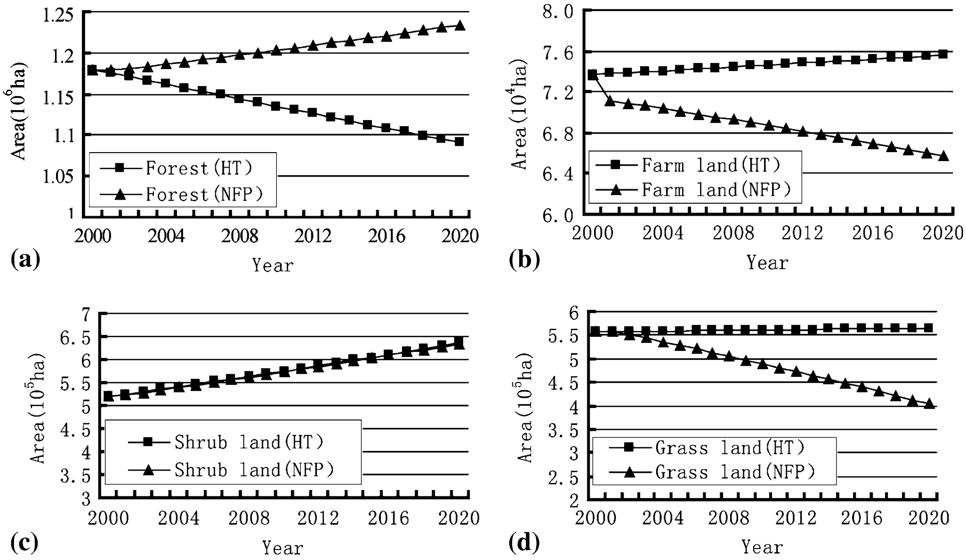

Fig. 2 Area change of four main land cover types under two scenarios. **a** Forestland area change; **b** farmland area change; **c** shrubland area change; **d** grassland area change

location is based on the biophysical and socioeconomic conditions (Geist and Lambin 2002; Lambin and others 2001). The coefficients are estimated through logistic regression with the actual land use pattern.

The factors taken into account as potential determinants were selected based on the literature and on fieldwork in the study area, including DEM, slope, aspect, distance to river, distance to settlement, distance to road, rainfall, evapotranspiration, topographic position index (TPI), and compound topographic index (CTI). The CTI is a steady-state wetness index (also called the topographic wetness index) and it is a function of both the slope and the upstream contributing area per unit width orthogonal to the flow direction (Gessler and others 1995). The TPI is a measure of location within the overall landscape. That is, in relative terms, the topographic position of a place may be a hilltop, a valley bottom, a slope, an exposed ridge, a flat plain, or some other feature (Jenness 2006).

The logistic regression results are reported in Table 1. The spatial distribution of all land use types could be explained well by the selected driving variables as indicated by the high relative operating characteristic (ROC) test statistics (scale, 0.5–1). Although other factors may have influenced land use decision making, they are not easy to represent in landscape-level data. They are, therefore, approximated by proximate factors, such as

Table 1 Beta values and exponent beta values for logistic regression for diferent land use types

	Forestland		Shrubland		Grassland		Farmland		Other	
	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)
Dem	−6.06E−05	0.9999	0.0002	1.0002	−0.0001	0.9999	0.0002	1.0002	0.0003	1.0003
Slope	0.0002	1.0002	−9.61E−07	1.0000	−0.0003	0.9997	−0.2486	0.7799	−0.0003	0.9997
Aspect	0.0039	1.0039	−0.0031	0.9969	0.0037	1.0037	0.0035	1.0036	−0.0326	0.9679
Distance to river	5.16E-05	1.0001	0.0001	1.0001	−0.0001	0.9999	8.48E-05	1.0001	−0.0001	0.9999
Distance to settlement	3.42E−05	1.0000	−1.87E−05	1.0000	−9.13E−05	0.9999	0.3460	1.4134	2.26E−05	1.0000
Distance to road	4.90E−05	1.0000	2.07E−05	1.0000	−2.12E−05	1.0000	0.2905	1.3371	0.0001	1.0001
Rainfall	0.0005	1.0005	−0.0034	0.9966	0.0036	1.0036	0.0039	1.0039	−0.0035	0.9965
Evapotranspiration	−0.0056	0.9944	0.0128	1.0129	−0.0090	0.9911	−0.0071	0.9929	0.0040	1.0040
CTI	−0.0245	0.9758	0.0238	1.0241	0.0072	1.0073	0.1088	1.1149	0.0511	1.0525
TPI	−7.78E−06	1.0000	2.22E−05	1.0000	−2.62E−05	1.0000	−6.26E-05	0.9999	7.80E−05	1.0001
Constant	−0.0877	0.9160	−1.8486	0.1575	−0.6436	0.5254	−4.8885	0.0075	−5.4778	0.0042
ROC value	0.705		0.748		0.851		0.927		0.93	

Note: CTI, compound topographic index; TPI, topographic position index; ROC, relative operating characteristic. Exp(β) values indicate the change in odds upon a 1-unit change in the independent variable. When exp(β) >1 the probability increases upon an increase in the value of the independent variable, when exp(β) <1 the probability decreases

All variables significant at $p < 0.01$

accessibility. The derived regression models were used to calculate suitability maps for different types of land use/cover.

Spatial policies and restrictions indicate areas where land use changes are restricted by policy or tenure status. There were no zones or regions within the study area where special restrictions on land conversion were applicable.

Conversion settings for specific types of land use determine the temporal dynamics of the simulations. Conversion elasticties in two scenarios were set based on related articles (Veldkamp and others 2001; Verburg and Veldkamp 2004) and the study area situation (Table 2). The number of ELAS parameters means the stable percentage that will not change. For example, the 0.9 for grassland in the HT scenario means that 10% of the grassland area can change to other land use. The ELAS parameter of 1.0 means that forest land cannot change to other land use in the NFP scenario because of the policies 'Natural forest protection' and 'grain for green.'

The conversion matrix was configured based on our understanding of the land use system in the study area. All land use types can convert to one another with the exception of settlement converting to another type, except for forestland to others in the NFP scenario.

We predicted the land use/cover in 2000 based on the land use/cover in 1974 with the CLUE-S model to validate its applicability in the study area. The forecasting period was 26 years. The predicted land use/cover map in 2000 was compared with the actual map for 2000 utilizing the ROC method (Pontius and Schneider 2001). The ROC technique applies to any model that predicts a homogeneous category in each grid cell. The ROC result was 0.87, which indicates that the two maps show a relatively high consistency. CLUE-S was then used to predict land use/cover change for the 20-year period beginning in 2000 in the study area.

Table 2 Arrangement of ELAS parameters

	HT	NFP
Forestland	0.9	1.0
Shrubland	0.9	0.9
Grassland	0.9	0.8
Farmland	0.8	0.7
Other	0.6	0.7

Note: HT, historic trend scenario; NTP, natural forest protection scenario

Results

Forestland, grassland, and shrubland were the main landscape categories in the study area, covering more than 90% of the total area (Table 3). Forest was the largest land cover type, accounting for about 50% of the total area in 2000. Due to deforestation, forest area decreased dramatically from 1974 to 2000, declining by 180,000 ha, or 13.33% of the forest area, in 1974. On average, 7638 ha of forest was lost per year from 1974 to 1986, followed by 6183 ha/year from 1986 to 1994 and 6716 ha/year from 1994 to 2000. The area of farmland and settlement increased steadily throughout the entire period. The area of farmland increased 12.61% from 1974 to 2000. The shrubland and grassland also increased throughout the study period, while the area of river, lake, and swampland remained relatively stable.

According to the cross-tabulation (Table 4), forestland was converted primarily to shrubland and grassland and, partly, to farmland. The conversion of forestland to other categories was the main component of LUCC, accounting for 42.03% of all the changed landscape area. While 210,068 ha of forestland was converted to other landscape categories, only 29,164 ha shifted to forests. The LUCC with respect to forests occurred primarily due to continuous deforestation. The area of forest loss mirrored that of shrubland and grassland gain, which showed that the increasing area of shrubs and grassland came from deforestation. The increase in farmland and settlement land resulted from population increase and economic development.

Changes in landscape pattern were analyzed with landscape metrics (Table 5). The increasing values for patch number and patch density indicated an accelerated rate of landscape fragmentation. The patch density was low overall. There was less than 0.32 patch per 100 ha, indicating that the landscape is composed of a few large patches. The LSI provides a standardized measure of total

Table 3 Landscape area (ha) in 4 years studied

	Farmland	Grassland	Settlement	Forestland	Shrubland	Water	Bare rock
1974	62,242	510,339	735	1,356,601	413,876	23,402	105,166
1986	80,631	528,667	827	1,264,947	468,803	23,450	105,036
1995	89,173	553,768	900	1,209,293	491,500	23,444	104,284
2000	90,332	556,760	1,063	1,175,713	519,740	23,484	105,270

Table 4 Cross-tabulation of landscape change from 1974 to 2000 (ha)

	Farmland	Grassland	Settlement	Forestland	Shrubland	Water	Bare rock	Sum	Loss
Farmland	58,991	247	206	706	2,069	13	6	62,238	3,246
Grassland	674	493,112	10	12,186	3,554	12	769	510,315	17,203
Settlement	4	1	727	0	1	0	0	734	7
Forestland	18,630	36,632	58	1,146,537	153,279	62	1,407	1,356,605	210,068
Shrubland	12,020	25,147	62	15,720	360,611	35	290	413,886	53,275
Water	0	7	0	0	0	23347	30	23,385	38
Bare rock	0	1,591	0	551	249	0	102,791	105,182	2,391
Sum	90,319	556,737	1,063	1,175,701	519,763	23469	105,292		
Gain	31,328	63,626	336	29,164	366,484	122	2501		

Table 5 Landscape pattern change from 1974 to 2000

	1974	1986	1994	2000
Patch number (PN)	7392	7521	7569	7795
Patch density (PD)	0.23	0.30	0.31	0.32
Landscape shape index (LSI)	66.52	70.63	72.46	73.82
Shannon's diversity index (SHDI)	1.24	1.30	1.32	1.34
Aggregation index (AI)	92.62	92.15	91.94	91.79

edge or edge density that adjusts for the size of the landscape. The increasing LSI showed that the edge density increased. The increasing SDI indicated that the landscape diversity improved, which was caused by the decrease in area gap among different landscape category numbers used. The high value of the aggregation index demonstrated an aggregated patch distribution. Both the increasing LSI and the decreasing aggregation index showed that the landscape became disaggregated. According to the landscape metrics analysis, the landscape of the study area was still dominated by a few land types and large patches, but the landscape was becoming more and more fragmented.

The land cover from 2001 to 2020 was simulated utilizing the CLUE-S model under two scenarios. In the HT scenario, four land cover types would continue the same historical trends as in the past two decades. Forestland decreases due to deforestation, while shrubland, farmland, and grassland increase correspondingly (Fig. 2). In the NFP scenario, forestland, shrubland, and grassland reverse the respective change trends from 1974 to 2000 due to prohibitions on deforestation issued under the policies of "natural forest protection" and "grain for green." Shrubland, however, would continue to increase, possibly from the natural succession of grassland (Fig. 2).

We chose four landscape metrics to reflect future landscape change: number of patches (NP), LSI, SHDI, and contagion index (CONTAG). All the metrics were calculated in Fragstats3.3 at the landscape level. NP (Fig. 3a) increased, and patch shape (Fig. 3b) was more complicated than in the HT scenario. In contrast, PN and shape remain stable in the NFP scenario. Landscape diversity is greater in the HT scenario than the NFP scenario (Fig. 3c), since in the latter PN would be increasing and gaps between patches shrinking. CONTAG is inversely related to edge density. The edge density would be more complex in the HT scenario than the NFP scenario (Fig. 3d).

The policies of "natural forest protection" and "grain for green" would reverse the landscape fragmentation trend in the future two decades, thereby increasing the proportion of forestland in the study area.

Discussion

A decrease in forestland and increases in grassland, shrubs, and farmland were the main characteristics of LUCC in the study area. The gathering of herbs in the study area had severe effects on the grassland, especially worm grass (*Eordyeepssinensis*) gathering at elevation 4000–4500 m. Increasing population pressures have resulted in an increase in farmland and settlement land. The result of these changes has served to aggravate to the landscape fragmentation. According to our field survey, the unreasonable utilization of natural resources, such as continuous deforestation, land reclamation in steep areas, and overgrazing, created a series of ecological problems in the vulnerable ecosystem of the study area, including increased soil erosion, increased mudslides, and biodiversity loss. Landscape fragment resulted in the loss of wildlife habitat, especially for mammals. In 1974, 31 species, belonging to 24 genera, 10 families, and 3 orders, were found in the study area. However, by 2000 the number of medium and large-sized mammal species had decreased to 24. Seven species had disappeared from the region (Hu and others

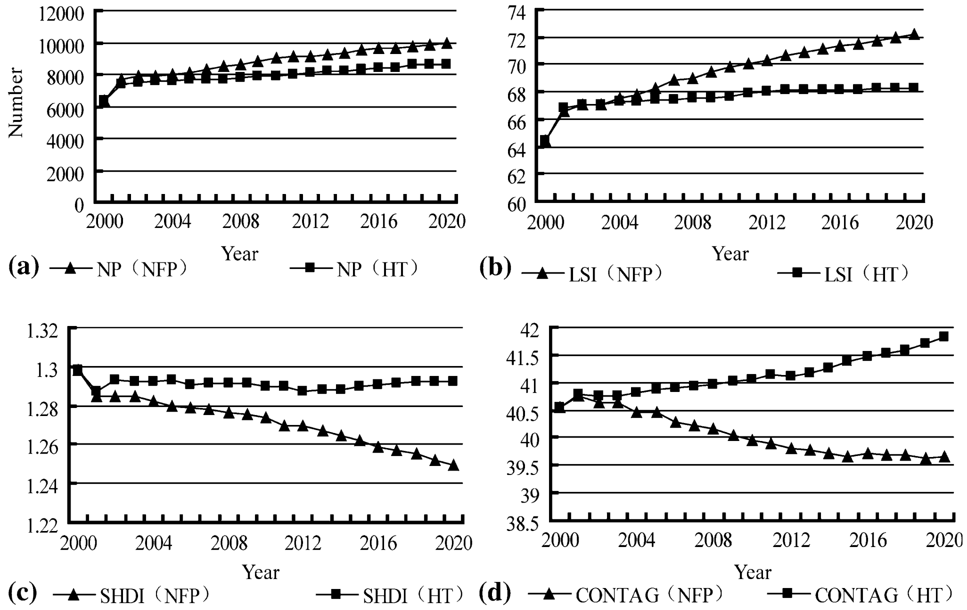

Fig. 3 Landscape metrics change for study area under two scenarios. **a** Number of patches; **b** landscape shape index; **c** Shannon's diversity index; **d** contagion index

2001, 2002). Results from the CLUE-S model simulation based on the land use/cover change suggest that polices of "natural forest protection" and "grain for green" would reverse the trend of declining and slow the pace of landscape fragmentation.

Landscape can be seen as the contingent and historical outcome of the interplay between socioeconomic and biophysical forces. Five major types of driving forces can be identified: socioeconomic, political, technological, natural, and cultural (Brandt and others 1999). In this study, natural factors were longer-term variables, spanning several decades, while more immediate social factors related to policy change, socioeconomic activities, and technology were major forces for change (Bürgi and others 2004). Continuous deforestation caused the loss of forestland and the increase in grassland and shrubs, which was the most important and direct manifestation of LUCC in the study area. The increasing population was another major driving force which contributed to the increase in farm and settlement areas. The political driving forces were reflected in the emphasis on deforestation brought about by the view that the study area was basically a forest region and, therefore, to be harvested. In 1956, 12 forestry bureaus were set up for deforestation in study area. Henceforth, deforestation exceeded net forest production per year in the last decades, e.g., in 1994 deforestation was 1270,000 m^3, while net forest production was 1,120,000 m^3 in 1994 (Sichuan Forestry Bureau 1994). The amount and location of deforestation were determined exclusively by the administrative agent of the forest bureau in the study area.

LUCC studies have thus far tended to focus primarily on the documentation and analysis of spatial patterns and have paid considerably less attention to landscape function and processes. This bias is common to the entire field of landscape ecology (Wiens 1995; Hobbs 1997). LUCC caused by excessive deforestation will inevitably bring harm to the local ecosystem. To reflect the effect, the index of carrying capacity was chosen, which was estimated using the ecological footprint (EF) approach. An EF was built in 1996 to measure sustainable development and ecological carrying capacity; details of the approach are given in related articles (Wackernagel and Rees 1996; Erb 2004). The ecological carrying capacity (ECC) is calculated on the basis of the area of different land use categories and biological production data. The data came from interpreter results from RS and statistic yearbooks for the study area.

The ECC of the study area maintained a decreasing trend from 1974 to 2000 (Fig. 4). The ECC dropped 17.44% from 1974 to 2000, and it decreased on average 0.47% per year from 1974 to 1986, 1.04% per year from 1986 to 1994, and 0.77% per year from 1994 to 2000. The

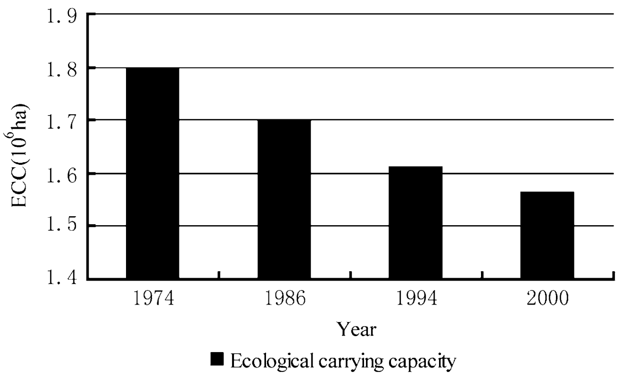

Fig. 4 The ecological carrying capacity dynamics

dramatic decrease in carrying capacity was mainly caused by the area and quality decrease in forest.

If deforestation in the study area were to continue, CLUE-S model simulation shows that LUCC would continue along the same trajectory over the next two decades. On the other hand, it also indicates that the new policies applied in 2000 may begin to prevent accelerating landscape fragmentation, biodiversity loss, and other ecological problems, while the obvious ecological effects of such a reversal in LUCC trajectory are not reflected in this study because of the short time period covered. The vitality of the landscape and the longer-term effect on the ecosystem of the two polices merit continuing attention in future works.

Conclusion

Results of this study conducted in the upper reaches of the Minjiang River indicate that the forest area decreased, and landscape fragmentation accelerated, from 1974 to 2000. Continuous deforestation and population increases were the main driving forces. Recently adopted forestry policies represent a potentially powerful driving force for shaping future LUCC in the study area. The LUCC has led to biodiversity loss, a decline in ECC, and other ecological problems. The landscape will become more fragmented and ecological problems will continue to worsen if the historical pattern of deforestation is maintained. While polices of ‘return farmland to forest’ and ‘grain for green’ will undoubtedly engender positive effects in terms of future LUCC. The time period looked at here is too short to adequately reflect the potential scope and long-term effects of such changes. The long-term LUCC resulting from the adoption of these policies should be studied in future work.

Acknowledgments This project was supported by the National Basic Research Program of China, Mechanism of Forest Vegetation Regulating Agricultural Eco-environment in the Typical Regions of Western China (No. 2002CB111506), and the National Natural Science Foundation of China (No. 40801069).

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