MONITORING FOREST LANDSCAPE USING PHOTOGRAMMETRIC TECHNIQUES AND LANDSCAPE MODELS

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ABSTRACT: Scattered unlawful patches in forest landscape not only cause adverse effects on soil and water conservation, but also deteriorate the integrity and functionality of the forest ecosystem. This study took a 548ha government-managed experimental forest as an example to investigate the effects of unlawful cultivation on the forest landscape. Based on land use maps of 1971 and 1998 produced by digital photogrammetry, a Markov model was constructed to project the extent of land cover changes in the future. A binary logit model was used to examine the possible factors contributing to the observed land cover changes, and to simulate the spatial patterns of cultivation in the future. Finally, 4 landscape indices were used to assess the effects of unlawful cultivation on the forest landscape. The results of this study showed that the occurrences of cultivation were related to elevation and proximity to private land. Cultivated areas have more-significant edge effects than shape effects on the landscape. Among the 4 indices examined, the total edge length was more sensitive to cultivation than were the others. On the other hand, cultivated areas appeared to have little effect on the fractal dimension of the dominant forest patch.

1. INTRODUCTION

In human-dominated landscapes, changes in a landscape are often due to human factors (di Castri and Hadley 1988). Therefore, protecting ecosystems requires the ability to predict the direct and indirect, and temporal and spatial effects of human activities (Costanza 1987). Various landscape models have been developed to describe, explain, or predict landscape dynamics. Baker (1989) classified models of landscape change into 3 levels: whole-landscape models, distributional models, and spatial models. Whole-landscape models are well suited for assessing cumulative effects of disturbances on environmental quality (Pastor and Johnston 1992). In landscape studies, indices are often used to describe or assess the structural condition of a landscape, by measuring spatial configurations of patches on a landscape such as their density, size, shape, edge, diversity, interspersion, and juxtaposition (McGarigal and Marks 1995); In the distributional models, Markov model is a widely used approach to evaluate the change of landscape distribution. The change in a landscape is summarized by a series of transition probabilities from 1 state to another over a specified period. These probabilities can be subsequently used to project the landscape properties at alternate future time points (Burham 1973). As for the spatial landscape models, logit (or probit) models have been widely used to evaluate landscape or land use changes. Logit models assume that decisions of land use change are based on the utility maximization behavior of the decision makers, and that the magnitude of the utility can be determined by some explanatory variables. For example, Dale et al. (1993) used a multinomial logit model to predict the "attractive index" of a land lot to a tenant.

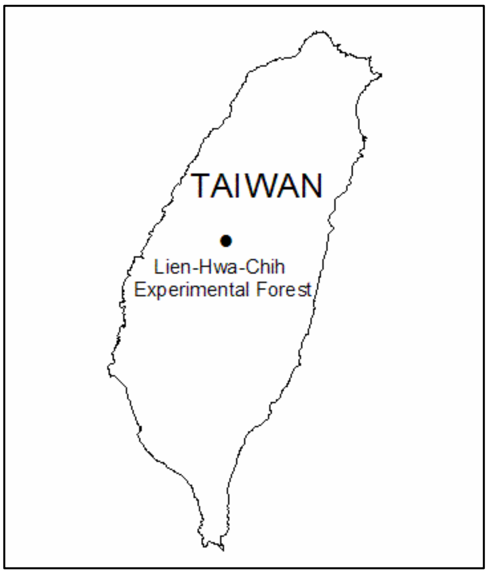

Fig. 1. Location of the study area.

The objective of this study was to integrate landscape models at 3 levels to assess the effects of landscape change both temporally and spatially. The study area selected for the empirical analysis was the Lienhwachih Experimental Forest located in central Taiwan (Fig. 1). Managed by the Taiwan Forestry Research Institute (TFRI), the forest has been dedicated to forestry research since 1943. Although the 548-ha landscape chosen was dominated by forestlands, nearly 60 ha of private lands exist within its boundary. Although land cover converted was relatively insignificant in terms of the entire landscape, continuing land conversion in the future could eventually lead to forest fragmentation and ecosystem deterioration. Therefore, it is necessary to estimate what impacts cultivation will have in the future before making management decisions.

2. MATERIALS AND METHODS

2.1 Materials

Data collected for the empirical analysis included land cover maps of the study area in 1971 and 1998. The land cover maps, which contain the boundary of each land cover patch as well as roads and streams, were digitized from base maps and cadastral maps. In addition, a digital terrain model (DTM) in 5 m resolution was used to derive the topographic characteristics of the study area. The land cover types within the study area were classified into 3 categories: public forestland, private land, and cultivated areas with the public forestland (Fig. 2).

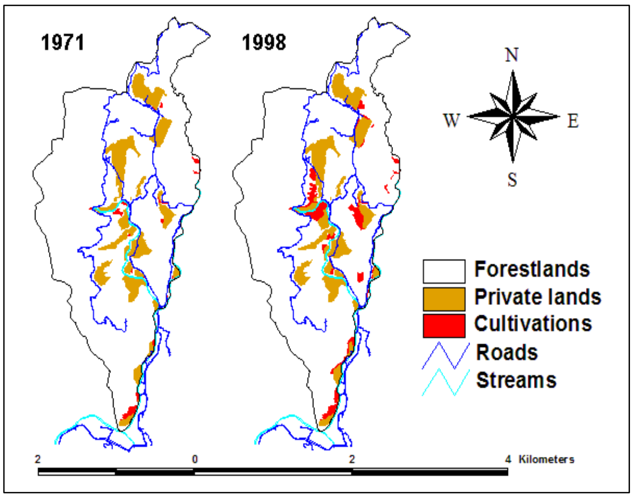

Fig. 2. Land cover maps in 1971 and 1998.

2.2 Methods

2.2.1 Projection of the land-cover changes

The analytical procedures included 4 steps. In the first step, it was assumed that the land cover changes of the study area could be depicted as a Markov process. A transition matrix, in which the element T_{ij} represents the amount of land cover change from cover type i to cover type j during 1971 and 1998, were derived from the land cover maps. The transition probability P_{ij}, which represents the factions of land cover changes on each land cover type, was estimated by:

$$\hat{P}_{ij} = T_{ij} \Big/ \sum_{j=1}^{m} T_{ij} \; ; \quad i = 1, 2, \ldots m, \tag{1}$$

where m is the number of land cover types, and is equal to 3 in this case.

To determine whether it is appropriate to apply the Markov model to the observed land cover changes, Goodman's Chi-squared statistic (Goodman 1968) was used to test the null hypothesis that the land cover conditions in 1971 and 1998 were independent of each other:

$$\chi^2 = \left\{ \sum_{i=1}^{m} \sum_{j=1}^{m} \left[T_{ij} \times \ln(P_{ij} / A_j) \right] \right\}^2 ; df = (m-1)^2 , \tag{2}$$

where the definitions of T_{ij} and P_{ij} are same as in equation (1), and A_j denotes the fraction of land cover in each of the 3 land cover types in 1998.

Assuming that the transition probabilities will remain constant in the future, the Markov model was then used to project the land cover at the next stage:

$$n_{t_2} = P \cdot n_{t_1} \; ; \tag{3}$$

where P is the transition probability matrix, and n_{t1} and n_{t2} are column vectors denoting the fractions of land cover types at t_1 and t_2.

2.2.2 Examination of the factors contributing to the land-cover changes

In the second step, a binary logit model was used to examine the possible factors contributing to the observed land cover changes. The logit model was specified as:

$$\text{logit}(p) = \log\left[\frac{p}{1-p} \right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \; ; \tag{4}$$

where p is the probability of a plot of forestland being converted to farmland under a certain given situation.

It was assumed that the probability of land conversion was dependent on a linear function of explanatory variables X's. The probability of the binary logit model can be calculated by:

$$p = \frac{1}{1-e^{-z}} \qquad \text{where } \; z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \tag{5}$$

Potential explanatory variables considered in this study included elevation (ELEV), slope (SLOP), distance to private lands (DSTP), distance to the nearest roads (DSTR), and distance to the nearest streams (DSTS). The parameters in equation (5) were estimated using the maximum likelihood method.

2.2.3 Simulation of the spatial patterns of cultivated areas

In the third step, the spatial patterns of cultivated areas in the future were simulated. Two simulation scenarios were compared. The first scenario, or the "random" scenario, simply assumed that the probabilities of cultivation would be the same across all locations. The cultivated plots projected by the Markov model were allocated to randomly simulated patches matching the size distribution of the existing cultivated plots. In the second scenario, or the "modeled" scenario, the logit model was used to spatially differentiate the probabilities, that is, locations with higher probabilities would be more likely to be cultivated. Furthermore, based on the fact that in 1971 and 1998, 80% of the cultivated patches and 91% of the cultivated area were adjacent to private land or other existing cultivated areas, adjacent patches and isolated patches were distinguished during the simulations. Both simulation scenarios were run for 5 consecutive periods (for a total of 135 years), and each simulation was repeated 100 times to examine the variability of the outcomes.

2.2.4 Evaluation of the effects of unlawful cultivation on the forest landscape

In the fourth step, 4 landscape indices were used to assess the effects of unlawful cultivation on the forest landscape. The edge effects resulting from cultivation were quantified by measuring the changes in the total edge length (TE) and the size of the total core areas (TCAS) of the forestlands. Core areas were defined as areas interior to forest edges, and the edge width was conventionally specified as 50 m. To measure the shape effects, the shape index (SHAPE) and the fractal dimension (FRACT) of the dominant (i.e., the largest) forest patch were calculated to monitor the increasing shape irregularity and shape complexity caused by unlawful cultivation. The shape index was denoted as

$$SHAPE = \frac{0.25p}{\sqrt{a}}; \tag{6}$$

where p is the perimeter of a patch, and a is the size of that patch. The shape index equals 1 if a patch is circular, and increases as the patch shape becomes more irregular.

The fractal dimension was measured by

$$FRACT = \frac{2\ln(0.25p)}{\ln a}. \tag{7}$$

FRACT approaches 1 when a patch has a very simple perimeter (such as a circle or square), and approaches 2 when a patch has a highly convoluted and plane-filling perimeter.

3. RESULTS

3.1 Projection of the land-cover changes

Based on the land cover maps in 1971 and 1998, the transition matrix of the observed land cover changes are shown in Table 1. About 2.8% of the public forestland had been converted to farmland during the 27 yr period. The extent of the private lands and cultivated areas in 1971, on the other hand, remained unchanged. Goodman's Chi-squared statistic in equation (2) was statistically very significant ($p << 0.001$), suggesting that the land cover changes during the period were not random.

Table 1. Transition matrix of land cover changes from 1971 to 1998

Land cover type	Conversion from 1971 to 1998 (ha)			Total area in 1971(ha)
	Forestland	Private land	Cultivated land	
Forestland	470.76	13.66	0	484.42
Private land	0	4.94	0	4.94
Cultivated land	0	0	58.92	58.92
Total area in 1998(ha)	470.76	18.61	58.92	548.29

The projected land cover conversions during the next 5 periods (27 yr per period) are shown in Fig. 3. The cultivated areas were projected to 62.74 ha during the next 135 yr, and reach 81.35 ha in the year 2133.

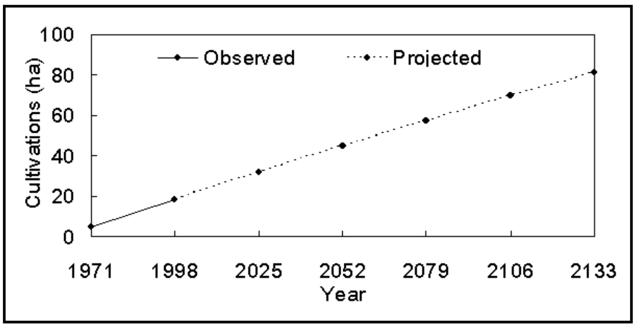

Fig. 3. Observed and projected areas of cultivated land.

3.2 Examination of the factors contributing to the land-cover changes

Parameters of the binary-logit model were estimated using the maximum likelihood method based on 250 randomly selected samples. Stepwise forward selection was used to determine which factors should be included as explanatory variables. Results of the model estimation are shown in Table 2. The likelihood ratio test statistic, which is asymptotically distributed as χ^2 (df = 2), was very significant, suggesting that relationship existed between the observed cultivated areas and the explanatory variables. The cultivations were found to be conversely related to the natural logarithm of elevation (Log ELEV) and the natural logarithm of distance to private land (Log DSTP). That is, as the elevation increases and the location is farther away from private lands, the likelihood of cultivation rapidly diminishes. The observed cultivated areas were also conversely related to slope (SLOP) and to the nearest distances to road and stream (DSTR and DSTS), but the relationships were not statistically significant.

Table 2. Estimation results of the binary logit

Variable	Coefficient	*t* statistic
Constant	59.22123	3.90992
Log Elev	-9.04369	-3.79351
Log DSTP	-0.50838	-2.86689
Number of observations	250	
Log-likelihood test statistic	56.626	
Percent correctly predicted	84.8	

3.3 Simulation of the spatial patterns of cultivated areas

Fig. 4 compares the observed cultivated areas and the probabilities predicted by the logit model. The predicted probabilities were fairly low for most of the forestlands because the existing cultivated areas only constituted a small portion of the landscape. However, the *t*-test statistic showed that the mean probability of the observed cultivation was significantly greater than that of the uncultivated forestland ($p << 0.01$). That is, the model was able to spatially differentiate the probability of cultivation; Examples of the simulated landscape patterns in year 2133 (i.e., 135 yr after 1998) for the 2 scenarios are compared in Fig. 5. As can be seen, the 2 scenarios gave quite different outcomes. The cultivation patches in the random scenario were very scattered, while the patches in the modeled scenario were much more congregated.

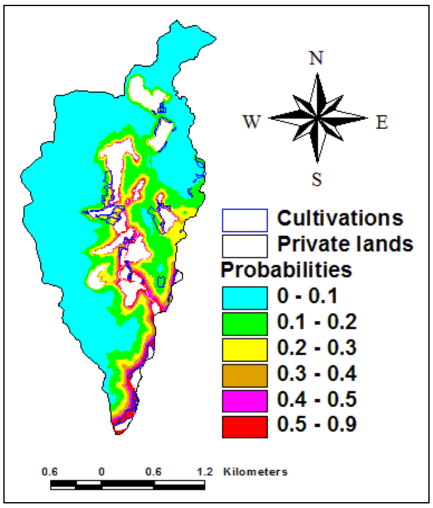

Fig. 4. Observed cultivated areas and projected probabilities.

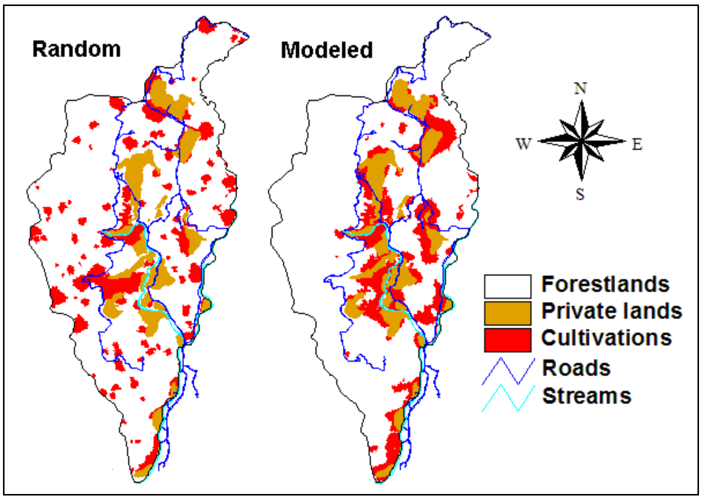

Fig. 5. Examples of simulated landscape patterns in 2133 for the 2 scenarios.

3.4 Evaluation of the effects of unlawful cultivation on the forest landscape

The means and coefficients of variation of the landscape indices derived from 100 simulation outcomes are reported in Table 3; and the projected temporal trends of the 2 scenarios are compared in Fig. 6. The standard deviations of the projected results were relatively low; therefore the temporal changes were statistically significant. Judging from the curves, the modeled scenario apparently gave more reasonable projections than did the random scenario. The random scenario tended to overestimate the effects of cultivation on the forestland, especially the increase in total edge length. In the modeled scenario, the shape index and the total edge length increased 12% and 31% respectively, and the total core area decreased 20%, in 135 yr. In contrast, the simulated cultivated areas only caused a 1.4% increase in the fractal dimension. However, the total edge length of the simulated outcomes also had the highest variations, indicating a wider range for the estimated confidence interval.

Table 3. Means and coefficients of variation in landscape indices

Year	Shape index		Fractal dimension		Total edge (km)		Total core area (ha)	
	Random	Modeled	Random	Modeled	Random	Modeled	Random	Modeled
1971	4.7275		1.2020		22.275		343	
1998	4.9549		1.2085		24.950		325	
2025	5.0733 (2.51)*	5.8256 (1.50)	1.2119 (0.27)	1.2301 (0.16)	26.695 (2.55)	32.238 (1.80)	311.345 (0.89)	286.786 (1.08)
2052	5.1887 (3.29)	6.6838 (1.61)	1.2152 (0.35)	1.2485 (0.17)	28.316 (3.49)	39.211 (1.82)	297.606 (1.28)	252.638 (1.68)
2079	5.3296 (3.38)	7.5234 (2.18)	1.2191 (0.36)	1.2644 (0.23)	29.880 (3.69)	45.829 (2.14)	284.770 (1.46)	221.497 (2.22)
2106	5.4587 (3.49)	8.3499 (2.53)	1.2227 (0.37)	1.2786 (0.25)	31.388 (3.72)	52.201 (2.31)	272.611 (1.71)	193.149 (3.19)
2133	5.5722 (3.76)	9.1239 (2.79)	1.2258 (0.40)	1.2909 (0.27)	32.737 (3.88)	58.043 (2.30)	261.178 (1.85)	168.899 (3.60)

* Coefficient of variation (%) in parentheses.

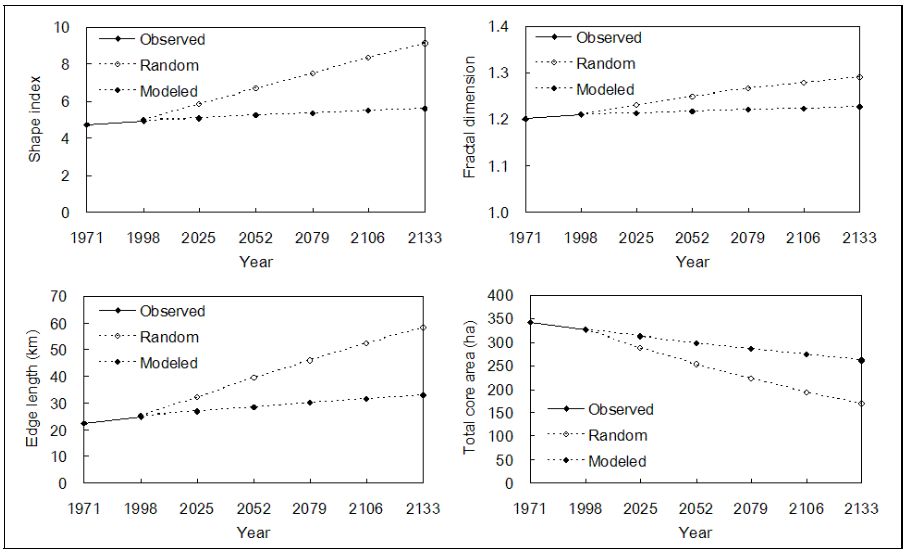

Fig. 6. Projected temporal trends of the 2 scenarios.

4. CONCLUSIONS

The results of this study showed that land cover conversions in human-dominated landscapes are not a random process either temporally or spatially. Although suitable for projecting temporal land cover changes, Markov models can not spatially predict land cover patterns. It can be seen in this study, ignoring the spatial differences may result in misleading interpretations. In this respect, probabilistic models such as logit models are helpful in identifying spatial characteristics of land cover changes. The simulated results in this study also showed that cultivated areas would have stronger edge effects than shape effects. Of the 4 landscape indices examined, the total edge length appeared to be more sensitive to cultivated areas than were the others. The higher coefficient of variation suggests that the index is also sensitive to cultivation patterns. For the measurement of shape effects, the fractal dimension is not recommended because cultivated areas would have little effect on it.

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