Model comparison applied to deforestation and reforestation

2 Land use / Land cover change dynamics in the Mexican highlands: current situation and long term scenarios

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Abstract
This paper examines the land use/land cover change dynamics in the Purepecha Region of the Michoacan State, Central Mexico. This region is representative of the Mexican Highlands in both its socioeconomic and ecological aspects.The vegetation consists primarily of pine-oak forests and pine forests. There are large areas used for agriculture and permanent crops –particularly avocado orchards-. The region is undergoing a complex pattern of land use/land cover change, including a rapid process of forest degradation and deforestation as well as the abandonment of agricultural areas leading to forest regrowth. We use remote sensing techniques to determine the regional land use/land cover change transition matrix for the period 1986-2000, and discuss the land use/land cover change dynamics. We then apply the GEOMOD model (Hall et al. 1995) to build long-term scenarios in the region. With this tool we identify the most important drivers for the deforestation process and build vulnerability maps on potential deforestation sites within the region in 2025.

Keywords: Land Use/Land Cover Change, GEOMOD, Purepecha region, Spatial Models, Deforestation

2.1 Introduction

Mexico has been classified as a megadiverse country. Because the country suffers from one of the highest rates of deforestation in the world (Velázquez et al. 2002a), the situation for forests in Mexico is critical (Masera 1996). Based upon the comparison of LU/LC maps for the entire Mexican territory between 1976 and 2000, the deforestation rates were evaluated as 0.25 and 0.76% per year for temperate and tropical forests, respectively (Mas et al. 2004).

The State of Michoacan, in the Central Mexican Highlands, is no exception. The state's temperate forests reach 1.5 million hectares, 40% of which have been degraded and show secondary vegetation. Twenty percent of the temperate forests in the Michoacan State are located within the Purepecha Region; this region has environmental and socio-economic conditions representative of the Mexican highlands. Timber harvesting is intense, and migration has accelerated in recent years bringing about structural changes in economic activities, which have created complicated processes of land use change (Alarcón-Chaires 1998).

Land use and land cover change processes represent a complex dynamics that depend on the type of cover, the ecological interactions, physical environmental, socioeconomic activities and other meteorological phenomena (Lindenmayer and Franklin 2002, Kaimowitz and Angelsen 1998). This chapter describes the land use change dynamics in the Purepecha Region and emphasizes the understanding of the deforestation process. We used the model GEOMOD2 to simulate land use/land cover change (Pontius et al. 2001), and to examine those factors that have a direct relationship with the regional deforestation process.

2.2 Text areas and data sets

The study area is located in the western center of Mexico in the state of Michoacan. Because most of the Purepecha population (name of the dominant ethnic group) lives in the central and northern regions of Michoacan, the area is denominated as the "Region Purepecha" (Fig. 2.1). It comprises 19 municipalities covering an area of 652,000 hectares. The region accounts for approximately 11.1% of the state's area, with a population of approximately 732,000 inhabitants (18.3% of the state total) dispersed among 927 settlements. The population density is of 1.12 inhabitants/ha. In Michoacan State, as well as in the Purepecha Region, emigration is very high; approximately 150,000 inhabitants from Michoacan immigrated to United States between 1987 and 1992 (Mendoza 2003). The migratory process has accelerated in recent years, particularly to the United States (Rivera 1998). Michoacan is the main producer of avocado worldwide. Since 1997, due to the end of the restrictions of exportation to United States, production notably increased. For 2000, the Tancitaro and Uruapan region produce almost one million tons of avocado (Hinojosa et al. 1999).

The region is mountainous; elevation ranges from 620–3,860 masl. Due to recent volcanic activity, andosols are the dominant soil type. The climate is temperate sub-humid with an average rainfall between 800 and

1,100 mm mainly concentrated in the summer, and average temperatures between 11°C and 14°C. The rough topography of the region results in a wide variety of microclimates. Michoacan presents a great variety of vegetation types. According to the National Institute of Statistics, Geography and Informatics (INEGI), the vegetation in the region Purepecha consists primarily of pine-oak forest, pine forest, agriculture and permanent crops.

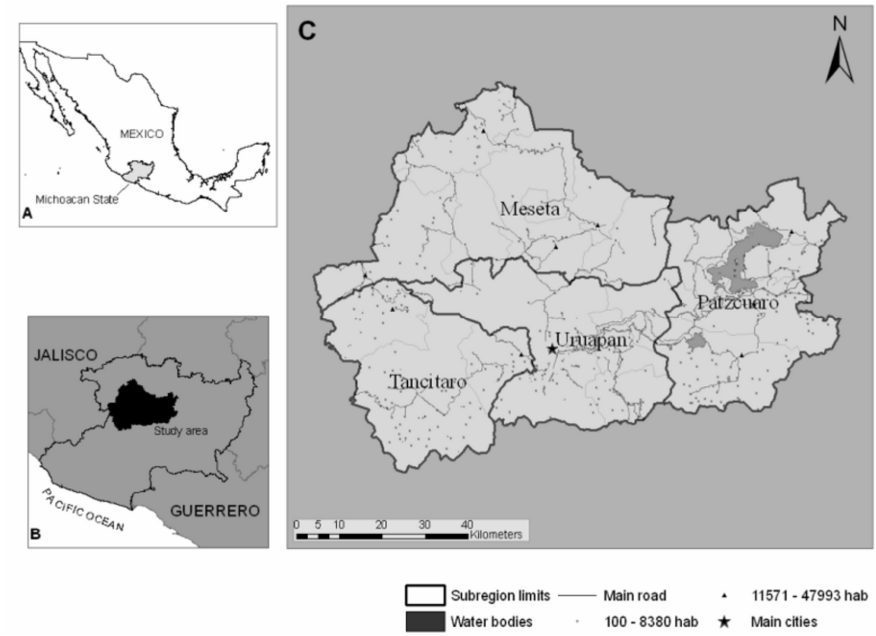

Fig. 2.1 Location of the study area. The area is located in the western center of Mexico in the state of Michoacán (A and B). The study area includes the Paztcuaro and Zirahuen lakes and was subdivided into four sub regions: Meseta, Patzcuaro, Uruapan, and Tancitaro (C)

2.2.1 Image classification

A classification of two Landsat images was carried out that corresponds to the years 1986 and 2000. The images were taken in the same months (February-April). The first one is part of the Landsat Thematic Mapper TM series, and the second one belongs to the Enhanced Thematic Mapper Plus ETM+ series. The interpretation of remotely sensed images was realized by a maximum likelihood supervised classification, using the IDRISI32 software. We created spectral signatures using training site data of fourteen vegetation types. For ten land-use categories we used 88 field validation points, for the remaining four categories the INEGI land use and cover and National Forest Inventory map were used (Palacio et al. 2000, INEGI 1980).

Table 2.1 Land Use/Land Cover classes in the Purepecha Region

Land use/Land Cover used in the National Forest Inventory (NFI 2000)	Land Use/Land Cover used in this study	Major Land Use/Land Cover clusters
Agriculture Rain-fed agriculture	Agriculture	Man Made Land Cover
Rain-fed agriculture with permanent and semi permanent cultures	Orchards	
Irrigation agriculture	Irrigated agriculture	
Oak Forest Montane cloud Forest	Oak Forest	Forest
Pine Forest	Pine Forest	
Pine-oak (Oak-pine) Forest	Pine-Oak Forest	
Fir Forest	Fir Forest	
Pine Forest with secondary vegetation Oak Forest with secondary vegetation Oak-Pine Forest with secondary vegetation	Forest with secondary vegetation	Forest with secondary vegetation
Subtropical Shrubs Subtropical shrubs with secondary vegetation	Scrubland	Scrubland/Grassland
Induced Grass land	Grassland	
Forest Plantations	Forest Plantations	Forest
Area without vegetation	Area without vegetation	Man Made Land Cover
Human settlements	Human settlements	
Water bodies	Water bodies	Water bodies
Tropical deciduous and subdeciduous forest Hygrophilous vegetation	Without classification	Without classification

We used the National Forest Inventory (NFI) (Palacio et al. 2000) in order to identify the same vegetation types. For the aim of this study, the 21 classes in the NFI, were regrouped into 15 classes (Table 2.1). We also grouped these 15 categories into five major land use/land cover clusters to better examine the overall dynamics of the regional land use change process. The first cluster included all primary forests LU/LC classes. The second cluster included secondary forests LU/LC classes. The third comprised all man-made LU/LC classes such as crops, orchards and human settlements. The fourth included all grasslands and the scrublands with or without secondary vegetation. The fifth included only the water bodies (Velázquez et al. 2002b).

2.2.2 Land Use/Land Cover Change Analysis

The land use/land cover change (LU/LC) analysis was performed using the ArcView3.2a software. An overlaying analysis was performed in order to assess pathways of change and locate sites where these changes occurred. Four processes of LU/LC change were identified: deforestation, degradation, recovery, and revegetation. Deforestation occurs when primary and/or secondary forests change to a man-made land cover. Any transformation from a primary land cover cluster into a secondary land cover cluster indicates degradation. Recovery includes changes from a secondary land cover cluster into a primary land cover cluster. Revegetation comprises changes from a man-made land cover into a secondary or primary land cover cluster.

Data Collection and Preparation

The methods used to estimate and simulate deforestation in the GEOMOD model are detailed in Hall and Dushku (2002) and Pontius (2006). The model requires as input the following mapped information: 1. Land use/land cover maps for two points in time used as the primary inputs; 2. A political map with the sub-regions used to highlight different patterns of land use change at a sub-regional level; 3. A selection of multiple potential candidate driver maps that conditioned changes to clear forest for agriculture or other human-dominated land use (e.g. elevation, soil type, precipitation, roads, hydrography). In our case, all digital map data required by the model was collected, corrected for projection differences, and converted to grid data layers of the same origin and extents. These consist of 914 rows by 1,245 columns, with a grid cell resolution of 100 by 100 meters. Then reclassified each land use/land cover map, the soils map, and the sub-regions map to represent land (1) and non-land (0) in order to create a 'MASK' that would ensure that information was available for analysis on all input maps. We did this by overlaying the binary maps until only the non-zero cells coincided. The final mask, therefore, included only those areas that were consistently identified as "land" in all maps. Then the distance from roads, towns, rivers and lakes was calculated. In the initial analysis each candidate driver map was classified into categories representing ½ kilometer distance from each of these potential physical features. After a first calibration these were reclassified to represent much smaller distances. Table 2.2 shows the final set of candidate driver maps, it includes the 5 "distance from" maps. The land use/land cover maps were reclassified to include only two classes. The land use type 1 for this study represents "only forest with primary vegetation". The land use type 2 represents human-impacted land use categories and includes secondary forests (Brown et al. 2007). The final set of candidate driver maps includes six maps, for the most significant see Table 2.3; all were then converted to ASCII format as required.

Table 2.2 Category delineation for candidate spatial pattern drivers used in the simulation with the GEOMOD model

Driver	Range of values	Units	# Classes	Class Width
Elevation	622-3836	Meters	20	200
Slope	52	Grades	10	1=0°, 2-9=5°, 10=10°
Aspect	0-360	Grades	10	1=plano, 2=0-22.5°, 3-9=45°, 10=22.5°
Soils	12	Nominal	12	1
Precipitation	700-2,000	Millimeters	7	1-3=100mm, 4-5=200mm, 5-7=300mm
Temperature (Dry season)	12°-33°	Grades	7	3°
Temperature (Raining season)	6°-36°	Grades	10	3°
Sub-regions	4	Nominal	4	1
Dist. From towns	8,528	Meters	30	284
Dist. From roads	4,709.56	Meters	24	200
Dist. From all water sources	15,368	Meters	32	500
Dist. From perennial water Source	20,976	Meters	42	500
Dist. From perennial streams	22,483	Meters	30	750

2.3 Methodology

2.3.1 Conversion rates

Conversion rates were assessed based on forest cover data, using a lineal formula:

$$\mathrm{D}R = \left[\frac{\mathrm{A}_1 - \mathrm{A}_2}{\mathrm{n}} \right] \tag{2.1}$$

Where D*R* is the deforestation rate (area/year); A_1 and A_2 are, respectively, initial and final forest areas, and n is the interval (years) during which the change in forest coverage is evaluated.

2.3.2 Long-term scenarios

In order to simulate the future evolution of the deforestation in the study area for the period 2000-2025, we used the GEOMOD model, which uses spatially distributed data. GEOMOD was developed by researchers at SUNY College of Environmental Science and Forestry (Hall et al. 1995) and uses digital raster maps of bio-geophysical attributes and socio-economic factors such as infrastructure, as well as digital maps of existing land use, to extrapolate the known pattern of land use/land cover from one point in time to other points in time.

2.3.3 Model calibration and validation

GEOMOD begins by categorizing each potential pattern driver map into categories or classes and adding the number of cells of each class that exist in the entire geographic region being analyzed. The model then adds how many cells of each of these categories lies in areas deforested between the first and second points in time. Then GEOMOD calculates the proportion of this sum for each class versus the sum of all cells of that exist in the region. This proportion indicates the degree to which land had been deforested in the past and is assigned to all forested cells of that class to indicate their "vulnerability" of being deforested in the future. We use individual driver maps and multiple combinations of calibrated driver maps to show areas of highest overall likelihood of deforestation, GEOMOD uses this map of "vulnerability" or "risk map" to simulate deforestation for a second point in time (see Fig. 2.6). The results were validated comparing the simulated 2000 deforestation map with the actual 2000 deforestation map to determine which combination of drivers yielded the most accurate prediction, the goodness of fit test for each simulated map produced is based on both the percent of cells simulated correctly and the positional agreement measured through the Kappa Index of Agreement (Pontius 2000). Since GEOMOD is interested in the more accurate spatial precision, we have used the Kappa for location or K location statistic, to measure goodness of fit. Kappa for location measures the degree to which a simulated map agrees with a reality map with respect to location; i.e., it estimates the success rate between the percentage of success of the model and the success due to chance alone (Pontius 2000). A kappa value of 0 indicates that GEOMOD cannot predict the landscape at the year 2000 better than at random (i.e., without information). Simulated maps do not necessarily match pixel-by-pixel with observed maps, however, they can present similar spatial patterns and land cover distributions. A fuzzy similarity index was used for comparing both maps. This index is based on the concept of fuzziness of location, in which a representation of a cell is influenced by the cell itself and, to a lesser extent, by the cells in its neighborhood (Hagen 2003) (see Chap. 8).

2.4 Results

2.4.1 Analysis of real LUCC between 1986 and 2000 for model calibration

2.4.1.1 Image classification

Fig. 2.2 shows the LU/LC map for the Purepecha Region for the year 2000. We also obtained the area of each LU/LC class (Table 2.3).

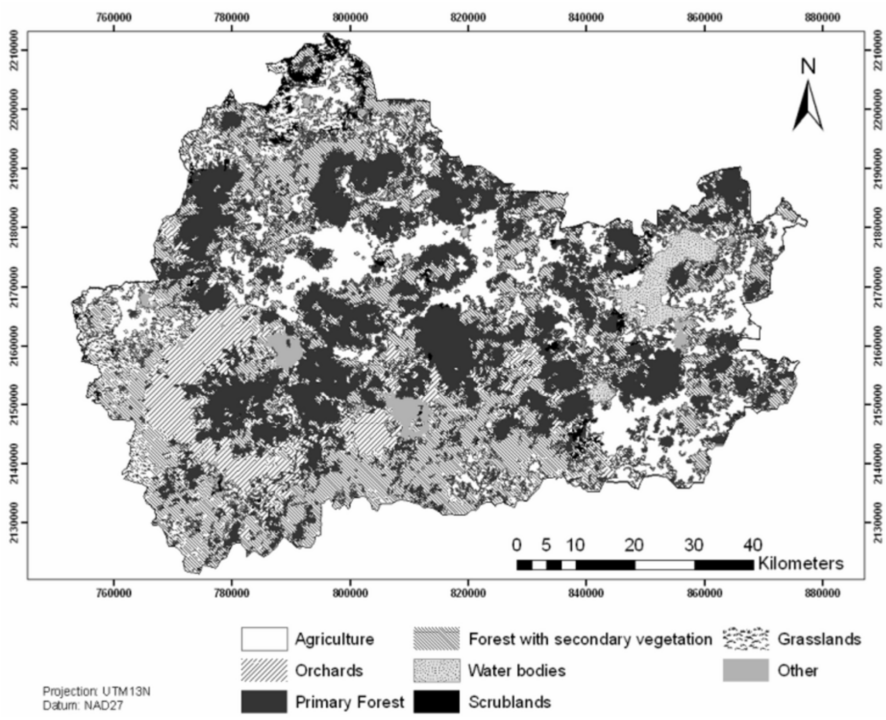

Fig. 2.2 Land Use/Land Cover map for the Purepecha Region in 2000

Table 2.3 Extent of Land use /Land covers classes in the Purepecha Region (ha and % of total area)

LU/LC class	1986		2000	
	Ha	%	ha	%
Pine Forest	102,013	17.71	82,310	14.35
Pine-Oak forest	86,926	15	85,449	14.89
Oak forest	11,996	2.0	9,609	1.67
Fir-forest	7,729	1.34	7,384	1.29
Forest Plantation	580	0.13	768	0.2
Secondary forest	95,541	16.59	150,864	26.2
Scrubland	8,159	1.41	10,052	1.75
Grassland	12,440	2.16	14,463	2.52
Area without vegetation	5,961	1.03	3,771	0.6
Human settlements	7,219	1.2	8,655	1.51
Agriculture	187,792	32.6	132,425	23.08
Irrigated Agriculture	7,435	1.29	5,071	0.88
Orchards	28,011	4.86	51,120	8.91
Water bodies	11,994	2.08	11,832	2.06

2.4.1.2 Land use cover change processes

Table 2.4 shows the land use/land cover change matrix for the period 1986-2000 for the five clusters. The last column shows the area (in hectares) for each cluster in the year 2000, while the last row shows the area of each class in the year 1986. From the 573,621 ha included in the study area, 27% of primary vegetation, 10% of secondary vegetation and 29% of man-made land classes showed no change during the period.

The process of land use change in the Purepecha Region is very complex with a net average loss of 4,232 ha of forests per year. 68% of total deforestation resulted from the transformation of primary to secondary forests. These last are very dynamic and play an important role within the region. In absolute terms, secondary forests increased 54,000 ha during the period, due to both the degradation of primary forests and also to the revegetation of abandoned agriculture lands. Approximately 16,000 ha of secondary forests were converted to agricultural lands, particularly to avocado orchards. As described by Velázquez et al. (2002b) this process shows that secondary forests are basically a transitional phase for the change from primary forests to non-forests land classes.

Table 2.4 Land cover change matrix for the Purepecha Region 1986 - 2000 (ha)

2000 (t_2)	1986(t_1)						
	Forests	**Scrubland/Grassland**	**Water bodies**	**Man-made**	**Sec Forest**	**Total**	**%**
Forests	156,915	428	19	10,287	17,870	185,521	32.34
Scrubland/ Grassland	436	9,852	61	10,057	4,109	24,515	4.27
Water bodies	0	5	11,686	79	60	11,831	2.06
Man-made	11,764	5,388	155	167,063	16,597	200,965	35.03
Sec Forest	39,984	4,926	73	48,912	56,894	150,789	26.29
Total	209,098	20,599	11,994	236,398	95,531	573,621	
%	36.45	3.59	2.09	41.21	16.65		100.00

Transition probabilities among the different clusters are shown in Fig. 2.3. It can be seen that forests and agriculture are the most stable classes with 75% and 71% of their respective area remaining as such in the study period. On the other hand, secondary forests and scrublands are very dynamic with only 60% and 48% of their respective area remaining in the same class during the 14 year of the study period. Secondary forests recover to primary forests or are degraded to agriculture roughly in the same proportion (17% and 19% respectively). Scrublands also degrade to man-made classes (26%) or recover to secondary forests (24%). Approximately 6% of total primary forests are deforested completely and another 19% are degraded to secondary forests.

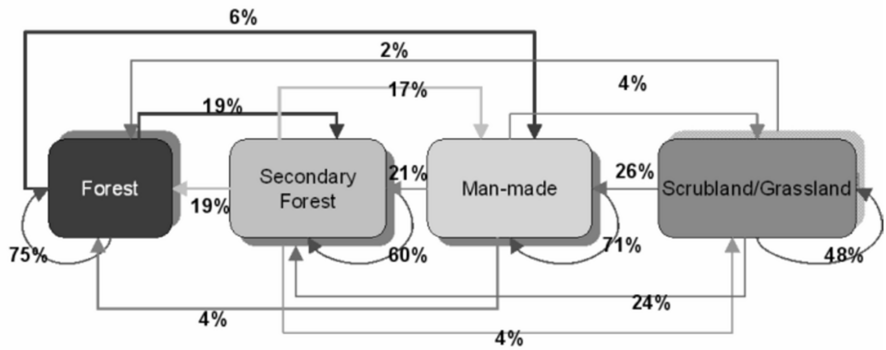

Fig. 2.3 Flowchart showing the transition probabilities among the different LU/LC classes in the period 1986-2000

The conversion rates between 1986 and 2000 are shown in Fig. 2.4 for all the land classes considered in the study. The bars above zero represent the types of cover which decreased during the period, whereas the bars under the zero indicate the increase of cover. All the primary forests lost areas, with the oak forest the one with the fastest deforestation rate. Rainfed agriculture also lost area at a high rate (2.5% per year). On the other hand, avocado orchards increased at a very fast rate (4.4%/yr) as well as forests with secondary vegetation (3.3%/yr).

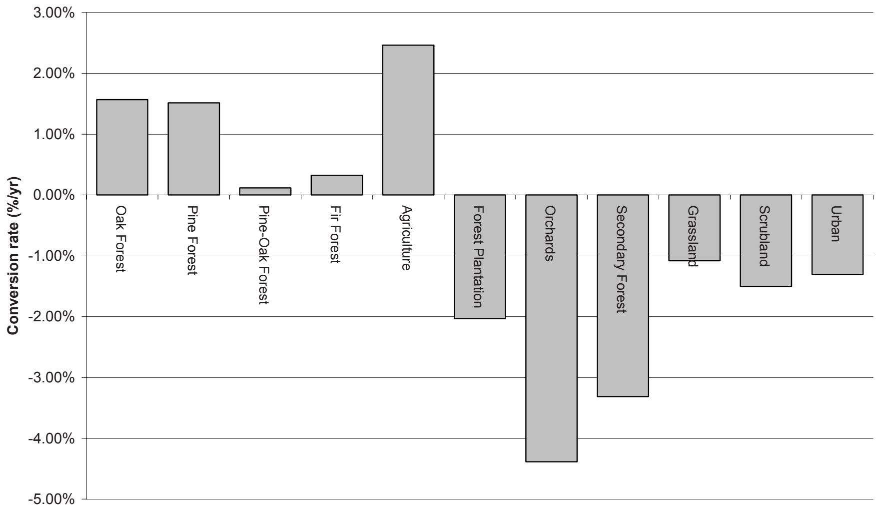

Fig. 2.4 Conversion rates associated to the different LU/LC classes

2.4.1.3 Land Use/Land Cover Change Dynamics

Several processes have contributed to the land use/land cover change dynamics within the region. These processes can be better understood dividing the region into 4 main sub-regions: Tancitaro, Patzcuaro, Uruapan, and Meseta (See Fig. 2.1). In Tancitaro, the deforestation process dominates the LU/LC change dynamics, particularly due to the establishment of avocado orchards. In fact the area devoted to avocado plantations increased 128% in Tancitaro between 1986 and 2000. Almost 8,000 ha of primary pine forests and 9,400 ha of secondary forests were lost to this cause. In Uruapan the deforestation and degradation were also the most important processes.

The opposite processes (revegetation and recovery) are particularly important in the Meseta and Patzcuaro Lake sub-regions. The total area of shrubs and forest with secondary vegetation has increased in these two sub-regions due to processes of land abandonment. Degradation is also present, particularly due to the conversion of pine primary forests to forests with secondary vegetation.

The extent of deforestation, degradation, recovery and revegetation within the region is displayed cartographically in Fig. 2.5 showing the critical areas where environmental loss prevails.

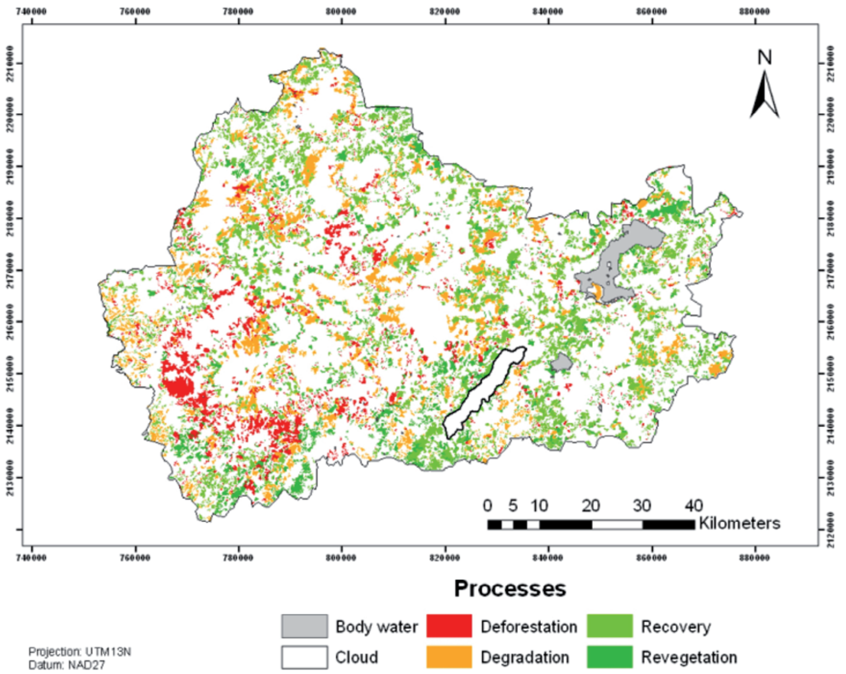

Fig. 2.5 Land use cover change processes (deforestation, degradation, recovery and revegetation) in the Purepecha Region (1986-2000)

2.4.2 Land use/Land Cover Change modelling

2.4.2.1 Long-Term Scenarios

As mentioned above, we used the GEOMOD2 model to simulate the spatial distribution of future deforestation in the region from the year 2000 to 2025. To understand those factors that explain the spatial distribution of forest clearing for human uses in the region, we analyzed four sub-regions. Then we reclassified each land use map in two land use types: as type 1 all primary forests and all other land used types included secondary forest and man-made vegetation type as type 2. Finally, we calculated the deforestation rate for each sub-region (Table 2.5).

Table 2.5 Deforestation rates for each sub-region

Sub region	Forest cover 1986 (ha)	Forest cover 2000 (ha)	Deforestation rate (ha/year)
Uruapan	52,640	40,097	896
Tancitaro	42,258	28,470	985
Patzcuaro	44,036	35,977	576
Meseta	72,206	53,239	1,355
			3,812

GEOMOD was run first with each of the eleven selected drivers, followed by the multiple combinations of driver maps with the addition of drivers, one driver at a time. The addition of each driver improved our ability to replicate the 2000 landscape for the entire region. The success of each driver is measured by the Kappa for location. Different pattern drivers exhibit more or less ability to improve on projections depending on the sub-region analyzed; however the best Kappa for the entire region (0.177) was a combination of four driver maps, because they were the most significant determinant of deforestation pattern. We used this combination of drivers to make the long term scenarios in Fig. 2.6.

As seen in Table 2.6, the individual most successful driver for the entire region and Uruapan sub-region was distance to localities, for the Tancitaro sub-region the most successful driver was precipitation, followed by elevation, and slopes; in the Meseta sub-region the best individual driver was slope. In the Patzcuaro sub-region, the combination of drivers was the most successful.

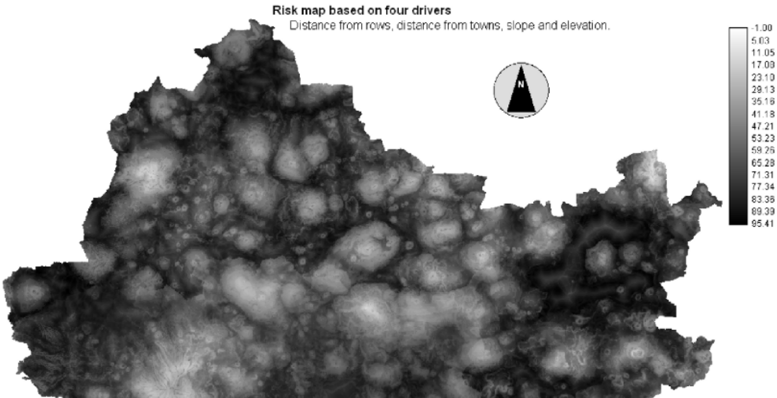

Fig. 2.6 Deforestation vulnerability map based on analysis of empirical areas of deforestation versus four candidate drivers maps

Table 2.6 Final set of candidate driver maps. The cells colored in dark gray, gray, and light gray indicate the three drivers (from high to low, respectively) giving the highest Kappa location index

		REGION		URUAPAN		TANCITARO		PATZCUARO		MESETA	
1	Distance from towns	88.800	0.128	88.880	0.216	86.760	0.131	91.680	0.068	87.910	0.095
2	Distance from roads	88.660	0.118	87.740	0.136	86.780	0.132	91.880	0.091	88.080	0.108
3	Elevation	88.590	0.112	87.900	0.148	88.980	0.277	91.480	0.047	86.770	0.009
4	Slope	88.480	0.103	86.840	0.073	85.560	0.118	91.880	0.091	88.258	0.121
5	Temperature (Rainy season)	88.328	0.091	87.715	0.134	84.769	0.235	91.070	0.006	86.648	0.007
6	Temperature (Dry season)	88.290	0.088	87.470	0.117	88.030	0.214	91.300	0.033	86.810	0.013
7	Precipitation (Rainy season)	88.220	0.083	86.180	0.026	89.190	0.291	91.110	0.005	86.924	0.083
8	Distance from water sources (rivers and lakes)	88.049	0.070	87.921	0.148	86.939	0.142	91.110	0.005	86.610	-0.022
9	Distance from permanent streams	87.970	0.064	87.850	0.144	86.800	0.134	91.040	-0.003	86.576	-0.005
10	Soils	87.910	0.059	86.780	0.068	86.342	0.103	90.790	-0.031	87.525	0.066
11	Distance from lakes	87.912	0.059	86.780	0.068	86.342	0.103	90.790	-0.031	87.520	0.066
12	Aspect	87.690	0.022	85.650	-0.011	85.410	0.042	91.360	0.033	87.750	0.083
Combinations											
13	Drivers 1 and 2	88.9424	0.1391	88.651	0.1999	86.929	0.1418	91.691	0.0693	88.3667	0.1287
14	Drivers 2 and 3	88.9124	0.1368	88.865	0.215	89.1425	0.2871	91.7384	0.0746	86.819	0.0128
15	Drivers 1, 2 and 3	89.2123	0.1601	88.879	0.216	88.7982	0.2645	91.8794	0.0904	87.79	0.0855
16	Drivers 1, 2, 3 and 4	89.4284	0.177	88.999	0.2244	88.5129	0.2458	92.1072	0.1159	88.3514	0.1276
17	Drivers 1,2,3,8 and 10	89.0298	0.1459	88.141	0.1639	88.1407	0.1639	91.7371	0.0744	87.7232	0.0805

We used the annual rate of deforestation and the final risk map to simulate the future (see Fig. 2.6). Assuming linear deforestation rates, 95,000 ha of forests will disappear in the 25 year period. This figure represents a loss of 24% of the forests by 2010 and up to 60% by 2025. The maps with the simulated deforestation process for the years 2000, 2005, 2010, 2015, 2020 and 2025, show those places more likely to be deforested. The most vulnerable forests are located in the surroundings of the Tancítaro Peak, close to the city of Uruapan and within the Meseta sub-region (Fig. 2.7). Within the different forest types, pine-oak forest loose 56% of their total area by the year 2025, oak forests 54%, pine forests 46% and fir forests 31%.

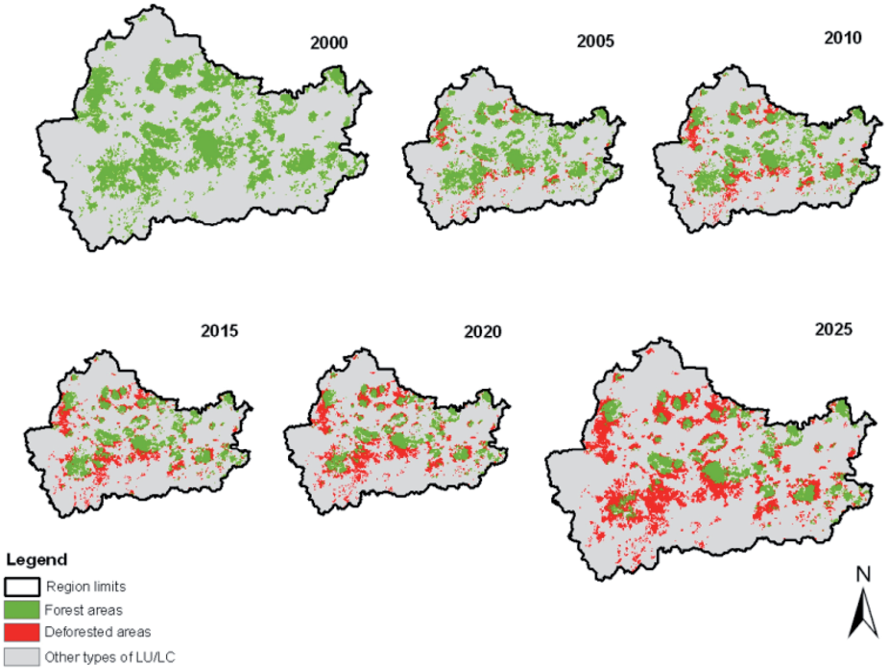

Fig. 2.7 Simulated maps of forest cover change between 2000 and 2025

2.5 Validation and discussion of results

2.5.1 Simulations

The success in the simulation process was measured by the Kappa statistics, measuring the different drivers individually and grouped. The driver with the highest Kappa was total rainfall during the rainy season (Kappa 0.291) within the Tancitaro sub-region. This latter sub-region also showed the most agreement between simulated and actual maps, and was the area with the highest deforestation rates within the Purepecha Region, particularly due to conversion of forests to avocado orchards.

In general, both within sub-regions as well as within the entire region, the percentage of cells successfully simulated was high (84-92%), but the Kappa statistics was low (-0.031 to 0.291). In fact, it has been found that low Kappa indicates that the deforestation pattern (exact location of clearings) is difficult to predict, at least using the present approach and variables. Hall (2002) has found a similar result in regions where little net change is detected in the time period analyzed, as is the case with the Purepecha Region.

On the other hand, we found that the model increased the predictive power when several drivers were grouped together. Specifically, the group of drivers: distance to villages, distance to roads, elevation, and slope was the most successful in our simulations. Mas (1996) reports that these last three drivers are usually important in the analysis of deforestation processes, as they are closely interconnected (e.g., at higher slopes less density of villages or roads).

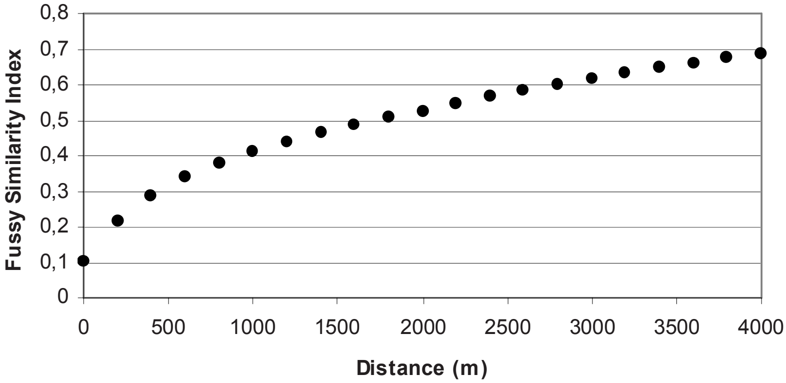

Fig. 2.8 Fuzzy Similarity Index as a function of distance (positional fuzziness)

Fuzzy similarity index was calculated using distance from 0 to 4,000 m. Based upon a null distance, this evaluation corresponds to an evaluation in which only exact coincidences of changes between the simulated and reality maps are considered as correct. In juxtaposition, based upon large distance, the evaluation tolerates positional shift between the simulated and the real patches of deforestation. Fig. 2.8 shows the fuzzy similarity index as a function of positional fuzziness. When increasing the positional fuzziness, the index is greatly augmented, which shows that the model is roughly able to identify the location of change.

2.5.2 Land Use /Land Cover Change Dynamics

As stated before, the pattern of land use change was complex, with many transitions among land classes and a few net changes between 1986 and 2000. One of the most important changes is the reduction of the area under rainfed agriculture, and the increase of forests with secondary vegetation.

This is the result, on the one hand, of the abandonment of agriculture fields on sloppy areas due to migration of local farmers, and their gradual re-vegetation. This process has been documented by several authors (Velázquez et al. 2002, López 2003, Alarcón-Chaires 1998). On the other hand, secondary forests have also increased as a result of the degradation of primary forests, which are subject to a non-sustainable forest harvesting regimes (Masera et al. 1996). Deforestation has also been important, mostly through the conversion of both primary and secondary forests to avocado orchards (a process that also affected rainfed agriculture) in those regions suitable for this commercial crop. This process is due entirely to economic reasons, as avocado plantations greatly increases the farmer's income per hectare relative to traditional crops (such as maize) (Ruiz 2003).

Because revegetation processes in the region are not linked to specific government policies, but mostly to migration due to lack of local economic opportunities, it is difficult to predict its future faith. On the other hand, evidence points out at a continuing of the degradation and deforestation of primary forests, as no integrated forest management plan has been successfully implemented within the region (Linck 1988, Masera et al. 1996, Klooster 2000, Klooster and Masera 2000).

2.6 Conclusions

Spatially-explicit models like GEOMOD are useful tools to evaluate the main drivers associated to LU/LC change processes. These models, also allow for the specification of the location of future projected deforestation (Menon et al. 2001). Plus, GEOMOD has demonstrated that it is reasonably easy to understand and to apply it in diverse projects (Menon et al. 2001). However, several constraints still limit the predictive power of the GEOMOD model. The model can simulate only one land use change process at a time, which limits capturing the complexity of the land-use change dynamics. In our case, only the deforestation proccess was modelled, setting aside other proccess of interest within the Purepecha Region, such as recovery, degradation and revegetation. We suggest that spatially explicit models must include at least more than one LU/LC change dynamic, in order to achieve a better diagnosis of areas more vulnerable to deforestation. At a methodological level, the simulations performed in this study can be greatly improved by using a third time period to validate the deforestation predictions.

In the future, it will be important to develop simulation models that incorporate the dynamic interactions among the different drivers. Specifically, it will be important to model the dynamic-temporal and spatial-processes associated with the decisions of the regional economic agents.

This approach will help isolate the effect of each of the exogenous variables, and to model their response given changes in the variables and parameters incorporated in the model. More importantly, it will be possible to perform predictions about the land use change patterns under different socio-economic, political and demographic conditions.

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