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Analyze and predict processes of deforestation using logistic regression and gis (a case study of northern ilam forests, ilam province, Iran)

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ABSTRACT

This study aims to predict spatial distribution of deforestation and detects factors influencing forest degradation of Northern forests of Ilam province. For this purpose, effects of six factors including distance from road and settlement areas, forest fragmentation index, elevation, slope and distance from the forest edge on the forest deforestation are studied. In order to evaluate the changes in forest, images related to TM1988, ETM^{+}2001 and ETM^{+}2007 are processed and classified. There are two classes as, forest and non-forest in order to assess deforestation factors. The logistic regression method is used for modeling and estimating the spatial distribution of deforestation. The results show that about 19,294 ha from forest areas are deforested in the 19 years. Modeling results also indicate that more deforestation occurred in the fragmented forest cover and in the areas of proximity to forest/non forest edge. Furthermore, slope and distance from road and settlement areas had negative relationships with deforestation rates. Meanwhile, deforestation rate is decreased with increase in elevation. Finally, a simple spatial model is presented that is able to predict the location of deforestation by using logistic regression. The validation was also tested using ROC approach which was found to be 0.96.

Introduction

Three well-known global changes are increasing carbon dioxide in the atmosphere, alterations in the biochemistry of the global nitrogen cycle and continuing land-use/land-cover change(LU/LC) (Vitousek, 1994), which generates many environmental consequences globally and locally, such as the release of greenhouse gases, the loss of biodiversity and the sedimentation of lakes and streams (Walker, 2004). In particular, it is recognized as the major driver of the loss of biodiversity and ecosystem services (Haines-Young, 2009). The effects of land-use changes on biodiversity may be greater than climate change, biotic exchange, and elevated carbon dioxide concentration at the global scale (Sala, 2000). Deforestation is known one of the most important elements in LU/LC. Globally, deforestation has been occurring at an alarming rate of 13 million hectares per year (FAO, 2005).

The Mediterranean area is one of the most significantly altered hotspots on Earth (Myers et al., 2000), It has been intensively affected by human activity for millennia (Covas and Blondel, 1998; Lavorel et al., 1998; Blondel and Aronson, 1999; Vallejo et al., 2005). As a result, only 4.7% of its primary vegetation has remained unaltered (Falcucci et al., 2007). Agricultural lands, evergreen woodlands and maquis habitats that dominate the Mediterranean basin are the result of anthropogenic disturbances over centuries or even millennia (Blondel and Aronson, 1995; Blondel, 2006).

Although Iran has 14.4 million hectares of forestlands, it is still not safeguarding its natural heritage properly. A report by, the United Nations' Food and Agriculture Organization (FAO), does not present a hopeful scenario for the Iranian environment. As an example, it reports that 11.5% of the country's northern forests have been destroyed beyond recognition (http://earthtrends.wri.org). Its high deforestation rate has placed

Iran among the top ten Asia and Pacific countries that destroy forests, with economic losses estimated at 6,800 billion rials (http://earthtrends.wri.org).

The Zagros region is located in the west of Iran running from northwest to southeast. Total forest area is about 5.2 million hectares. Population pressure has led to encroachments on the forestland, for agricultural and garden use, collection of fuel wood, mining, human settlements, grazing, utilization of branches and leaves of oak trees for feeding domestic animals, etc. People have been forced to be highly dependent on these degraded forests and so the forests have been reduced quantitatively and qualitatively. Since 1965 natural regeneration has been severely reduced while pests and diseases have increased (Fattahi, 2003).

Amini et al.(2009) carried out a study on deforestation modeling and correlation between deforestation and physiographic parameters, man made settlements and roads parameters in the Zagros forests (Armerdeh forests, Baneh, Iran) using remote sensing and Geographic Information System (GIS). The result of forest change detection using forest maps of 1955 and 2002 showed that 4853 ha of the forest area have been reduced and 953 ha increased in this period. The Spearman correlation test and logistic regression model were used to investigate correlation between changed forests and the mentioned parameters. The result showed that there is an inverse relationship between deforestation and distance from roads. Minimum and maximum deforestation were at north and east aspects, respectively. The result of applying logistic regression

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model indicated that distance from road is more effective than other parameters on deforestation in the study area.

Lambin (1994) and Mas et al. (2004) mention that deforestation models are motivated by the following potential benefits

(1) to provide a better understanding of how driving factors govern deforestation,
(2) to generate future scenarios of deforestation rates,
(3) to predict the location of forest clearing and,
(4) to support the design of policy responses to deforestation.

According to Kaimowitz and Angels(1998), one way to model deforestation is to make use of empirical models. Several studies have analyzed land-use change under these approaches (Mertens and Lambin, 2000; Pontius et al., 2004; Pontius and Spencer, 2005; Rogan et al., 2008 and Schneider and Pontius, 2001). Logistic regression performs binomial logistic regression, in which the input dependent variable must be binary in nature, that is, it can have only two possible values (0 and 1). Such regression analysis is usually employed in estimating a model that describes the relationship between one or more continuous independent variable(s) to the binary dependent variable. Logistic regression analysis fits the data to a logistic curve instead of the line obtained by ordinary linear regression. In addition to the prediction, logistic regression is also a useful statistical technique that helps to understand the relation between the dependent variable (change) and independent variables (causes) (Mas et al., 2004).

In the particular case of deforestation, the spatial forest change is a categorically dependent variable, which results from the interaction of several explanatory variables. Logistic regression and GIS have been demonstrated as useful tools to analyze deforestation by many authors (Echeverria et al., 2008; Etter et al., 2006c; Loza, 2004; Ludeke et al., 1990; McConnell et al., 2004; Rossiter and Loza, 2008 and Van Gils and Loza, 2006).

Logistic regression analysis has the advantage of taking into account several independent explanatory variables for prediction of a categorical variable (Van Den Eeckhaut et al., 2006). In this case, the dependent variable is either change or no change that has occurred in the forests areas.

Landsat MSS, TM and ETM^+ data have been broadly employed in studies toward the determination of LU/LC since 1972, the starting year of Landsat program, mainly in forest and agriculture areas (Campbell, 2007). The rich archive and spectral resolution of satellite images are the most important reasons for their use.

The aim of change detection process is to recognize LU/LC between two or more periods of time (Muttitanon and Tiipathi, 2005). There are many techniques developed in literature using post classification comparison, conventional image differentiation, image ratio, image regression and manual on-screen digitization of change principal components analysis and multi date image classification (Lu et al., 2005). A variety of studies have addressed that post-classification comparison was found to be the most accurate procedure and presented the advantage of indicating the nature of the changes(Mas, 1999; Yuan et al., 2005). In this study, change detection comparison technique (at the pixel level) (i.e., maximum likelihood method) was applied to the LU/LC maps derived from satellite imagery.

The main objective of this study is to analyze and predict processes of forest conversion in the Zagros forests in western Iran. In order to reach the goal, the following specific objectives are considered:

(1) To determine and quantify forest changes that occurred in the Zagros forests from 1988 to 2007.
(2) To identify and analyze the most significant explanatory variables that lead to forest conversion in the Zagros forests.
(3) To establish a predictive model based on logistic regression and its validation

Materials and Methods

Study area

The study area is situated in the province of Ilam, west of Iran between 33º35´ and 33º43´ latitude and between 46º17´ and 47º13´ longitude (Figure 1) and covers about, (225,593), ha. The main species of these forests consists; Quercus brantii, Q. infectoria and Q. libani that dominant species is Q. brantii. It covers a diversity of elevation, slope, population and land-use, etc. Beside the undamaged natural environment in some parts, a major part of the area has been changed by agriculture and grazing activities (Fattahi, 2003).

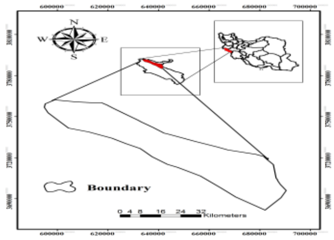

Fig. 1: Location of study area

Land-cover maps

Multi-temporal Landsat satellite images from April 01, 1988(path 167, row 37), March 20, 2001 and May 24, 2007, are obtained from the Global Land Cover Facility (http://www.landcover.org), University of Maryland. The dates of these three images are chosen to be as closely as possible in the same vegetation season. The resolutions of all images are adjusted from 28.5 m * 28.5 m to 30 m * 30 m. All visible and infrared bands (except the thermal infrared band) are used for the purpose of classification. Remote sensing image processing is performed using IDRISI Andes 15.0.

The 1:25,000 digital topographic maps of the national cartographic Center of Iran have been used for geo-referencing of above mentioned three images. A Digital Elevation Model (DEM) generated from 20-m contour lines are used to create slope and elevation maps. Digital Elevation Model (DEM) is produced from the standard topographic maps with the scale of 1:25,000. DEM is created by using ArcGIS 9.2 GIS software. Road networks and human settlements are manually digitized using ArcGIS 9.2 at the same scale. Pixel dimensions of all maps are in 30*30 m resolution.

Pre-processing

Landsat 2007 image is geo-referenced (Universal Transver Mercator-UTM(zone 38N), WGS84) to the maps of DEM, road networks, and human settlements, with an RMS error of less than 5 m by using nearest neighborhood resampling method. The other two Landsat images are then geo-referenced to the 2007 image (image to image registration), with an error of less than 10 m. The radiometric corrections and systematic errors are removed from the data set providers.

The model discussed in this paper follows four sequential steps: (1) Elaboration of maps of deforestation obtained by overlaying maps of forest-cover from more than one point in time, (2) Quantification of the relationships between deforestation and the causes (3) Statistical selection of the most significant explanatory variables, (4) Prediction of future deforestation in a business-as-usual way.

Methods

IDRISI Andes 15.0 was used to determine deforestation rates using three different land-use/land-cover maps from 1988, 2001 and 2007. The land-use/land-cover map of 1988 is produced by supervised maximum likelihood classification using training sites to identify forest, river, cropland, rangeland, barren land and settlement areas. The same methodology is applied to produce the land-use/land-cover maps of 2001 and 2007. Then, the classified land-use/land-cover maps are reclassified into two categories as forest and non-forest. Only forest areas are reclassified as "forest". While river, cropland, rangeland, barrenland and settlement areas are reclassified as "non-forest". The change from forest to non-forest is classified as deforestation. Finally, these maps are used to calculate the area of each land-use/land-cover type at each time period and to measure the deforestation rate from 1988 to 2007.

Classification accuracy is evaluated by calculating overall accuracy and Kappa coefficient using an independent sample of 116 Ground Control Points (GCPs) obtained from field work. Areas of forest are calculated for the three dates and then annual rates of forest clearing are estimated. As a following step, images are overlaid in order to produce a digital map of deforestation that represents changes in forest cover. Therefore, the deforestation maps present only two classes: forest persistence (forest in both dates) and deforestation coded 0 and 1, respectively (Figure 5 and 6).

The drivers

The first step for deforestation modelling is to identify and collect information about factors that play a major role in the deforestation occurrence. An attempt is made to determine the relationship between deforestation, and environmental and socioeconomic factors, which are considered as priori elements that could influence deforestation such as distance from settlements, distance from roads, distance from forest edge, elevation, slope and forest fragmentation index. All these variables are integrated in a GIS and co-registered geometrically with the forest-cover-change map derived from the analysis of remote sensing images. Several spatial explanatory variables describing potential proximate causes of deforestation are generated as follow:

1. Elevation: A Digital Elevation Model (DEM) is constructed from the contour lines. Where the lines are digitized at the 1:25,000 scale, at intervals of 20 meter. The resulting elevation map is binned with 200 meter intervals.
2. Slope: Slope is another important factor that is generated from elevation using ArcGIS 9.2.
3. Distance from forest edge: It is calculated as a series of one-pixel-wide buffers expanding from all interfaces between pixels classified as forest and non-forest. To remove the influence on this distance, calculations of isolated pixels are classified as forest or non-forest, and the land-cover map is first smoothed using a 3*3 pixel low pass filter. For this smoothing, the most frequently occurring class in the window is assigned to the central pixel of a moving window.
4. Distance to the nearest road: This variable is calculated as a series of buffers of 100 m expanding from each road segment. Most of the roads in the study area are gravel roads with quality largely dependent on the maintenance efforts and it is highly variable in time. Each road is, therefore, treated as equally suitable for transport of goods and people.
5. Distance to the nearest settlement: It is calculated as a series of buffers of 100 m, expanding from each center. Only the officially registered village, district and town centers are taken into account. The following procedure is used to obtain the variable distances for steps 4 and 5.

(1) Road networks and human settlements shape files were imported.
(2) Raster files were created from each of the vector files.
(3) The Operator DISTANCE was applied.

6. Forest fragmentation index: In this study, fragmentation index is estimated using Matheron method (Matheron, 1970). Matheron method, calculated in 3*3 pixels windows, is defined as:

$$M = \frac{N_{F-NF}}{\sqrt{N_F} * \sqrt{N}}$$

where N_{F-NF} is the number of boundaries between forest and non-forest pixels, N_f is the number of forest pixels and N is the total number of pixels. The numerator measures the number of pairs of adjacent pixels classified as forest and non-forest (i.e. the length of the perimeter line of forest pixels) and the denominator normalizes this count by the size of the forest and entire area (Mertens and Lambin, 1997).

Logistic Regression Model (LRM)

Forest conversion is modelled and analyzed using logistic regression model (LRM) in IDRISI Andes 15.0. The purpose of modelling was (i) to assess the relative signification of six explanatory variables on forest change during the period 1988-2007; and (ii) to predict probability of deforestation for future. LRM is a variation of ordinary regression which is used when the dependent (response) variable is a dichotomous variable.

In this study, as mentioned before, the dependent variable is a binary presence or absence event, where 1= forest change and 0= no change, for the period 1988-2007. The logistic function gives the probability of forest change as a function of the explanatory variables. In other words, the probability of forest change for each pixel is a function of the values that the other variables have for the same pixel. According to Schneider and Pointius (2001) the function is a monotonic curvilinear response bounded between 0 and 1, given by a logistic function of the form:

$$p = E(Y)\frac{exp^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots)}}{1 + exp^{(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots)}} \quad (1)$$

where: p is the probability of forest loss in the cell, E(Y) the expected value of the binary dependent variable Y, β_0 is a constant to be estimated, β_i's are coefficients to be estimated for each independent variable X_i. The logistic function can be transformed into a linear response with the transformation:

$$p' = \log_e\left(\frac{p}{1-p}\right) \quad (2)$$

Hence

$$p' = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \quad (3)$$

The transformation (Eq. (2)) from the curvilinear response (Eq. (1)) to a linear function (Eq. (3)) is called a logit or logistic transformation. The transformed function allows linear regression to estimate each β_i. Since each of the observations is a pixel, the final result is a probability score (p) for each pixel.

In LRM, the significance of the coefficients β_i is tested with the Wald test, which is obtained by comparing the maximum likelihood estimate of every β_i with its estimated standard error (Hosmer and Lemeshow, 1989; Eastman, 2006). It is the coefficient divided by its standard error. Thus, if the relative error is high, the Wald statistic is small. This gives an idea of the significance of each predictor: the greater the absolute value, the more significant. Note that the sign of the Wald statistic is the same as that of the coefficient, and thus gives the direction of the effect: increase or decrease in probability due to the predictor.

Accordinge to Ayalew and Yamagishi (2004), in order to appropriately interpret the meanings of Eq. (1), one has to use the coefficients as a power to the natural log(e). The result represents the odds ratio or the probability that an event will occur divided by the probability that it fails to do so. If the coefficient is positive, its transformation to log value will be greater than one, meaning that the event is more likely to occur. If it is negative, then the transformed log value will be less than one and the odds of the event occurring decrease. A coefficient of 0 has a transformed log value of 1, and it does not change the odds one way or the other. For a positive coefficient, the probability plotted against the values of an independent variable follows an S-shaped curve. A mirror image will be obtained for a negative coefficient (Ayalew et al., 2005).

Calibration of the Model

To calibrate the LRM, the explanatory variables are incorporated in the IDRISI's LRM as independent variables. The forest change for the period 1988-2001 is incorporated as the dependent variable. The stepwise method is used to select the best set of predictor variables since the study considered 6 different predictor sets. Finally, Van Gils and Loza (2006) methodology is used to select the best-fitted model with the minimum amount of predictors measured by means of the Akaike Information Criterion (AIC) index. The smaller the AIC is, the better the fit of the model. The results are the regression equation of the best-fitted predictors set and a map of probability of deforestation.

Prediction of the Model

The prediction for forest change between the year 2001 and the year 2007 is performed using the obtained probabilities of deforestation for the year 2001. For the new prediction, the dynamic variables such as distance from forest edge, distance from roads and fragmentation index are changed as long as they were in the year 2001. The variables, distance from settlements, elevation and slope remained the same. The result is a new map of probability of forest change for the year 2007.

Model Validation

The observed forest change map of 2007 is used to assess the accuracy of probability of forest change with the Relative Operation Characteristic (ROC) curve, which is an effective and widely used method for evaluating the discriminating power of a statistical model (Hu and Lo, 2007; Pontius and Schneider, 2001). Eastman (2006) also mentions that ROC can be used to determine how well a continuous surface predicts the locations given the distribution of a Boolean variable (in this study, forest change is the Boolean variable). A ROC curve is a graph of the true positive and false positives fractions. The ROC works for two or more land types. If a grid cell is simulated as change in a scenario, it is a 'positive'. Therefore, a 'true-positive' is a cell which is categorized as change in both actual and the modeled scenario. Conversely, a 'false-positive' is a cell that is categorized as non-change in reality and as change in the modeled scenario. ROC plots the rate of true-positives on the vertical axis versus the rate of false-positives on the horizontal axis. If the sequence of the suitability values matches perfectly the sequence in which real land-cover change has occurred, then ROC equal to 1. As model performance improves, the curve moves towards the upper left corner and the area under ROC increases accordingly.

Results

Accuracy assessment was performed for 1988, 2001 and 2007 LU/LC maps (forest/non-forest). The overall accuracy of the classified maps for the years 1998, 2001 and 2007 ranged from 83% to 87%, and Kappa indices varied from 0.71 and 0.73. Figures 2, 3 and 4 display the 1988, 2001 and 2007 land-cover maps (forest/non-forest) created for the study area, respectively. These images are then overlaid in order to generate the digital forest change detection maps for two intervals; namely, 1988–2001 and 2001-2007 (Figures 5 and 6). The results of forest change detection in the Zagros forests show that, 28.2% of primary forest has been lost from 1988 to 2007.

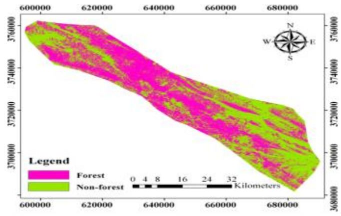

Fig. 2: Forest and non-forest map of 1988

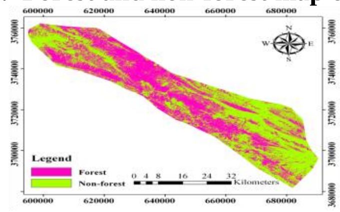

Fig. 3: Forest and non-forest map of 2001

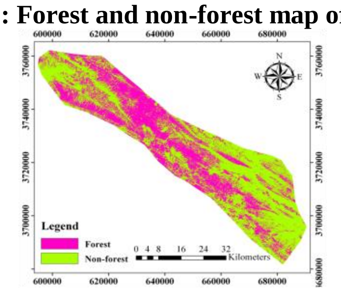

Fig. 4: Forest and non-forest map of 2007

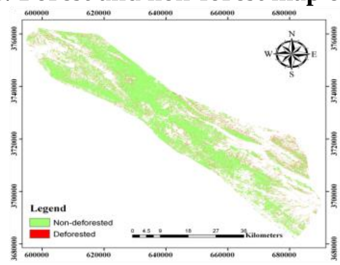

Fig. 5: Cross 1988-2001

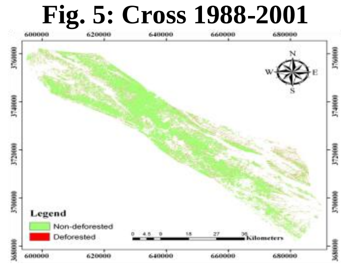

Fig. 6: Cross 2001-2007

This study selected the set predictor Step 6 as the best combination to be used in the prediction (Table 1). The selection procedure is performed as follows. According to Ayalew and Yamagishi (2005), a key starting point could be the model Chi-square, whose value provides the usual significance test for logistic regression. It is a difference between $-2\ln L$ (L=likelihood) for the best-fitting model (Predictor set) and $-2\ln L0$ for the null hypothesis in which all the coefficients are set to 0. The value measures the improvement in fit that the independent variables brought into the regression. In this study, the high value Chi-square (for the predictor set Step6) indicates that the occurrence of forest change is far less likely under the null hypothesis (without the forest conversion influencing parameters) than the full regression model (where the parameters are included). The goodness of fit is an alternative to Chi-square for assessing the significance of LRM. It is calculated based on the difference between the observed and the predicted values of the dependent variable. The smaller this statistic is the better fit it indicates. Model step6 has a value of 359,634, which is the smallest Goodness of fit statistic among the model sets. The pseudo R-square value, which can be calculated from $1-(\ln L/\ln L0)$, indicates how the logit model fits the dataset (Menard, 1995). Thus, pseudo R-square equal to 1 indicates a perfect fit,

whereas 0 shows no relationship. When a pseudo R-square is greater than 0.2, it shows a relatively good fit (Clark and Hosking, 1986; Ayalew et al., 2005). The pseudo R-square of the Step6 predictor set is 0.23. Under ROC, the step6 predictor set obtained an accuracy of 0.96% and provided the smallest AIC index making it the best-fitted predictor set(Table 2). Regression equation best-fitted step6 predictor set.

Linear probability (logit)=1.95
-0.36* Distance from roads log
-0.45* Distance from settlements log
-0.31* Distance from forest edge log
0.23* Fragmentation index
-0.35* Slope
-0.52* Elevation

The relative contribution of the explanatory variables can be assessed using the corresponding coefficients in the LRM. According to Eastman (2006), the intercept can be thought of as the value for the dependent variable when each independent variable takes on a value of zero. The coefficients indicate the effects of each of the explanatory variables on the dependent variable.

Figures 7 and 8 show the results of the calibration and the prediction of the LRM. The color in the figures indicates the degree of probability of deforestation. Areas in dark blue show high probability for forest conversion, while, areas in other colors have decreasing probability for deforestation. Figure 9 illustrates the real change occurred for the period 2001 to 2007, areas in black are areas of changes. Figure 10 illustrates the ROC curve for the LRM. The Area under the ROC Curve is 0.961.

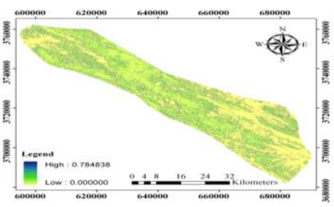

Fig. 7: Map of probabilities of deforestation obtained by LRM (calibration 2001)

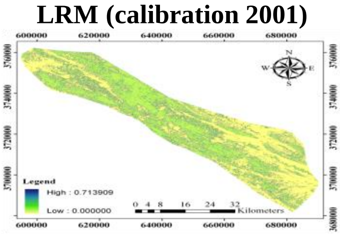

Fig. 8: Map of probabilities of deforestation obtained by LRM (Prediction 2007)

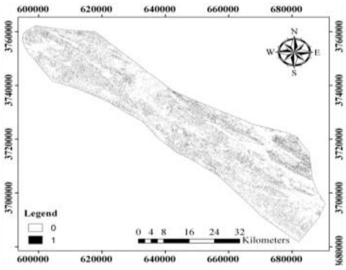

Fig. 9: Forest change year 2007(1=change; 0= No change)

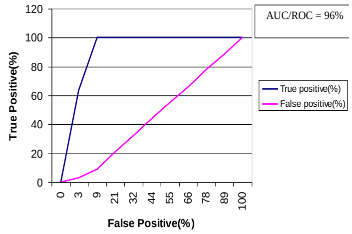

Fig. 10: Predictive performance assessment LRM (AUC/ROC)

Discussions

There may be many driving factors of forest conversion, and they may vary from place to place. In this case study, selected spatial variables comprise a considerable share of the factors driving forest changes. In particular, the accessibility variables seem to be more important than the topographical ones. Many of these factors have been found to be important in other areas. For example, Merten and Lambin (1997) identified proximity to road, town and forest/non-forest edge as important drivers of forest change in southern Cameroon. Elevation and proximity to road are highlighted as important factors of forest change in the lowlands of Sumatra, Indonesia (Linkie et al., 2004). Elevation, slope, proximity to road, settlement and proximity to forest/non-forest edge are the key factors of forest change in southeast Mexico (Mas et al., 2004). The modelling of forest conversion considered six explanatory variables: Distance from forest edge, distance from roads, distance from settlements, elevation, slope and fragmentation index. In the LRM analysis, six predictor sets are compared. The best fitted predictor set is a combination of all the variables incorporated into the model. For this combination, the AUC is 96% and the AIC index is the lowest for the tested predictor sets.

Among continuous variables, distance from settlements is the best single predictor for forest change (1988–2007), with a β value of -0.45. This means that the probability of forest change decreases in direct proportion to the increase in distance from the borders. In other words, the model assigns higher values of probability of change to areas, which are closer to the forest borders. Distance from roads and distance from forest edge have the nearly same negative value (β= -0.36; β= - 0.31). The model assigns the similar significance to these two variables. The negative value means that the probability of forest change decreases in direct proportion to the increase in distance from roads and forest edge. In other words, the model assigns higher values of probability of change to areas which are closer to roads and forest edge. Finally, forest change has positive relation with fragmentation index (β=+0.23). This means that fragmented forest is degraded more than protected area. Many studies have attributed road infrastructure to one main cause of deforestation. Geist and Lambin (2002) and Krutilla, et al., (1995) argued that the construction of roads requires clearing of vegetation that leads to deforestation. Greater access to forests and markets will accelerate the deforestation.

The variables, distance from settlements and distance from roads are significant factor for forest conversion in this study, as well as mentioned by other studies (Echeverria et al., 2008; Etter et al., 2006a; Etter et al., 2006b; Geist and Lambin, 2001; Loza, 2004; Vanclay et al., 1999), In the particular case of the deforestation in the Zagros forests, it is believed that first people settle land reached beyond existing roads and then they develop roads to reach the already taken lands. However, this is difficult to verify with the data and the analysis provided by this study.

Meanwhile, among categorical variables, elevation is the best single predictor for forest change (1988–2007), with a β value of -0.52. This means that the probability of forest change decreases in direct proportion to the increase in elevation from the lower elevations. In other words, the model assigns higher values of probability of change to areas, which are located in lower altitudes (in other words, more accessible areas). Finally, slope also has good negative association (β = -0.35) with forest change. It means with increase in slope, forest change decreases due to decreasing accessibility to that. The findings obtained in this study are in contrast to the study carried out by Loza (2004), who found that the topography is not a significant factor for forest conversion. In the Zagros forests, deforestation is less frequent in areas with steep slope and this study found that flat areas are strongly susceptible to forest conversion. The topography of Loza's study area presents mostly hills (lower altitude) and flat areas.

The involvement of some variables such as land tenure status, and other socio-economic data (level of income, level of education), which have contributed to deforestation might be incorporated in the model. Zagros forests have threats such as the construction of a road across the area, population density and agroforestry. The aim of this research is to predict probabilities of forest conversion. However, areas of change (not only probabilities) can be predicted by incorporation of methods such as Markov Chains, Geomod and Cellular automata. While this study considered only two categories, Forest and Disturbed Forest, further studies could model additional categories of land-cover.

Conclusion

The identification of the areas vulnerable to forest changes is fundamental in the Zagros forests and has important implications for biodiversity conservation in the region. One of the most important applications would be to relate the spatial patterns of forest changes to the spatial distribution of species. From a protected area management perspective, the prediction maps of forest change patterns can help protected area managers to identify places, where conservation and forest management efforts should be focused. At a larger scale, the prediction of forest change patterns can aid long-term sustainable forest management. Policy implication of the result model prediction is that the government should take more attention to the population problem and have to create non-agricultural sectors jobs in order to reduce pressure on forest, especially at district which will face serious deforestation. This study investigated the conversion of forest using remote sensing, GIS and logistic regression model in the Zagros forests of west of Iran. The LRM is parameterized to simulate the conversion of forest in the near future. It is shown that the utility of a combination of statistical modeling approach and spatial analysis is necessary in order to analyze and predict deforestation. Distance from forest settlements, distance from roads, distance from forest edge, fragmentation index, elevation and slope are found to be the important variables in the model for explaining the pattern of deforestation observed in the Zagros forests.

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Table 1: Coefficients of logistic regression using 6 sets of explanatory variables

	Coefficients					
Variables	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Intercept	0.39	1.01	1.21	1.80	2.23	1.95
Distance from roads	-0.60	-0.52	-0.38	-0.29	-0.30	-0.36
Distance from settlements		-0.57	-0.43	-0.40	-0.41	-0.45
Distance from forest edge			-0.38	-0.31	-0.30	-0.31
Fragmentation index				0.29	0.25	0.23
Slope					-0.44	-0.35
Elevation						-0.52

Table 2: Other statistics of logistic regression using 6 sets of explanatory variables

Statistics	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Total number of pixel	2,507,925	2,507,925	2,507,925	2,507,925	2,507,925	2,507,925
−2lnL (L=likelihood)	241,734	230,936	229,930	219,983	214,249	201,426
−2ln L0	435,731	430,328	356,701	383,941	361,618	340,231
Model chi square	51,928	53,765	55,321	570,551	589,318	59,601
Goodness of fit	401,369	400,187	391,442	376,964	368,980	359,634
Pseudo R-square	0.15	0.18	0.21	0.22	0.22	0.23
AUC	0.76	0.79	0.83	0.87	0.91	0.96
Odds ratio	4.21	4.37	4.41	4.46	4.30	5.05
AIC	247,651	238,756	220,908	217,781	215,645	201,341