Underlying driving forces of forest cover changes due to the implementation of preservation policies in Iranian northern Zagros forests

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SUMMARY

Many countries have implemented policies to reduce the negative effects of deforestation. In Iran, the Zagros Forest Preservation Plan (ZFPP) began in 2003. This study evaluates the effectiveness of ZFPP on land cover changes in two periods, before (1993–2002) and after (2002–2017) implementation of the plan. Logistic regression (LR) analysis was used to examine the effectiveness of key socio-economic, environmental and demographic drivers associated with deforestation activities. The results showed that despite the implementation of ZFPP forest conversion to other land-use types increased during the second period compared to the first. Calculating the annual rate of deforestation showed that this rate increased from -0.4% to -0.5%. The results of LR showed that the occurrence of deforestation in different years was significantly related to distance from rivers, croplands, cities, roads, and slope such that areas with low slope and close to these features have a high probability of deforestation activities.

Keywords: deforestation, forest conservation, land use land cover change, preservation policy, Sardasht

Souligner les forces motrices des changements de couvert forestier dus à la mise en place de politiques de préservation dans les forêts du nord du Zagros en Iran

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Plusieurs pays ont mis en place des politiques visant à réduire les effets négatifs de la déforestation. En Iran, Le Plan de préservation de la forêt de Zagros (ZFPP) débuta en 2003. Cette étude évalue l'efficacité du ZFPP dans les changements de couvert forestier au cours de deux périodes: avant (1993–2002) et après (2002–2017) la mise en œuvre du plan. L'analyse de régression logistique (LR) a été utilisée pour examiner l'efficacité des moteurs socio-économiques, environnementaux et démographiques clé associés aux activités de déforestation. Les résultats ont montré que malgré la mise en place du ZFPP, la conversion à d'autres types d'usage de la terre s'est accru durant la seconde période que durant la précédente. Le calcul du degré annuel de déforestation montra que ce taux s'accrut de -0.4% à -0.5%. Les résultats de la LR indiquèrent que la présence de la déforestation durant certaines années était fortement liée à la distance des rivières, des terres de culture, des villes, des routes et des degrés de pente, de tel fait que les régions à faible dénivellation et proches de ces éléments débouchaient sur une forte probabilité des activités de déforestation.

Las fuerzas motrices subyacentes de los cambios de la cobertura forestal debido a la aplicación de políticas de conservación en los bosques iraníes del norte de los Zagros

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Muchos países han aplicado políticas para reducir los efectos negativos de la deforestación. En Irán, el Plan de Preservación de los Bosques de los Zagros (PPBZ) comenzó en 2003. En este estudio se evalúa la eficacia del PPBZ en los cambios de la cobertura del suelo en dos períodos, antes (1993–2002) y después (2002–2017) de la aplicación del plan. Se utilizó un análisis de regresión logística (RL) para examinar la eficacia de los principales impulsores socioeconómicos, ambientales y demográficos asociados a las actividades de deforestación. Los resultados mostraron que, a pesar de la aplicación del PPBZ, la conversión de bosques a otros tipos de uso del suelo aumentó durante el segundo período en comparación con el primero. El cálculo de la tasa anual de deforestación mostró que esta tasa aumentó de -0,4% a -0,5%. Los resultados de la RL mostraron que la presencia de deforestación en diferentes años estuvo relacionada significativamente con la distancia a los ríos, las tierras de cultivo, las ciudades, las carreteras y la pendiente, de manera que las zonas con baja pendiente y cercanas a estos rasgos del paisaje tienen una alta probabilidad de actividades de deforestación.

INTRODUCTION

Land Use/Cover (LUC) is not constant and has often changed due to human activities, population growth but mostly because of forest conversion to croplands (Viña *et al.* 2016). Many studies have shown the negative effects land use/cover changes (LUCC) on the environment (Shi *et al.* 2009), land surface temperature (Boucher *et al.* 2014), ecosystem services (Maes *et al.* 2012, Tayyebi *et al.* 2016), soil (Celik 2005), biochemical cycles and declining biodiversity (Mas *et al.* 2004). LUCC can also affect economies at the national and regional scale (Pijanowski *et al.* 2002).

Forests provide numerous ecosystem services such as soil and water conservation, biodiversity, climate regulation (Tayyebi and Jenerette 2016), carbon storage, but direct conversion and degradation of forests to other land uses eliminates these benefits (Crowther *et al.* 2015). However, despite its high importance detailed statistics about deforestation are not available in many countries (Grainger 1993).

Estimating trends in forest degradation during different periods is important as it can help managers and planners to identify factors affecting the LUCC and to have useful and efficient programming for controlling them (Abbas *et al.* 2010).

Although degradation of forests ecosystems continues in many parts of the world (Li *et al.* 2013, Viña *et al.* 2016) the opposite of this trend, that is forest transition (FT) from loss to gain, has been reported from the late 18th century in France (Mather 1992), and then in many developed countries in Europe, Asia, North America and Latin America (Rudel *et al.* 2005, Li *et al.* 2013). Various factors play a role in FT (Rudel *et al.* 2005, Lambin and Meyfroidt 2011), however, governments, especially in developing countries (Jack *et al.* 2008) used different mechanisms and policies (such as strict rules, conservation policies and plans) that play an important role in protecting and increasing forest areas and FT (Lambin and Meyfroidt 2011, Viña *et al.* 2016). Meanwhile, the main challenge is quantifying the role of government policies and programmes against other effective factors on LUCC, such as socio-economic, environmental and anthropogenic disturbances.

Forest-protection policies are widely considered to be one of the most important strategies for FT and various plans have been implemented worldwide such as payments for environmental services (PES) and the increasing availability of off-farm employment (Andersen *et al.* 2017), the establishment of forest protected areas (Miranda *et al.* 2016) and sustainable forest management based on community-based management (Ellis and Porter-Bolland 2008) to protect forests. Forest management by local communities can play a crucial role in their economic and social sustainability (Carter and Gronow 2005).

The Zagros oak forests in western Iran with an area of about 4 749 000 ha (Roozitalab *et al.* 2018), covering 11 provinces of Iran, have great importance in terms of environmental issues, conservation of water and soil resources and socioeconomic status (Jazirehi and Ebrahimi Rostaghi 2003). However, over the recent past socio-economic disturbances, lack of comprehensive management, population growth, and the outbreak of pests and diseases, have impacted on the production potential of this region (Henareh Khalyani *et al.* 2012). Besides the managerial weakness of natural resources in Iran (Beygi Heidarlou *et al.* 2019), infrastructure development, new settlements, fuelwood, and timber extraction, livestock grazing and browsing, including defoliation and cutting oak trees for winter fodder for livestock (goat, sheep and cattle) are the main causes of the rapid decline of the Zagros forests in Iran (Torahi and Rai 2011, Henareh Khalyani *et al.* 2013).

Henareh Khalyani *et al.* (2013) in their research indicated a 69% decrease of forest in the north of Zagros (West Azerbaijan and Kurdistan provinces of Iran and Sulaymaniyah province of Iraq) from 1972 to 2009. This forest loss represented mainly a conversion to croplands (an increase of 249%, since 1972). The most significant driving force for forest loss was an increase in the urban population and climatic variables. Shooshtari and Gholamalifard (2015) found that the largest LUCC occurred on the margins of croplands in Neka Basin located in northern Iran, reflecting the role played by human activities in increasing forest decline. They showed that between 1987 and 2011 forest areas decreased by 1 690 ha, while Gholamalifard *et al.* (2013) recorded a reduction of forest area of 37% from 1995 to 2004 in the region.

Following nationalization of forests in 1965, Iran's forest management and conservation programmes began in 1977. However, Zagros forests management programmes were implemented in the form of a multi-purpose and participatory preservation and development forestry plan which began in 2003. The goals of this plan included preventing destruction, forest stands and habitat conservation, enhancing the status of protected forests, in addition to improving the livelihoods of forest dwellers. It was hoped that achieving these goals could lead to the sustainable management of forests and assist local communities' economic and social growth whose livelihoods depend on forest conservation and rehabilitation.

More than 90% of the Northern Zagros forests of West Azerbaijan Province are located in Sardasht County (about 91 117 ha). Forests of this region are not immune from anthropogenic disturbances and suffered extensive destruction due to the widespread distribution of rural populations within Sardasht, population growth, poverty and the need for food, jobs, roads and general urban development. Through the important role of these forests in water and soil regulation, the ecological balance of the region, and by-product production, their restoration and protection is essential. However, historical observations of forest conservation policies in Iran suggest that they ignore local communities, and due to the existence of common resources and interests, conflicts with local communities are taking place.

Principal management of these regions requires the availability of accurate and up-to-date information from land-use areas and factors affecting these changes. Considering the national and regional importance of the Northern Zagros forests in meeting the livelihood needs of a large part of the residents of this region of the country, the following goals were examined in this study:

1. Detecting, mapping and quantifying changes in the Zagros forests' land cover in Sardasht before (1993–2002) and after (2002–2017) the implementation of ZFPP using remote sensing tools.
2. Identifying and analysis of the most important explanatory variables affecting deforestation in Sardasht.

METHODS

Study area

Sardasht County with an area of 138 183 ha, is located in a region of northwestern Iran characterized by a semi-Mediterranean climate (Beygi Heidarlou *et al.* 2015) and is one of the most important and sensitive ecosystems of Zagros forests in Iran selected for LUCC analysis (Figure 1). The main tree species in Sardasht forests are oaks, particularly oak manna tree (*Quercus persica* Jaub. & Spach.), pure Brant's oak (*Q. brantii* Lindley), Lebanon oak (*Q. libani* Oliv.) and gall oak (*Q. infectoria* Oliv.), all of which grow in coppice form (Sabeti 1994, Goodarzi *et al.* 2019). Current forest utilization practices are traditional and support subsistence livelihoods. The most important of these activities are cutting of oak branches and whole trees for use as fodder and fuel, non-sustainable extraction of sap from pistachio trees (*Pistacia mutica*) for producing a traditional chewing-gum, and converting forests to rainfed agriculture (specifically wheat and barley) (Pourhashemi *et al.* 2004, Henareh Khalyani *et al.* 2013). The region consists of three cities and 352 villages, and according to the latest population census of Iran in 2016, 68 162 and 50 687 people live in urban and rural areas respectively, and their main activity is agriculture and animal husbandry.

FIGURE 1 *Location of the study area (Sardasht) in Southwest of West Azerbaijan province, Iran*

The maximum and minimum height above sea level of the study area is 2 583 m and 591 m, respectively, with average annual precipitation of 724 mm. The average maximum and minimum temperature of Sardasht is 21°C and 6°C, respectively, with a semi-arid and Mediterranean climate (Beygi Heidarlou *et al.* 2015).

Remote sensing analysis

LUCC analysis was performed based on the overlapping time of before and after the implementation of ZFPP. For this purpose, we used multi-temporal Landsat imagery classification (Baumann *et al.* 2015) due to the availability of the images and their suitability for spectral and spatial resolution for mapping LUC based on seasonal coverage and cloud cover (Baumann *et al.* 2012) in 1993, 2002 and 2017 (Table 1).

Subsequently, two different periods including 1993–2002, nine years before implementation of ZFPP (change detection before the plan), and 2002–2017, 15 years after the implementation of ZFPP (change detection after the plan) were considered.

For each LUC class of Sardasht (including forest, croplands, built-up areas, and rangelands) training data were collected using GPS ground-truthing points and visually interpreting of the Landsat images in 2017. LUC attribution of each point was confirmed using high-resolution imagery in Google Earth, and then using EnMAP-Box software (van der Linden *et al.* 2015) and prepared training data, Landsat images were classified using a nonparametric random forest classifier (Waske *et al.* 2012). Also, the majority filter was applied to eliminate single pixels derived from misclassifications of the images (Baumann *et al.* 2015).

Classification accuracy assessment of the 1993, 2002 and 2017 land cover maps were conducted based on GPS points (collected during a field visit in 2017) and ground control points. LUC attribution of these points should not have been changed over the studied periods which was explored by visually interpreting the Landsat imageries. Accuracy assessment results, shown in table 2, resulted in an overall accuracy of 85.6%, 88.1% and 91.6% for 1993, 2002 and 2017, respectively.

To evaluate land cover changes, forest degradation, and deforestation, we reclassified LUC images to two classes, forest, and non-forest. Then we combined the binary images for two time periods (e.g. 1993–2002, and 2002–2017). Two new images with four classes were prepared: (1) conversions from the forest (or new deforestation), (2) remained deforested, (3), forest persistence and (4) conversions to the forest

TABLE 1 *Details of acquisition images from Landsat imagery used in the study*

Year	Acquisition dates	Landsat	Sensor	Path/Row
1993	1993-05-16	Landsat 5	TM	168/35
	1993-07-19	Landsat 5	TM	168/35
2002	2002-09-06	Landsat 7	ETM+	168/35
2017	2017-05-18	Landsat 8	OLI	168/35
	2017-09-23	Landsat 8	OLI	168/35

TABLE 2 *Accuracy assessment of image classifications for the years 1993, 2002 and 2017*

Map class	1993				2002				2017			
	PA	UA	Co	Om	PA	UA	Ce	Oe	PA	UA	Cee	Oe
Forest	78.1	100.0	21.9	0.0	93.2	92.8	6.8	7.9	81.4	96.0	18.6	4.0
Croplands	90.0	80.0	9.1	20.0	89.3	54.3	10.7	38.9	88.2	90.0	11.8	10.0
Built-up areas	90.9	88.0	2.2	12.0	80.0	100.0	20.0	0.0	100.0	96.0	0.0	4.0
Rangelands	97.8	76.0	30.9	24.0	76.7	92.9	23.3	7.1	91.3	84.0	8.7	16.0
OA	85.6				88.1				91.6			
Kappa	0.8				0.8				0.9			

OA: Overall accuracy (%), PA: Producer Accuracy (%), UA: User Accuracy (%), Ce: Commission error (%) and Oe: Omission error (%).

(or forest regrowth). Deforestation rates for the periods 1993–2002 and 2002–2017 were calculated for Sardasht applying the below formula:

$$r = \left(\frac{1}{t_2 - t_1}\right) \times \ln\left(\frac{A_2}{A_1}\right)$$

Where r = deforestation rate, A_1 and A_2 = forest cover at time t_1 and t_2, respectively (Puyravaud 2003).

Logistic regression (LR) analysis

A variety of management, environmental and socio-economic factors play a role in LUCC and deforestation (Hostert *et al.* 2011, Nurwanda *et al.* 2016) and LR has advantages in describing the relationship between response and explanatory variables of changes in statistical analysis (Ellis and Porter-Bolland 2008, Arekhi 2011, Nurwanda *et al.* 2016). In this study, we used binary LR to assess the effects of different explanatory variables or major drivers of changes that may results in present deforestation in each period (before and after implementation of ZFPP) in Sardasht, such as environmental and socio-economic variables. For this purpose, at first, we reclassified LUC maps of 1993, 2002 and 2017 to two classes (forest and non-forest), then for our binary response or dependent variable we created change maps between 1993–2002 and 2002–2017. In these maps we assigned 1 to non-forest and deforested areas and 0 for forest areas (Ellis and Porter-Bolland 2008, Arekhi 2011). Explanatory variables were used for LR including distance from the perennial river, distance from intermittent rivers, distance from croplands, distance from cities, distance from other settlements, distance from roads, elevation, slope (%) and Aspect (Table 3, Figure 2). Because azimuth is a circular measurement of aspect, in this study, we transformed it using the cosine relationship described by Beers *et al.* (1966).

For LR analysis, we used 100 random points generated within the Sardasht analysis area by ArcGIS 10.5 (Figure 3). Using the global Moran's Index, a test for spatial autocorrelation was performed on the residuals of the response variable (0, forested and 1, deforested). The value of Moran's Index varied from +1 to -1. A value of +1 and -1 means perfect positive and negative spatial autocorrelation, respectively, and a value of 0 indicates perfect spatial randomness (Tu and Xia 2008). Moran's Index for periods 1993–2002 and 2002–2017 was calculated 0.053 and 0.074 respectively (Table 4), that indicates failing to reject the null hypothesis and there is no spatial autocorrelation with the points (Mitchel 2005).

The cell value corresponding to dependent and explanatory variables of each random point were extracted and the LR models in XLStat 2016 (XLstat 2016) were run using the stepwise backward LR model. LR is a statistical method that evaluates the relationship between a set of independent and

TABLE 3 *Explanatory variables and their descriptions*

Dependent variable (Y)	Independent variable (X)		Analysis
Deforestation in 1993, 2002 and 2017	X1	Distance from perennial river	Euclidian distance
	X2	Distance from intermittent rivers	Euclidian distance
	X3	Distance from croplands	Euclidian distance
	X4	Distance from cities	Euclidian distance
	X5	Distance from other settlements	Euclidian distance
	X6	Distance from roads	Euclidian distance
	X7	Elevation	Grid map
	X8	Slope (%)	Grid map
	X9	Aspect	Grid map

FIGURE 2 *Maps of the explanatory variables used for LR modelling in 1993, 2002 and 2017 in Sardasht*

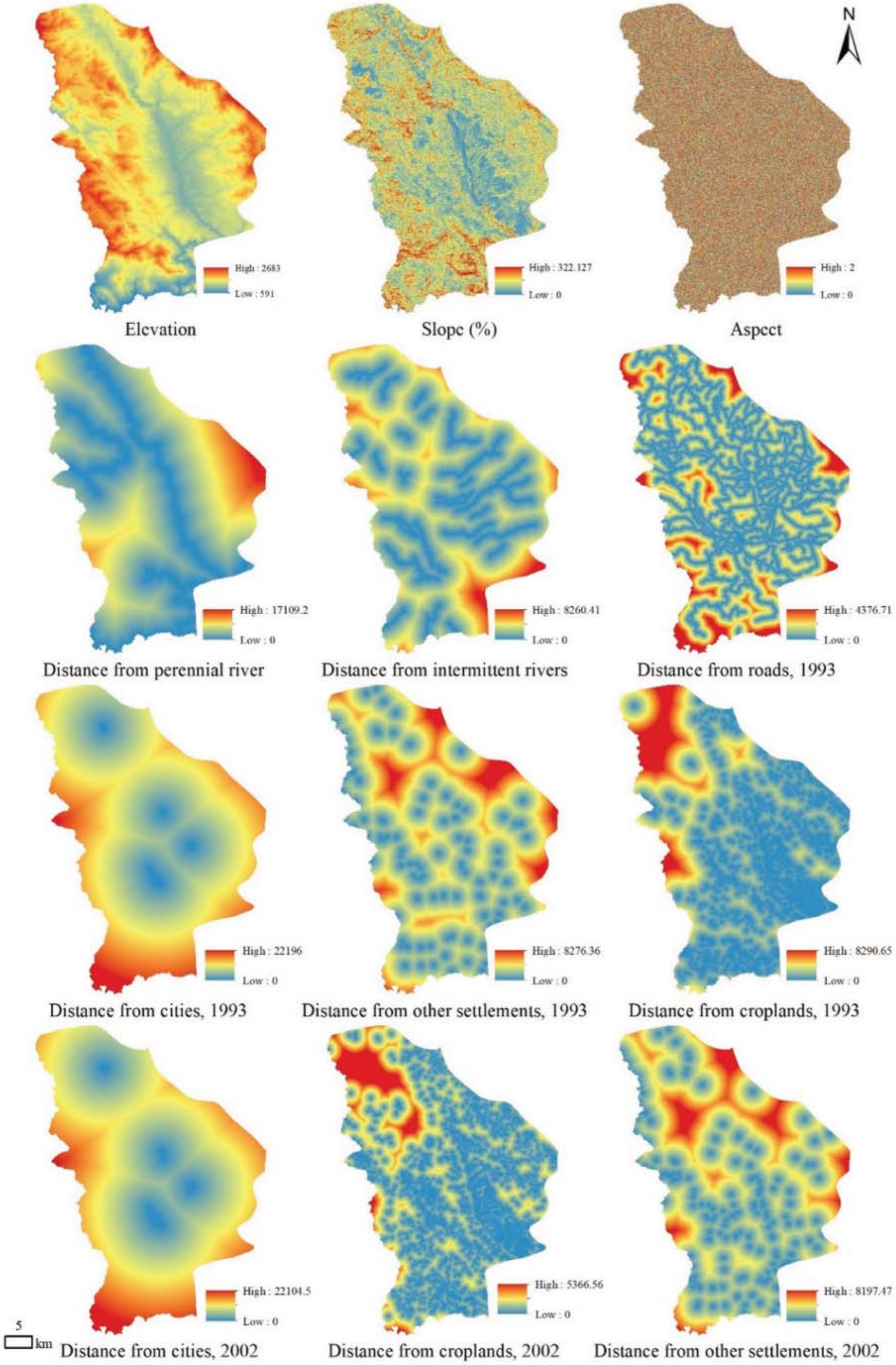


FIGURE 2 (*Continued*)

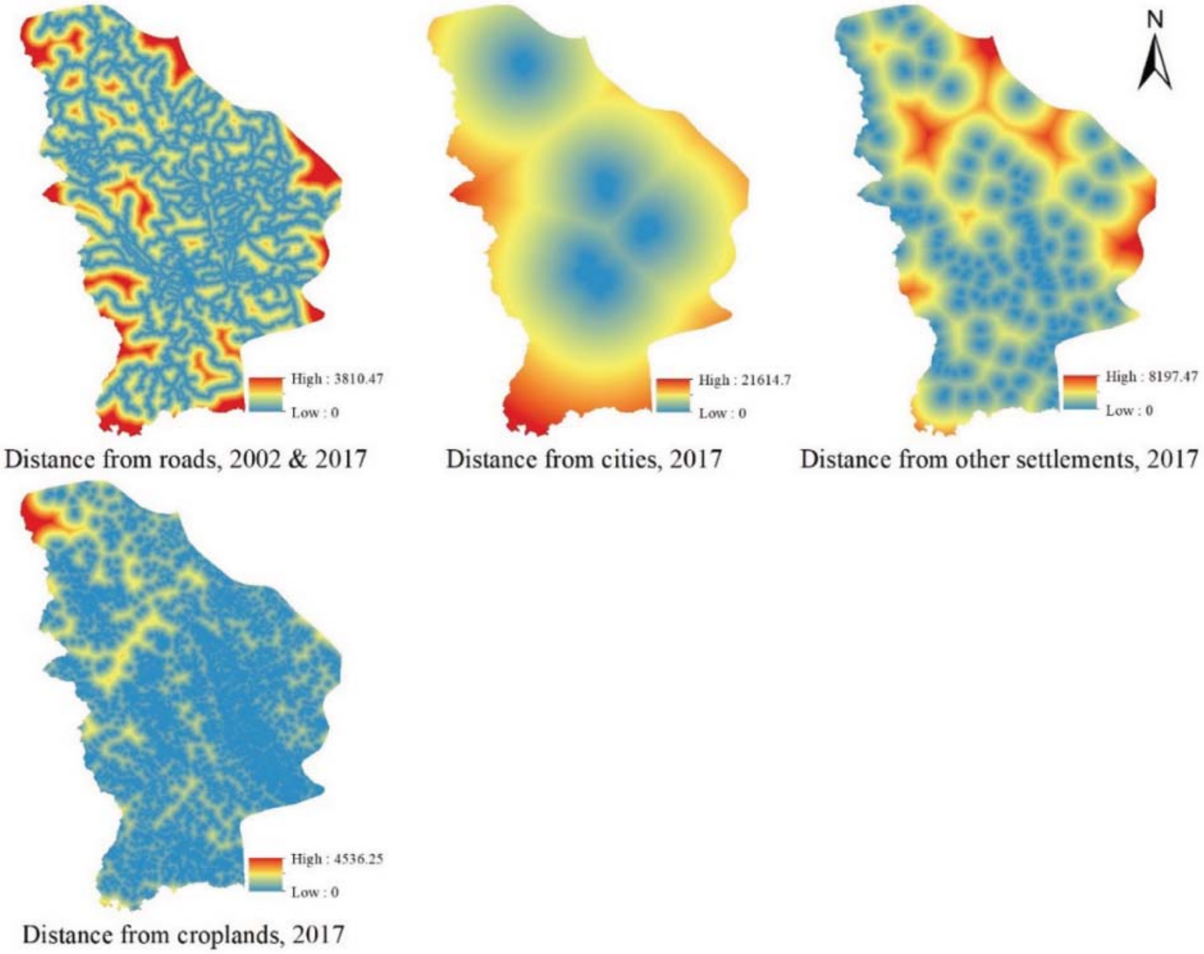


FIGURE 3 *Generated random points within the Sardasht analysis area*

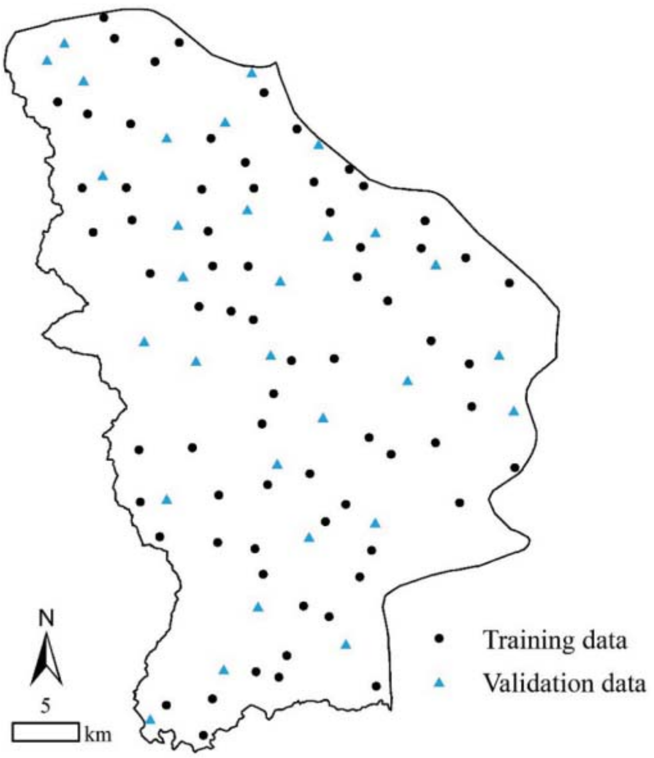


TABLE 4 *Results of calculating Global Moran's I index*

Global Moran's I Summary	1993–2002	2002–2017
Moran's Index	**0.053**	**0.074**
z-score	0.830	0.764
p-value	**0.645**	**0.432**

continuous variables and a binary dependent variable. LR uses the maximum likelihood estimation (MLE) method to find the best set of parameters that fits the model better (Breslow and Holubkov 1997). LR is used assuming that the probability of the dependent variable being 1 follows a logarithmic curve and its value is estimated by the following equation (Eastman 2002):

$$P\left(y=1|X\right)=\frac{exp^{\left(\sum BX\right)}}{1+exp^{\left(\sum BX\right)}}$$

Where P denotes the probability of the event of interest, X is the independent variable, B is the estimated parameter and Y is the dependent variable that here is deforestation. By logarithmic transformation of the above equation, the following equation for binary LR model is obtained (Eastman 2012, Achmad *et al.* 2015):

$$log_e\left(P/(1+P)\right)=b_0+b_1x_1+b_2x_2+\ldots+b_kx_k$$

The logarithmic transformation causes the predicted probability to be in the range of 0 and 1 (Clark and Hosking 1986). The prediction of the models' parameters is not accurate and their interpretation in terms of odds ratios may be erroneous when there is multicollinearity (high correlation) among the explanatory variables (Aguilera *et al.* 2006). Multicollinearity is a statistical phenomenon in which two or more predictor variables in a multiple LR model are highly associated (Graham 2003, Midi *et al.* 2010). Although multicollinearity does not bias coefficients, it does make them unstable (Belsley *et al.* 1980). Therefore, to detect possible multicollinearity between variables we calculated correlation coefficients, tolerance and each predictor's variance inflation factor (VIF) to quantify collinearity between independent variables in the models (Belsley *et al.* 1980, Miles 2014) using multicollinearity statistics test under XLSTAT 2019 software (Addinsoft 2019). We have perfect multicollinearity if the correlation between two independent variables is equal to 1 or -1 (Belsley *et al.* 1980). VIF is a positive value, and values greater than 3 indicate moderate or high collinearity (Acevedo *et al.* 2011). The variable's tolerance is one minus R^2. A small tolerance value indicates that the variable under consideration is almost a perfect linear combination of the independent variables (Miles 2014).

Also, the performance of models (1993–2002 and 2002–2017) was evaluated using the Relative Operating Characteristic (ROC) (Tayyebi *et al.* 2010). The area under the ROC curve shows the binary model's accuracy (Pontius Jr and Batchu 2003). For this, the total number of data points used in LR analysis in the study area split into two parts, 70 and 30 points as the training and validation data, respectively (Figure 3). ROC is defined as a plot of false-positive (FP) rate (1 specificity) on the *x*-axis and true-positive (TP) rate (the sensitivity) on the *y*-axis (Gonçalves *et al.* 2014), which is calculated with following equations (Pontius and Parmentier 2014):

$$X = 1 - specificity = 1 - \left[\frac{True\ negative}{True\ negative + False\ positive}\right]$$

$$Y = sensitivity = \left[\frac{True\ negative}{True\ positive + False\ negative}\right]$$

RESULTS

LUCC in Sardasht

Figure 4 shows the spatial patterns of four major LUC types of Sardasht during 1993, 2002 and 2017. Despite the large area of the forest before and after implementation of ZFPP in Sardasht (64% and 58% of the entire area in Sardasht during 1993–2002 and 2002–2017, respectively), our results show an increasing deforestation process in Sardasht County with rates of -0.4% and -0.5% before (1993–2002) and after (2002–2017) implementation of ZFPP, respectively (Table 5 and Figure 5).

Comparing major trends of net changes from forest to other land uses (Table 6) indicates that before the implementation of ZFPP (1993–2002), 2 331 ha (-29.90%), 64 ha (-13.12%) and 1 223 ha (-3.61%) of these areas converted to croplands, built-up areas, and rangelands, respectively. While, after enacting the plan (2002–2017) these values increased to 4 160 ha (-39.83%), 149 ha (-20.52%) and 1 679 ha (-4.73ha), respectively.

Logistic regression

According to the obtained correlation matrix, tolerance and VIF values (Table 7), no effects of multicollinearity were expected in LR the models.

FIGURE 4 *Land use/land cover classification for 1993, 2002 and 2017 of Sardasht*

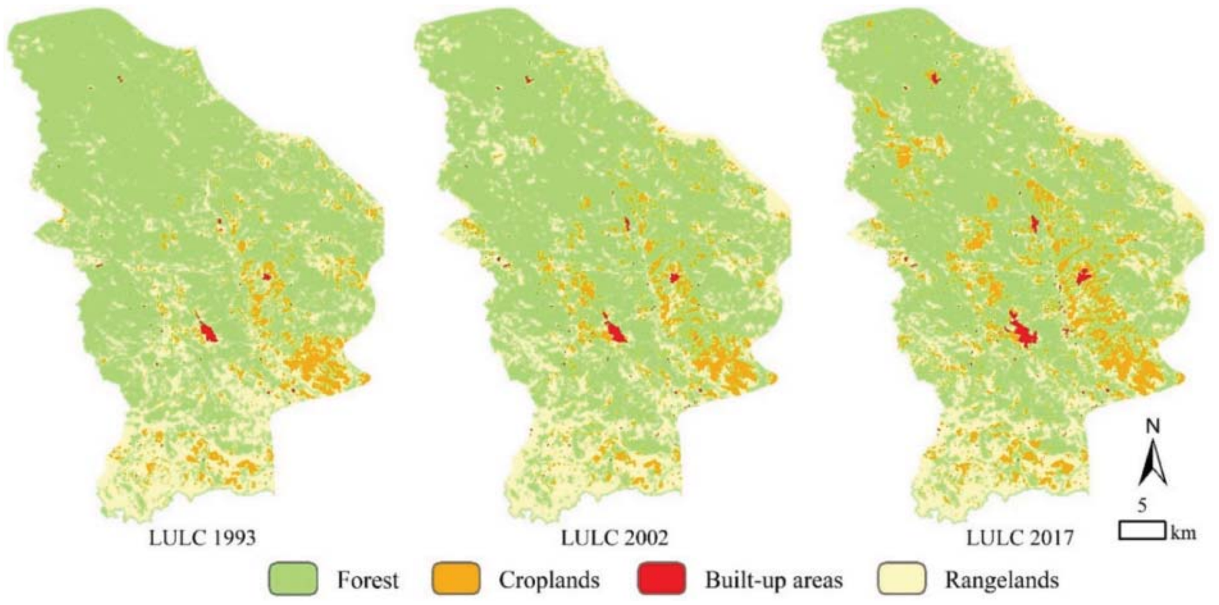


TABLE 5 *LUCC in Sardasht, 1993–2002 and 2002–2017*

LUCC	Area	Before implementing forest Preservation Plan	After implementing forest Preservation Plan
		1993–2002	2002–2017
Forest persistence	(ha)	88123.46	80612.19
	(%)	**63.77**	**58.25**
Conversion to forest	(ha)	3386.56	2794.41
	(%)	2.45	2.02
Remained deforested	(ha)	39681.59	46195.92
	(%)	28.71	33.38
Conversion from forest	(ha)	7004.47	8789.85
	(%)	5.07	6.35
Annual deforestation rate	(%)	**-0.4**	**-0.5**

FIGURE 5 *LUCC processes in Sardasht for the periods 1993–2002 and 2002–2017*

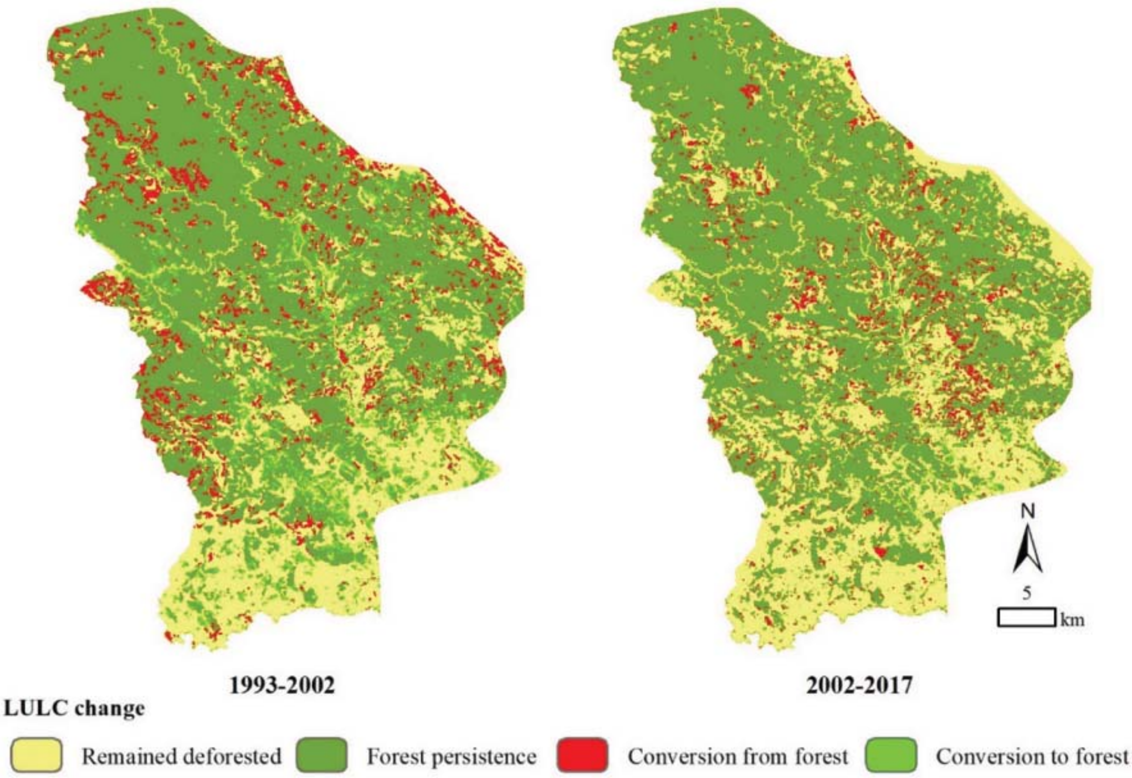


TABLE 6 *Major change trajectories and their contributions to net change from forest to other land use types*

From forest to:	1993–2002		2002–2017	
	ha	% change	ha	% change
Croplands	-2331	-26.9	-4160	-39.83
Built-up	-64	-13.21	-149	-20.52
Rangelands	-1223	-3.61	-1679	-4.73

The overall LR model for 1993–2002 and 2002–2017 in Sardasht was significant (Table 8). The most effective and significant explanatory variables before implementation of ZFPP (1993–2002) were (1) distance from intermittent rivers of the region (Chi-Square = 15.4, ρ = <0.0001), (2) distance from cities (Chi-Square = 4.1, ρ = 0.043) and (3) distance from roads (Chi-Square = 3.9, ρ = 0.049) (Table 9).

These variables after implementation of ZFPP (2002–2017) were (1) distance from croplands (Chi-Square = 28.2, ρ = <0.0001), (2) distance from perennial river of the region (Chi-Square = 13.6, ρ = 0.000) and (3) slope (Chi-Square = 3.671, ρ = 0.050) (Table 10).

TABLE 7 *Result of multicollinearity test using Pearson correlation matrix and multicollinearity statistics*

	Variables	1	2	3	4	5	6	7	8	9	Multicollinearity statistics		
											R^2	Tolerance	VIF
1	Elevation	1	0.254	0.038	0.367	0.536	0.461	0.369	0.309	0.400	0.575	0.425	2.352
2	Slope (%)		1	-0.007	-0.001	0.115	0.251	0.148	0.255	0.235	0.168	0.832	1.201
3	Aspect			1	-0.021	0.004	-0.014	0.058	0.084	0.045	0.023	0.977	1.024
4	Distance from perennial river				1	0.047	0.238	0.118	-0.217	0.312	0.381	0.619	1.615
5	Distance from intermittent rivers					1	0.254	0.168	0.211	0.299	0.343	0.657	1.523
6	Distance from cities						1	0.315	0.147	0.266	0.281	0.719	1.390
7	Distance from other settlements							1	0.073	0.290	0.199	0.801	1.248
8	Distance from croplands								1	0.068	0.367	0.633	1.580
9	Distance from roads									1	0.282	0.718	1.392

TABLE 8 *Results of overall logistic regression models for Sardasht*

		1993–2002	2002–2017
-2 Log(Likelihood):	Chi-square	74.339	71.223
	$\rho <$	< 0.0001	< 0.0001
Goodness of fit:	R^2 (Nagelkerke)	0.414	0.452

The negative values of β Coefficient for each variable show that the probability of deforestation increase in direct proportion to the decrease in distance from these variables and areas with a low slope.

Based on the coefficient of each independent variables for models in tables 8 and 9, the LR models for 1993–2002 and 2002–2017 are:

Before the implementation of ZFPP (1993–2002):

Y (probability of deforestation) = $-3.560 + 4.008\,(X_2) - 1.139\,(X_3) + 2.958\,(X_4) - 1.436\,(X_5) + 3.323\,(X_6) + 3.053\,(X_7) - 2.481\,(X_8) + 0.388\,(X_9)$

After the implementation of ZFPP (2002–2017):

Y (probability of deforestation) = $1.886 - 3.607\,(X_1) + 1.161\,(X_2) - 9.552\,(X_3) - 1.022\,(X_4) + 0.796\,(X_5) + 1.764\,(X_6) - 2.350\,(X_8) + 0.552\,(X_9)$

The ROC values of each periods before and after implementation of ZFPP (1993–2002 and 2002–2017) for training data were 0.831 and 0.804 and for validation data were 0.811 and 0.823, respectively (Figure 6), which reflects suitable goodness of fit of the LR models with reasonable accuracy for studied periods in Sardasht during studied periods.

DISCUSSION

There are complex interactions between different types of land use/cover (Irwin and Geoghegan 2001, Lambin and Geist 2008) due to a variety of factors including management (Geist and Lambin 2002, Luyssaert *et al.* 2014), political (Braimoh and Onishi 2007, Liu *et al.* 2014), socio-economic (Van Oort 2007, Shi *et al.* 2009, Hostert *et al.* 2011, Krug *et al.* 2015), environmental (Pijanowski *et al.* 2002, Hietel *et al.* 2004) and demographic (Mather and Needle 2000, Basnyat 2009, Li *et al.* 2013). During the 25 years of this study (1993 to 2017) 9 685.88 ha of Sardasht forests have been destroyed with the main causes of deforestation being the expansion of croplands, rangeland, and built-up areas respectively (Table 6). Calculation of the annual rate of deforestation for the period before the implementation of ZFPP (1993–2002) was -0.4%. However, despite the implementation of the plan after 2002 in Sardasht, the deforestation rate increased annually to -0.5% during the period 2002–2017.

According to the results, the highest forest degradation occurred in discrete forest parts and was related to proximity to the forest and non-forest boundary. Similar cases have also been reported by other researchers (Mas *et al.* 2004, Brink

TABLE 9 *Binary logistic regression model and results for the probability of deforestation in Sardasht before implementation of ZFPP (1993–2002)*

Variables	β Coefficient	Standard error	Wald Chi-Square	*Pr* > Chi²
Intercept	-3.560	0.610	34.052	< 0.0001
X1 Distance from perennial river	0.000	0.000	-	-
X2 Distance from intermittent rivers	4.008	1.023	15.359	< 0.0001
X3 Distance from croplands	-1.139	1.012	1.266	0.260
X4 Distance from cities	2.958	2.958	4.082	0.043
X5 Distance from other settlements	-1.436	0.944	2.312	0.128
X6 Distance from roads	3.323	1.689	3.870	0.049
X7 Elevation	3.053	1.592	3.677	0.055
X8 Slope (%)	-2.481	1.470	2.846	0.092
X9 Aspect	0.388	0.543	0.510	0.475

TABLE 10 *Binary logistic regression model and results for the probability of deforestation in Sardasht after implementation of ZFPP (2002–2017)*

Variables	β Coefficient	Standard error	Wald Chi-Square	*Pr* > Chi²
Intercept	1.886	0.882	5.259	0.022
X1 Distance from perennial river	-3.607	0.979	13.569	0.000
X2 Distance from intermittent rivers	1.161	0.794	2.140	0.144
X3 Distance from croplands	-9.552	1.799	28.201	< 0.0001
X4 Distance from cities	-1.022	1.078	0.899	0.343
X5 Distance from other settlements	0.796	0.961	0.687	0.407
X6 Distance from roads	1.764	1.196	2.177	0.140
X7 Elevation	0.000	0.000	-	-
X8 Slope (%)	-2.350	1.226	3.671	0.050
X9 Aspect	0.552	0.491	1.265	0.261

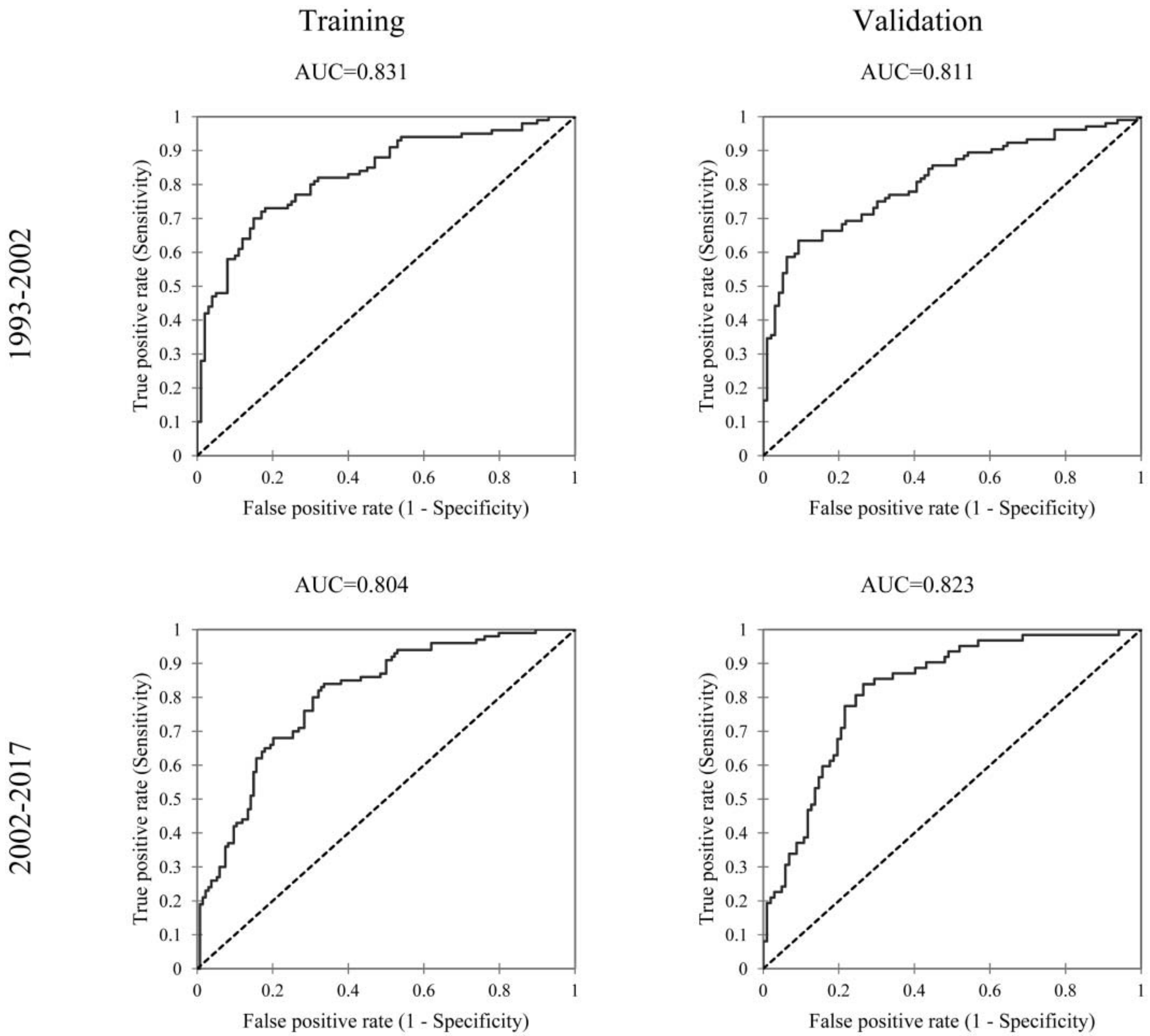
and Eva 2009, Shooshtari and Gholamalifard 2015). Also, due to the negative coefficients of effective variables on deforestation, it can be noted that reducing the distance to these factors, expansion of urbanization and built-up areas, construction of new roads, cropland expansion and the need for water resources have played effective roles in deforestation and forest degradation of the region.

Many driving factors are effective in forest transition to other LUCs, which may vary from place to place. Various studies have pointed to the effects of elevation, slope, distance from the city, built-up areas, roads and river in deforestation (Mas *et al.* 2004, Ellis and Porter-Bolland 2008, Nurwanda *et al.* 2016). In this study, modeling of 1993–2002 and 2002–2017 was performed using 9 different variables including distance from the perennial river of the region, distance from intermittent rivers, distance from croplands, distance from cities, distance from other built-up areas, distance from roads, elevation, slope, and aspect.

According to the results of LR modeling for 1993–2002 (before the implementation of ZFPP), distance from intermittent rivers, distance from cities and distance from roads were the most effective criteria for forest degradation, respectively (Table 9). After almost eight years of a war between Iraq and Iran (1980–1988), since 1989 the construction era began in Iran and has led to major changes in various parts of the country (Sarmadi and Badri 2017). After the end of the war, deforestation activities increased because of the return of people to their homes and their gradual resettlement in the region, the existence of non-standard roads that were used for military purposes in the past, expansion of croplands and reconstruction and development of built-up areas (Stevens *et al.* 2011). (Grunberg 2000) showed that the distance from built-up areas had a significant effect on the phenomenon of forest destruction if less than 4 km from residential regions. Driver variables such as distance from cities, in general, show the effects of demographic factors which are often associated with deforestation activities.

As already demonstrated by Kaimowitz and Angelsen (1998), Wickham *et al.* (2000) and Nelson *et al.* (2001) the distance to rivers and roads from each forested area were negatively linked to the probability of forest degradation. Riparian areas are often chosen for agriculture within the Sardasht because of their more fertile alluvial soils. The forest cover proximate to the permanent river of Sardasht (called

FIGURE 6 *Relative Operating Characteristic (ROC) curves of regression models in studied time periods*



Zab) is an important water source for agricultural activities and the forest lands adjacent to it that have irrigation potential for conversion croplands. Various studies have shown that this factor increased the pressure on the forest and land-use changes (Du *et al.* 2014, Pijanowski *et al.* 2014, Tayyebi *et al.* 2014, Phompila *et al.* 2017). Wyman and Stein (2010) argue that riparian areas (is the interface between land and a river or stream) were more likely to be deforested, as were areas closer to roads.

Distance from roads is related to social, economic and infrastructure development (Ellis *et al.* 2010). Various studies have highlighted road infrastructure as one of the major causes of deforestation (Geist and Lambin 2002, Echeverria *et al.* 2008) and shown that the construction of roads has led to vegetation clearance and deforestation (Grunberg 2000). The development of road networks in Sardasht is a result of organizational policies and measures for the development of this region during the construction era in Iran. Chomitz and Gray (1999), Geist and Lambin (2001) and Gautam *et al.* (2004) also showed that distance to roads (access to transportation routes, markets, croplands, and forests) influences deforestation, as do areas more suitable to agricultural activities, such as forests or rangelands in level areas or higher soil fertility. Chomitz and Gray (1999) suggested that road-building in forest areas with agriculturally poor soils may be a lose-lose proposition, causing forest fragmentation and providing low economic returns.

Coefficients of variables based on LR for 2002–2017 (after the implementation of ZFPP) also showed that distance from croplands and distance from the perennial river of the region, as well as slope, were the most important driver variables for deforestation in these years (Table 10).

In the 2002 model, the slope had a negative coefficient indicating the relationship between the slope percentage changes and forest degradation. This means that with increasing the slope and people's lack of access to these areas the destruction of forests reduced. The major destruction of Sardasht forests is due to agricultural activities, and lands with low slope are suitable for these activities. Agricultural activities are often a major variable and driving force in the dynamics of landscape (Abdullah and Nakagoshi 2006, Shooshtari and Gholamalifard 2015). Forest areas located on high slopes or highlands make people's access difficult to utilize forest resources or transition them to croplands (Vu *et al.* 2014).

In Sardasht, most of the destruction of forests has occurred close to croplands. This reflects the role of human activities in deforestation (Beygi Heidarlou *et al.* 2019). Although some studies have predicted that techniques for improving efficiency in agriculture will be consistent with increasing demand (Makowski *et al.* 2014), with increasing population and poverty, increasing demand for food and biomass energy-based is very important (Gutzler *et al.* 2015). Therefore, it is always assumed that the adjacent and marginal areas of croplands have a high probability of changing through development of croplands by farmers. Zak *et al.* (2008) also showed that the main proximate cause of deforestation in the Chaco forests of central Argentina has been agricultural expansion. A report of 152 subnational cases in tropical ecosystems of Asia, Africa, and South America concluded that in 96% of the cases deforestation is linked with cropland expansion (Geist and Lambin 2002), which denotes a negative consequence of economic, socio-political and demographic factors (Zak *et al.* 2008). In Indonesia, the main driver causes of forest change also include smallholder cropland expansion (Indrabudi *et al.* 1998).

According to the results, it seems that conservation and management plans have not been successful under the preservation plan for the protection of forests and the prevention of forest destruction and deforestation in Sardasht, according to the cropland development model and conservation programmes and without consideration of major factors of forest degradation and deforestation. The pressures from population growth have led to a widespread expansion of croplands and built-up areas to meet the demand for food and housing in forest lands (Lambin *et al.* 2003). According to spatial analysis, it has been shown that in recent years, the pattern of changes in LUC has mostly occurred near roads and croplands. Preserving the Zagros forests in the west of Iran is difficult and in many cases impossible due to the economic structure of local communities in the west of the country, which are dependent on livestock and agriculture. These forests are located in the semi-arid, mountainous and impassable region of the country with particular geographical conditions, but the unprecedented growth of the population over the past years, as well as an increase in the number of livestock and destruction of forests to develop croplands, fuel supply, general poverty and unemployment, have provided conditions for intensifying excessive utilization.

CONCLUSION

The accessibility of local communities to the forests of the region has been an important factor in exlaining deforestation patterns in Sardasht. The results showed that the distance from population centers, roads, rivers and croplands, and slope have a high correlation with deforestation. These results regarding suitable goodness of fit of the LR models highlight the role of access factor. The results of LUCC analysis and its relation to explanatory variables indicate the continuing destruction trend of Sardasht forests during the studied period.

This study showed the value of producing deforestation models regarding various physiographic and anthropogenic factors based on LR. Therefore, based on the most influential deforestation factors, management and conservation programmes can be implemented more intensively (Wilson *et al.* 2005, Linkie *et al.* 2010). In this regard, it is necessary that the managers and decision-makers of Iran's natural resources make intelligent decisions in order to prevent land destructions near roads, croplands, cities, rivers, and areas with a low slope. Increasing monitoring programmes in forest lands near roads and croplands, agricultural mechanization, modern irrigation methods, increasing productivity per unit area and applying more strict rules on agricultural and forest land cover changes are among methods that can reduce the dependence of local communities on forests. Adopting such programmes can stop or reduce forest destruction as much as possible.

The implementation of ZFPP in Sardasht has not reduced the degradation of forest lands. Reasons such as lack of local communities' participation in management, inadequate employment and lack of alternative livelihoods are factors in this situation. Local community participation in designing and decision-making stages of forestry plans increases their activity in implementing the plan and achieving its desired goals. Conversely, not using local communities has led to inefficient planning, discouraging residents, a lack of sense of responsibility in protecting forests, and difficulties in accepting the plan. Many researchers believe that conservation programmes are effective when decision-making and management have taken a unique approach to local communities (Bruner *et al.* 2001) and local communities have participated in the decision-making process for resources conservation and management (DeFries *et al.* 2007).

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REFERENCES

ABBAS, I., MUAZU, K. and UKOJE, J. 2010. Mapping land use-land cover and change detection in Kafur local government, Katsina, Nigeria (1995–2008) using remote sensing and GIS. *Research Journal of Environmental and Earth Sciences* **2**(1): 6–12.

ABDULLAH, S.A. and NAKAGOSHI, N. 2006. Changes in landscape spatial pattern in the highly developing state of Selangor, peninsular Malaysia. *Landscape and Urban Planning* **77**(3): 263–275.

ACEVEDO, P., FARFÁN, M.A., MÁRQUEZ, A.L., DELIBES-MATEOS, M., REAL, R. and VARGAS, J.M. 2011. Past, present and future of wild ungulates in relation to changes in land use. *Landscape Ecology* **26**(1): 19–31.

ACHMAD, A., HASYIM, S., DAHLAN, B. and AULIA, D.N. 2015. Modeling of urban growth in tsunami-prone city using logistic regression: Analysis of Banda Aceh, Indonesia. *Applied Geography* **62**: 237–246.

ADDINSOFT. 2019. XLSTAT Statsitical and Data Analysis Solution, Addinsoft Long Island, New York.

AGUILERA, A.M., ESCABIAS, M. and VALDERRAMA, M.J. 2006. Using principal components for estimating logistic regression with high-dimensional multicollinear data. *Computational Statistics & Data Analysis* **50**(8): 1905–1924.

ANDERSEN, L.E., GROOM, B., KILLICK, E., LEDEZMA, J.C., PALMER, C. and WEINHOLD, D. 2017. Modelling land use, deforestation, and policy: a hybrid optimisation-heterogeneous agent model with application to the Bolivian Amazon. *Ecological Economics* **135**: 76–90.

AREKHI, S. 2011. Modeling spatial pattern of deforestation using GIS and logistic regression: A case study of northern Ilam forests, Ilam province, Iran. *African Journal of Biotechnology* **10**(72): 16236–16249.

BASNYAT, B. 2009. Impacts of demographic changes on forests and forestry in Asia and the Pacific. Bangkok, FAO of the United Nations Regional Office for Asia and the Pacific: 82 pp.

BAUMANN, M., OZDOGAN, M., KUEMMERLE, T., WENDLAND, K.J., ESIPOVA, E. and RADELOFF, V.C. 2012. Using the Landsat record to detect forest-cover changes during and after the collapse of the Soviet Union in the temperate zone of European Russia. *Remote Sensing of Environment* **124**: 174–184.

BAUMANN, M., RADELOFF, V.C., AVEDIAN, V. and KUEMMERLE, T. 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. *Regional Environmental Change* **15**(8): 1703–1716.

BEERS, T.W., DRESS, P.E. and WENSEL, L.C. 1966. Notes and observations: aspect transformation in site productivity research. *Journal of Forestry* **64**(10): 691–692.

BELSLEY, D.A., KUH, E. and WELSCH, R.E. 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. New York, John Wiley & Sons, 300 pp.

BEYGI HEIDARLOU, H., BANJ SHAFIE, A. and ERFANIAN, M. 2015. Evaluating the Fuzzy Weighted Linear Combination Method in Forest Fire Risk Mapping (Case study: Sardasht Forests, West Azerbaijan Province, IRAN). *Journal of Wood & Forest Science and Technology* **22**(3): 29–52.

BEYGI HEIDARLOU, H., BANJ SHAFIE, A. and ERFANIAN, M. 2015. Forest fire risk mapping using analytical hierarchy process technique and frequency ratio method (Case study: Sardasht Forests, NW Iran). *Iranian Journal of Forests and Poplar Research* **22**(4): 559–573.

BEYGI HEIDARLOU, H., BANJ SHAFIEI, A., ERFANIAN, M., TAYYEBI, A. and ALIJANPOUR, A. 2019. Effects of preservation policy on land use changes in Iranian Northern Zagros forests. *Land Use Policy* **81**: 76–90.

BOUCHER, D.H., ELIAS, P., FAIRES, J. and SMITH, S. 2014. *Deforestation success stories: Tropical nations where forest protection and reforestation policies have worked*, Union of Concerned Scientists, 51 pp.

BRAIMOH, A.K. and ONISHI, T. 2007. Spatial determinants of urban land use change in Lagos, Nigeria. *Land Use Policy* **24**(2): 502–515.

BRESLOW, N.E. and HOLUBKOV, R. 1997. Maximum likelihood estimation of logistic regression parameters under two-phase, outcome-dependent sampling. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **59**(2): 447–461.

BRINK, A.B. and EVA, H.D. 2009. Monitoring 25 years of land cover change dynamics in Africa: A sample based remote sensing approach. *Applied Geography* **29**(4): 501–512.

BRUNER, A.G., GULLISON, R.E., RICE, R.E. and DA FONSECA, G.A. 2001. Effectiveness of parks in protecting tropical biodiversity. *Science* **291**(5501): 125–128.

CARTER, J. and GRONOW, J. 2005. *Recent experience in collaborative forest management: a review paper*. Jakarta, Center for International Forestry Research, 57 pp.

CELIK, I. 2005. Land-use effects on organic matter and physical properties of soil in a southern Mediterranean highland of Turkey. *Soil and Tillage Research* **83**(2): 270–277.

CHOMITZ, K. and GRAY, D.A. 1999. *Roads, lands, markets, and deforestation: a spatial model of land use in Belize*, The World Bank.

CLARK, W. and HOSKING, P.L. 1986. *Statistical methods for geographers*. State University of New York, Buffalo, USA, John Wiley & Sons, 528 pp.

CROWTHER, T.W., GLICK, H., COVEY, K., BETTIGOLE, C., MAYNARD, D., THOMAS, S., SMITH, J., HINTLER, G., DUGUID, M. and AMATULLI, G. 2015. Mapping tree density at a global scale. *Nature* **525**(7568): 201.

DEFRIES, R., HANSEN, A., TURNER, B., REID, R. and LIU, J. 2007. Land use change around protected areas: management to balance human needs and ecological function. *Ecological Applications* **17**(4): 1031–1038.

DU, S., WANG, Q. and GUO, L. 2014. Spatially varying relationships between land-cover change and driving factors at multiple sampling scales. *Journal of Environmental Management* **137**: 101–110.

EASTMAN, J.R. 2002. *Idrisi for windows user's guide ver.32.*, Clark labs for cartography technology and geographic analysis (Worcester: Clark University).

EASTMAN, J.R. 2012. *Idrisi selva tutorial*, Idrisi Production, Clark Labs-Clark University.

ECHEVERRIA, C., COOMES, D.A., HALL, M. and NEWTON, A.C. 2008. Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. *Ecological Modelling* **212**(3–4): 439–449.

ELLIS, E. and PORTER-BOLLAND, L. 2008. Is community-based forest management more effective than protected areas?: A comparison of land use/land cover change in two neighboring study areas of the Central Yucatan Peninsula, Mexico. *Forest Ecology and Management* **256**(11): 1971–1983.

ELLIS, E.C., KLEIN GOLDEWIJK, K., SIEBERT, S., LIGHTMAN, D. and RAMANKUTTY, N. 2010. Anthropogenic transformation of the biomes, 1700 to 2000. *Global Ecology and Biogeography* **19**(5): 589–606.

GAUTAM, A.P., SHIVAKOTI, G.P. and WEBB, E.L. 2004. Forest cover change, physiography, local economy, and institutions in a mountain watershed in Nepal. *Environmental Management* **33**(1): 48–61.

GEIST, H.J. and LAMBIN, E.F. 2001. What drives tropical deforestation?: a meta-analysis of proximate and underlying causes of deforestation based on subnational case study evidence. *LUCC Report Series* **4**: 136.

GEIST, H.J. and LAMBIN, E.F. 2002. Proximate causes and underlying driving forces of tropical deforestation: Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience* **52**(2): 143–150.

GHOLAMALIFARD, M., JOORABIAN SHOOSHTARI, S.H.K., SAYED HAMZEH and MIRZAEI, M. 2013. Land cover change modeling of coastal areas of Mazandaran Province using LCM in a GIS environment. *Journal of Environmental Studies* **38**(4): 109–124.

GONÇALVES, L., SUBTIL, A., OLIVEIRA, M.R. and BERMUDEZ, P. 2014. ROC curve estimation: An overview. *REVSTAT–Statistical Journal* **12**(1): 1–20.

GOODARZI, M., POURHASHEMI, M. and AZIZI, Z. 2019. Investigation on Zagros forests cover changes under the recent droughts using satellite imagery. *Journal of Forest Science* **65**(1): 9–17.

GRAHAM, M.H. 2003. Confronting multicollinearity in ecological multiple regression. *Ecology* **84**(11): 2809–2815.

GRAINGER, A. 1993. Rates of deforestation in the humid tropics: estimates and measurements. *Geographical Journal* **159**(1): 33–44.

GRUNBERG, W. 2000. Modeling deforestation risk in the Maya Biosphere Reserve, Guatemala. School of Renewable Natural Resources. Tucson, Arizona, USA, The University of Arizona. Master's Theses: 77 pp.

GUTZLER, C., HELMING, K., BALLA, D., DANNOWSKI, R., DEUMLICH, D., GLEMNITZ, M., KNIERIM, A., MIRSCHEL, W., NENDEL, C. and PAUL, C. 2015. Agricultural land use changes–a scenario-based sustainability impact assessment for brandenburg, germany. *Ecological Indicators* **48**: 505–517.

HENAREH KHALYANI, A., FALKOWSKI, M.J. and MAYER, A.L. 2012. Classification of Landsat images based on spectral and topographic variables for land-cover change detection in Zagros forests. *International Journal of Remote Sensing* **33**(21): 6956–6974.

HENAREH KHALYANI, A., MAYER, A.L., FALKOWSKI, M.J. and MURALIDHARAN, D. 2013. Deforestation and landscape structure changes related to socioeconomic dynamics and climate change in Zagros forests. *Journal of Land Use Science* **8**(3): 321–340.

HIETEL, E., WALDHARDT, R. and OTTE, A. 2004. Analysing land-cover changes in relation to environmental variables in Hesse, Germany. *Landscape Ecology* **19**(5): 473–489.

HOSTERT, P., KUEMMERLE, T., PRISHCHEPOV, A., SIEBER, A., LAMBIN, E.F. and RADELOFF, V.C. 2011. Rapid land use change after socio-economic disturbances: the collapse of the Soviet Union versus Chernobyl. *Environmental Research Letters* **6**(4): 045201.

INDRABUDI, H., DE GIER, A. and FRESCO, L. 1998. Deforestation and its driving forces: a case study of Riam Kanan watershed, Indonesia. *Land Degradation & Development* **9**(4): 311–322.

IRWIN, E. and GEOGHEGAN, J. 2001. Theory, data, methods: developing spatially explicit economic models of land use change. *Agriculture, Ecosystems & Environment*, **85**(1–3): 7–24.

JACK, B.K., KOUSKY, C. and SIMS, K.R. 2008. Designing payments for ecosystem services: Lessons from previous experience with incentive-based mechanisms. *Proceedings of the National Academy of Sciences* **105**(28): 9465–9470.

JAZIREHI, M. and EBRAHIMI ROSTAGHI, M. 2003. *Silviculture in zagros*. Tehran, Iran, University of Tehran, 570 pp.

KAIMOWITZ, D. and ANGELSEN, A. 1998. *Economic models of tropical deforestation: a review*, Cifor, 140 pp.

KRUG, J., ERIKSSON, H., HEIDECKE, C., KELLOMÄKI, S., KÖHL, M., LINDNER, M. and SAIKKONEN, K. 2015. Socio-economic Impacts—Forestry and Agriculture. *Second Assessment of Climate Change for the Baltic Sea Basin*, Springer: 399–409.

LAMBIN, E.F. and GEIST, H.J. 2008. *Land-use and land-cover change: local processes and global impacts*. Berlin, Heidelberg, Germany, Springer Science & Business Media, 221 pp.

LAMBIN, E.F., GEIST, H.J. and LEPERS, E. 2003. Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources* **28**(1): 205–241.

LAMBIN, E.F. and MEYFROIDT, P. 2011. Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences* **108**(9): 3465–3472.

LI, Y., VIÑA, A., YANG, W., CHEN, X., ZHANG, J., OUYANG, Z., LIANG, Z. and LIU, J. 2013. Effects of conservation policies on forest cover change in giant panda habitat regions, China. *Land Use Policy* **33**: 42–53.

LINKIE, M., ROOD, E. and SMITH, R.J. 2010. Modelling the effectiveness of enforcement strategies for avoiding tropical deforestation in Kerinci Seblat National Park, Sumatra. *Biodiversity and Conservation* **19**(4): 973–984.

LIU, Y., HUANG, X., YANG, H. and ZHONG, T. 2014. Environmental effects of land-use/cover change caused by urbanization and policies in Southwest China Karst area–A case study of Guiyang. *Habitat International* **44**: 339–348.

LUYSSAERT, S., JAMMET, M., STOY, P.C., ESTEL, S., PONGRATZ, J., CESCHIA, E., CHURKINA, G., DON, A., ERB, K. and FERLICOQ, M. 2014. Land management and land-cover change have impacts of similar magnitude on surface temperature. *Nature Climate Change* **4**(5): 389.

MAES, J., EGOH, B., WILLEMEN, L., LIQUETE, C., VIHERVAARA, P., SCHÄGNER, J.P., GRIZZETTI, B., DRAKOU, E.G., LA NOTTE, A. and ZULIAN, G. 2012. Mapping ecosystem services for policy support and decision making in the European Union. *Ecosystem Services* **1**(1): 31–39.

MAKOWSKI, D., NESME, T., PAPY, F. and DORÉ, T. 2014. Global agronomy, a new field of research. A review. *Agronomy for Sustainable Development* **34**(2): 293–307.

MAS, J.-F., PUIG, H., PALACIO, J.L. and SOSA-LÓPEZ, A. 2004. Modelling deforestation using GIS and artificial neural networks. *Environmental Modelling and Software* **19**(5): 461–471.

MATHER, A. 1992. The Forest Transition. *Area* **24**: 367–379.

MATHER, A. and NEEDLE, C. 2000. The relationships of population and forest trends. *The Geographical Journal* **166**(1): 2–13.

MIDI, H., SARKAR, S.K. and RANA, S. 2010. Collinearity diagnostics of binary logistic regression model. *Journal of Interdisciplinary Mathematics* **13**(3): 253–267.

MILES, J. 2014. Tolerance and variance inflation factor. *Wiley StatsRef: Statistics Reference Online*.

MIRANDA, J.J., CORRAL, L., BLACKMAN, A., ASNER, G. and LIMA, E. 2016. Effects of protected areas on forest cover change and local communities: evidence from the Peruvian Amazon. *World Development* **78**: 288–307.

MITCHEL, A. 2005. The ESRI Guide to GIS analysis, Volume 2: Spartial measurements and statistics. *ESRI Guide to GIS analysis*, 240 pp.

NELSON, G.C., HARRIS, V., STONE, S.W., BARBIER, E.B. and BURGESS, J.C. 2001. Deforestation, land use, and property rights: empirical evidence from Darien, Panama. *Land Economics* **77**(2): 187–205.

NURWANDA, A., ZAIN, A.F.M. and RUSTIADI, E. 2016. Analysis of land cover changes and landscape fragmentation in Batanghari Regency, Jambi Province. *Procedia-Social and Behavioral Sciences* **227**: 87–94.

PHOMPILA, C., LEWIS, M., OSTENDORF, B. and CLARKE, K. 2017. Forest Cover Changes in Lao Tropical Forests: Physical and Socio-Economic Factors are the Most Important Drivers. *Land* **6**(2): 23.

PIJANOWSKI, B.C., BROWN, D.G., SHELLITO, B.A. and MANIK, G.A. 2002. Using neural networks and GIS to forecast land use changes: a land transformation model. *Computers, Environment and Urban Systems* **26**(6): 553–575.

PIJANOWSKI, B.C., TAYYEBI, A., DOUCETTE, J., PEKIN, B.K., BRAUN, D. and PLOURDE, J. 2014. A big data urban growth simulation at a national scale: configuring the GIS and neural network based land transformation model to run in a high performance computing (HPC) environment. *Environmental Modelling & Software* **51**: 250–268.

PONTIUS JR, R.G. and BATCHU, K. 2003. Using the relative operating characteristic to quantify certainty in prediction of location of land cover change in India. *Transactions in GIS* **7**(4): 467–484.

PONTIUS, R.G. and PARMENTIER, B. 2014. Recommendations for using the relative operating characteristic (ROC). *Landscape Ecology* **29**(3): 367–382.

POURHASHEMI, M., MOHAJER, M.R.M., ZOBEIRI, M., AMIRI, G.Z. and PANAHI, P. 2004. Identification of forest vegetation units in support of government management objectives in Zagros forests, Iran. *Scandinavian Journal of Forest Research* **19**(S4): 72–77.

PUYRAVAUD, J.-P. 2003. Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management* **177**(1–3): 593–596.

ROOZITALAB, M.H., SIADAT, H. and FARSHAD, A. 2018. *The Soils of Iran*. Switzerland, Springer International Publishing, 255 pp.

RUDEL, T.K., COOMES, O.T., MORAN, E., ACHARD, F., ANGELSEN, A., XU, J. and LAMBIN, E. 2005. Forest transitions: towards a global understanding of land use change. *Global Environmental Change* **15**(1): 23–31.

SABETI, H. 1994. *Forest, Trees and Shrubs of Iran*. Iran, Yazd, Yazd University, 886 pp.

SARMADI, H. and BADRI, M. 2017. The Effect of Hashemi Rafsanjani's Technocrat Government and changing of foreign policy of Iran from power to pragmatism. *Academia Journal of Educational Research* **5**(2): 29–33.

SHI, Z.-H., CHEN, L.-D., HAO, J.-P., WANG, T.-W. and CAI, C.-F. 2009. The effects of land use change on environmental quality in the red soil hilly region, China: a case study in Xianning County. *Environmental Monitoring and Assessment* **150**(1–4): 295.

SHOOSHTARI, S.J. and GHOLAMALIFARD, M. 2015. Scenario-based land cover change modeling and its implications for landscape pattern analysis in the Neka Watershed, Iran. *Remote Sensing Applications: Society and Environment* **1**: 1–19.

STEVENS, K., CAMPBELL, L., URQUHART, G., KRAMER, D. and QI, J. 2011. Examining complexities of forest cover change during armed conflict on Nicaragua's

Atlantic Coast. *Biodiversity and Conservation* **20**(12): 2597–2613.

TAYYEBI, A., DELAVAR, M.R., YAZDANPANAH, M.J., PIJANOWSKI, B.C., SAEEDI, S. and TAYYEBI, A.H. 2010. A spatial logistic regression model for simulating land use patterns: a case study of the Shiraz Metropolitan area of Iran. *Advances in Earth Observation of Global Change*. E. Chuvieco, J. Li and X. Yang. Dordrecht, Springer: 27–42.

TAYYEBI, A. and JENERETTE, G.D. 2016. Increases in the climate change adaption effectiveness and availability of vegetation across a coastal to desert climate gradient in metropolitan Los Angeles, CA, USA. *Science of the Total Environment* **548**: 60–71.

TAYYEBI, A., MEEHAN, T.D., DISCHLER, J., RADLOFF, G., FERRIS, M. and GRATTON, C. 2016. SmartScape™: A web-based decision support system for assessing the tradeoffs among multiple ecosystem services under crop-change scenarios. *Computers and Electronics in Agriculture* **121**: 108–121.

TAYYEBI, A., PIJANOWSKI, B.C., LINDERMAN, M. and GRATTON, C. 2014. Comparing three global parametric and local non-parametric models to simulate land use change in diverse areas of the world. *Environmental Modelling & Software* **59**: 202–221.

TORAHI, A.A. and RAI, S.C. 2011. Land cover classification and forest change analysis, using satellite imagery-a case study in Dehdez area of Zagros Mountain in Iran. *Journal of Geographic Information System* **3**(01): 1.

TU, J. and XIA, Z.-G. 2008. Examining spatially varying relationships between land use and water quality using geographically weighted regression I: Model design and evaluation. *Science of the Total Environment* **407**(1): 358–378.

VAN DER LINDEN, S., RABE, A., HELD, M., JAKIMOW, B., LEITÃO, P.J., OKUJENI, A., SCHWIEDER, M., SUESS, S. and HOSTERT, P. 2015. The EnMAP-Box—A toolbox and application programming interface for EnMAP data processing. *Remote Sensing* **7**(9): 11249–11266.

VAN OORT, P. 2007. Interpreting the change detection error matrix. *Remote Sensing of Environment* **108**(1): 1–8.

VIÑA, A., MCCONNELL, W.J., YANG, H., XU, Z. and LIU, J. 2016. Effects of conservation policy on China's forest recovery. *Science Advances* **2**(3): e1500965.

VU, Q.M., LE, Q.B., FROSSARD, E. and VLEK, P.L. 2014. Socio-economic and biophysical determinants of land degradation in Vietnam: An integrated causal analysis at the national level. *Land Use Policy* **36**: 605–617.

WASKE, B., VAN DER LINDEN, S., OLDENBURG, C., JAKIMOW, B., RABE, A. and HOSTERT, P. 2012. ImageRF–A user-oriented implementation for remote sensing image analysis with Random Forests. *Environmental Modelling & Software* **35**: 192–193.

WICKHAM, J.D., O'NEILL, R.V. and JONES, K.B. 2000. Forest fragmentation as an economic indicator. *Landscape Ecology* **15**(2): 171–179.

WILSON, K., NEWTON, A., ECHEVERRIA, C., WESTON, C. and BURGMAN, M. 2005. A vulnerability analysis of the temperate forests of south central Chile. *Biological Conservation* **122**(1): 9–21.

WYMAN, M.S. and STEIN, T.V. 2010. Modeling social and land-use/land-cover change data to assess drivers of smallholder deforestation in Belize. *Applied Geography* **30**(3): 329–342.

XLSTAT, A. 2016. Leading data analysis and statistical solution for microsoft excel. Avaliable online: www.xlstat.com (accessed on 2 November 2016).

ZAK, M.R., CABIDO, M., CÁCERES, D. and DÍAZ, S. 2008. What drives accelerated land cover change in central Argentina? Synergistic consequences of climatic, socioeconomic, and technological factors. *Environmental Management* **42**(2): 181–189.