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Evaluating the effect of ongoing conservation policies and forest cover changes in Iranian Zagros forests based on a Land Transformation Model: transition to forest or deforestation?

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Abstract: In recent decades, Zagros forests from western Iran have experienced dramatic changes in cover and structure. Conservation policies, on the other hand, have existed or are being implemented in these forests since 2002 to prevent deforestation. There is, however, the question on how effective were the conservation policies in preventing forest loss. The goal of this study was to analyze the effect of conservation policies in preventing forest loss, as well as to forecast their future effectiveness. Since the spatio-temporal changes in forest cover, land-use and its patterns occur in a non-linear way, this study was based on the use of Land Transformation Model (LTM). Using geographic information systems (GIS) and artificial neural networks (ANNs), this model forecasts future forest changes for the next 30 years. Three scenarios were used for this purpose, in which the input patterns included the years 2002-2012, 2002-2022, and 2012-2022. Based on these, deforestation was predicted for the next three decades using 14 variables. Assuming no changes in the implementation of conservation policies in the Zagros forests, the model was characterized by a consistent accuracy and indicated a projected pattern of increased deforestation over the next years in the region. In other words, by the ongoing conservation policies, the net deforestation overtakes net reforestation. It appears that to stop further forest degradation, Iran's Forestry Service decision-makers must implement improved forest conservation policies.

Keywords: conservation, deforestation, forecasting model, land use/cover change, ANNs.

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Introduction

Land-Cover and Land-Use Change (LCLUC) is the end consequence of a complex interaction between several variables, including human activity, resource exploitation, agricultural activity, policy changes, management, environmental changes, and socioeconomic disturbances (Hostert et al. 2011, Baumann et al. 2015, Svoboda et al. 2022). These changes occur at various paces as a result of the conversion of natural lands such as forests to other land uses such as croplands, grasslands, urban or settlements (Ge et al. 2018). Due to LCLUC's detrimental effects on the environment and its processes, including increased soil erosion, runoff, CO_2 emissions, climate change, and a decline in biodiversity (Warth et al. 2020), understanding how and why LCLUC occurs is very important. Land use maps of previous years help provide valuable information about the background and past conditions of each region for the sustainable resource management and conservation programs (Munthali et al. 2020). Although the overall amount of forest cover has been declining in many countries (Li et al. 2013), at the same time, many other European, North American, and Asian countries are experiencing a forest transition (i.e., forest expansion) to meet the United Nations' Sustainable Development Goals (Katila et al. 2019).

By considering the wide range of climatic variation in Iran, researchers have divided Iran's forests into five vegetation regions (forests and other wooded lands with a canopy cover of more than 5%) as follows: The Hyrcanian Forests (2,073,000 ha), Arasbaran Forests (174,000 ha), Iran-Touranian Forests (4,666,000 ha), Persian Gulf and Sea of Oman Region forests (2,039,000 ha), and Zagros Forests (4,749,000 ha) (Sagheb Talebi et al. 2014, Roozitalab et al. 2018). According to the U.N. FAO, Iranian forests cover about 10,751,870 ha (FAO 2020).Iran's forest resources were nationalized under government development plans, starting from 1963, to control forest loss then, from 1967 the government moved to nationalize all the natural resources (i.e., natural forests and pastures), which led to the preparation of protective plans on a large scale (Roudgarmi & Mahdiraji 2020). Since then, the Iran's government has gradually gained control over the forest use, and various policies have been adopted since 1997 (such as Zagros Forests conservation policy from 2002), which had different effects (Beygi Heidarlou et al. 2019). Beginning in the early 20th century, a system of development planning was implemented to enhance capital-intensive sectors and quickly modernizing society while also supporting the nation's economic growth. This led to many challenges in forest management and law enforcement (Sotoudeh Foumani et al. 2017), resulting in losses of large forest areas in the Alborz (Hyrcanian forests) and Zagros mountains (Zagros forests) and the extinction of many valuable tree and plant species due to illegal logging, which is not recorded in the official statistics.

About 60 years have passed since the implementation of the first forest management plan in Iran. Hundreds of forest management plans have been implemented in these 60 years, 90% of which are related to the Hyrcanian forests. Before the nationalization, forests were managed under private ownership and were used as pastures. In the past, forestry projects were implemented only for the utilization of industrial wood products. Then, multi-purpose plans were proposed and economic and social considerations were added, especially in the Zagros forests. These plans include Charcoal-making schemes (1950-1959), "*Savadkuh Frame*" development plan (1962-1978), "*Neka Choob*" Mazandaran Company (1969), exclosure and rehabilitation (1972-1981), afforestation with people's participation, by-products operation, "*Tuba*" plan (1999-2005), and Zagros Forests conservation policy ("*Siyanat*" plan) (since 2002). *Siyanat* plan is implemented to reduce deforestation and increase people's participation in Zagros forests protective projects (Beygi Heidarlou et al. 2019). These policies did not take into account the forest-dependent people (especially in the Zagros); as such, forests and grasslands were managed with both traditional and governmental participation. With an area of around 4,749,000 ha, the Zagros oak forests cover 20% of the vegetative area and 11 provinces of Iran, playing an important socio-economic role (Roozitalab et al. 2018, Beygi Heidarlou et al. 2020b).

Remote sensing, as a cutting-edge technology, is useful in extracting land use maps, enables short-term access to valuable data at low cost, and it is being used to track the changes that occurred in space and time based on satellite data (Legdou et al. 2020). To date, several techniques, models, and computer algorithms have been developed to use the data provided by remote sensing instruments to identify LCLUC (Thyagharajan & Vignesh 2019); since these data are simply entered into geographic information system (GIS) environments, they can be widely used in modelling using GIS technology. Land-use models are useful reproductible tools which complement the existing capabilities in analysing LCLUC to make more informed decisions (Verburg et al. 2004). To date, LCLUC models are able to link biophysical, socio-economic, and political factors and to evaluate LCLUC based on hybrid methods and models (Schürmann et al. 2020). Several studies have been able to identify areas susceptible to deforestation as well as its main contributing factors, by using land-use models (Dávalos et al. 2011, Armenteras et al. 2013).

LCLUC is a complex process (Lambin and Geist 2008, Guan et al. 2019), and modelling these systems is always challenging (Tayyebi and Pijanowski 2014). Veldkamp and Lambin (2001) showed that the drivers of LCLUC operate nonlinearly at spatio-temporal scale. Therefore, to model the dynamics of land use, nonlinear learning techniques are required, such as artificial neural networks (ANNs) (Živković et al. 2009). In addition, Liu et al. (2017) suggested a future land use simulation model (FLUS) model to predict the long-term spatial trajectories of multiple LCLUCs. They used Cellular automata (CA) to improve the model's capacity to accurately anticipate future land use patterns. Morshed et al. (2022) and Rahnama and Wyatt's (2021) studies, which used ANNs, also revealed the importance of a strategic land use plan for monitoring and controlling plant encroachment, as well as scientific mitigation approaches to maintain ecological sustainability. ANNs have been widely used by LCLUC modellers over the last two decades (Tayyebi & Pijanowski 2014, Pijanowski et al. 2020). The Land Transformation Model (LTM), which is an ANN-based model, has been applied as a forecasting tool in various parts of the world to analyze spatio-temporal dynamics of land use, and to model and predict the impacts of LCLUC in the future (Pijanowski et al. 2009, Newman et al. 2016). The LTM model is implemented in GIS and has been widely used as the most accurate ANN-based LCLUC model to forecast LCLUC (Newman et al. 2016). This model integrates the multi-layer perceptron (MLP) ANN and GIS, based on socio-economic and biological factors with the aim to simulate LCLUC (Pijanowski et al. 2002a, Pijanowski et al. 2014). Without any prior knowledge of their functional relationship, MLP performs a supervised learning which is useful in checking the agreement between input and output pairs of drivers (Tayyebi & Pijanowski 2014).

On the other hand, the failure of many environmental studies is a result of the absence of quantifiable indicators and quantitative projections of changes based on the conditions of each place (Mallard & François 2013). Spatial analysis models that generate forecasts of potential changes at the landscape scale should be used in conjunction with these evaluations (Gómez-Ossa & Botero-Fernández 2017). Natural resources of West Azarbaijan Province (northwest Iran) and especially the forests of Sardasht city, with an area of 91,117 ha, are considered an important and relatively one of the critical areas in Zagros forests for land-use change and forest decline (Beygi Heidarlou et al. 2019). This region has not been immune to human harm and has seen forest loss throughout the years as a result of population increase, poverty, and the demand for food, jobs, livable environments, roads, and urbanization growth, among other factors (Beygi Heidarlou et al. 2020a). As a result, the necessity for a careful planning and assessment in this region of the country has intensified in the last period.

This study aims at predicting deforestation of the Sardasht City for three periods (2002-2012, 2002-2022, and 2012-2022) and at modelling these changes for the next 10 (2032), 20 (2042) and 30 (2052) years by a LTM model assuming that conservation policies would be kept unchanged. Specifically, the study attempted to answer the following research questions: i) How will the future forests change by keeping the current state in the implementation of conservation policies in the area of study? and ii) Has the implementation of Zagros conservation policies enabled forest transition and did it prevented the forest loss?

Materials and Methods

Study area

City of Sardasht, which is located in Iran's West Azarbaijan province's southwest, was chosen as the research area. Sardasht has an average altitude of 1515 m (altitude ranges between 591 and 2683 m) and holds 3.8% (1381.83 km2) of the province's total area, being located between 35°37' and 36°28' N latitude and 45°13' to 45°42' E longitude (Figure 1). Over a 30-year period (1983-2013), the area's average yearly precipitation was 724 mm. Typically, Sardasht has the highest and lowest temperatures of 21°C and 6°C, respectively. According to the 2016 Iranian census, the city has 118,849 residents, with 68,162 living in the city and 50,687 in the countryside (Beygi Heidarlou et al. 2022).

Background of LTM

LTM was originally developed by Pijanowski et al. (1995) at the Human-Environment Modelling and Analysis Laboratory of Purdue University to simulate locally-scaled LCLUC patterns (Pijanowski et al. 2000, Pijanowski et al. 2014). In order to model the functional link between variables (both independent and

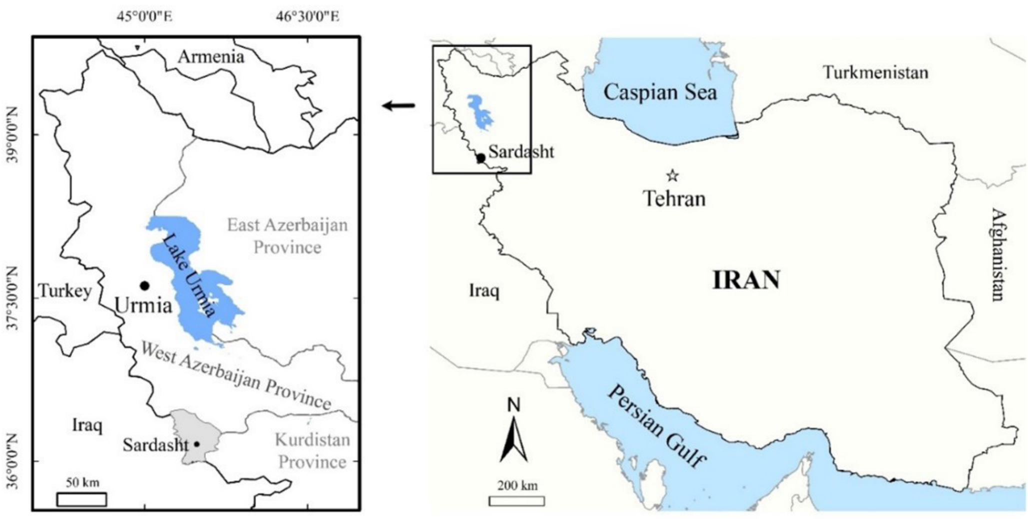

Figure 1 The geographic location of Sardasht City.

dependent drivers) and evaluate a model's potential to forecast them, ANNs based on GIS are used to learn the patterns of LCLUC. Four operational steps are required for LTM modelling (Pijanowski et al. 2002a): data processing, applying spatial information, integrating the grid, and temporal scaling of prediction output.

The modelling process of LTM includes data preparation, network creation, network learning pattern, network training and testing, prediction of change, and finally model validation. LTM requires data from a minimum of two time periods for ANN training, and the parameters of an optimal LTM model are estimated by running the ANN over a very large number of iterations (up to 250,000 iterations). A training cycle in LTM is defined as a set of all ANN training data, and the mean squared error (MSE) is recorded for every 100 cycles run in LTM. Typically, the difference between the reference data and the estimated output of the LTM is measured by the MSE (e Silva et al. 2020). Also, the difference between the MSE of each 100 cycles is used to evaluate the network training agreement, and the network training continues until the MSE of successive training cycles becomes stable. When this condition is met and the training is ended, the best network will be used on the testing data to estimate a suitability map. After that, the model will be used to develop a binary (change or no change) LCLUC map to predict future changes (Tayyebi & Pijanowski 2014).

Input data and model building

To examine forest cover changes due to the ongoing forest management in the Iranian Zagros forests, three time milestones were chosen. The LTM model was developed based on LCLUC patterns of Sardasht using GIS data of 2002, 2012 and 2022. The inputs of the model included 14 variables (Table 1) which were used to characterize the LCLUC. Their choice was based on how well they may describe the changes (Olmedo et al. 2015), our prior study-related knowledge, and earlier research done in western Iran (Beygi Heidarlou et al. 2019, 2022).

Table 1 List of used spatial predictors for deforestation in Sardasht.

Input variable	Layer source	Reference
Elevation	ASTER data	Mas et al. 2004, Tayyebi & Pijanowski 2014, Tayyebi et al. 2014
Slope	DEM	Mas et al. 2004, Pijanowski et al. 2006, Pijanowski et al. 2014, Gómez-Ossa & Botero-Fernández 2017
Aspect	DEM	Tayyebi & Pijanowski 2014, Tayyebi et al. 2014, Song et al. 2015
Distance from permanent river	1:25,000 scale INCC[1] topographic map	Tang et al. 2005, Oyebode 2007, Song et al. 2015, Gómez-Ossa & Botero-Fernández 2017
Distance from periodic rivers	1:25,000 scale INCC topographic map	Tayyebi & Pijanowski 2014, Tayyebi et al. 2014
Distance from primary roads	1:25,000 scale INCC topographic map	Pijanowski et al. 2002a, Pijanowski et al. 2002b, Mas et al. 2004, Pijanowski et al. 2006, Oyebode 2007, Pijanowski et al. 2014, Tayyebi & Pijanowski 2014
Distance from secondary roads	1:25,000 scale INCC topographic map	Pijanowski et al. 2002a, Tayyebi & Pijanowski 2014, Ordway 2015
Distance from tertiary roads	1:25,000 scale INCC topographic map	Pijanowski et al. 2006, Tayyebi & Pijanowski 2014
Distance from main city (Sardasht)	Land use map[2]	Pijanowski et al. 2002a, Tang et al. 2005, Oyebode 2007
Distance from other cities	Land use map	Tang et al. 2005, Oyebode 2007
Distance from other residential area	Land use map	Mas et al. 2004
Distance from croplands	Land use map	Pijanowski et al. 2006, Tayyebi & Pijanowski 2014, Tayyebi et al. 2014
Density of croplands	Land use map	Tang et al. 2005, Tayyebi et al. 2013
Density of forest	Land use map	Tayyebi & Pijanowski 2014, Tayyebi et al. 2014

Note: [1]INCC: Iran National Cartographic Center. [2] Produced land use maps in this study.

The croplands, rangelands, built-up areas, barren lands, and water body cells (pixels) in the land use maps of 2002, 2012, and 2022 were identified and aggregated in an exclusionary zone (layer) since these cells are less likely to be candidates for new deforestation areas in 2032, 2042 and 2052 (Newman et al. 2016). Using the ASCII file of variables as input layers, land use past changes as base maps and input patterns, and the one exclusionary layer (for modelling forest change), future forest change patterns of Sardasht were forecasted (Figure 2). Three input patterns (2002-2012, 2002-2022, and 2012-2022, hereafter, the first, second, and third scenario, respectively), corresponding to the periods of implementing the conservation plans (*Siyanat* plan, first ten years, second ten years and all period of implementation), were used to predict forest changes in Sardasht.

To study LCLUC patterns, powerful analytical methods can be used. These may be split into distance- and density-based methods (Pebesma 2018). To determine each pixel's distance from the closest land use class and the density of that land use class surrounding the centre pixel, respectively, in this study, distance and density functions were applied to the input data. The slope and aspect were calculated based on a 30-m digital elevation model (DEM) by using the Spatial Analyst tool of ESRI ArcGIS 10.8 software.

To generate multi-temporal land use maps for all time milestones following the implementation of the conservation policies, Landsat satellite time series were used (Table 1). In this regard, the Google Earth Engine (GEE) cloud computing platform was used to provide image collections, as well as for preprocessing, feature extraction, classification, and accuracy assessment of land use/cover maps. Landsat surface reflectance products from the period of 1 March to 30 October (for Landsat 9, all images between 1 March and 30 August) that had a cloud cover of less than 10%, were used for all time points. To effectively identify the land use classes, several spectral temporal metrics (STMs) including percentile metrics (5th, 25th, 50th, 75th, and 95th), standard deviation, mean, minimum and maximum of all spectral bands (B2:B7) were calculated. Along with spectral bands, several vegetation indices including Soil Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI), Green Normalized

Table 2 Details of used Landsat imagery and STMs for multi-temporal LULC classification.

Time milestone	Data type	Sensor	No. of images	STMs	No of STMs
2022	Landsat 9	Operational Land Imager-2 (OLI-2)	19	Percentile metrics (5th, 25th, 50th, 75th, and 95th) + standard deviation + mean + minimum + maximum of spectral bands and vegetation indices	90
2012	Landsat 5	Thematic Mapper (TM)	15		
2002	Landsat 7	Enhanced Thematic Mapper Plus (ETM+)	10		

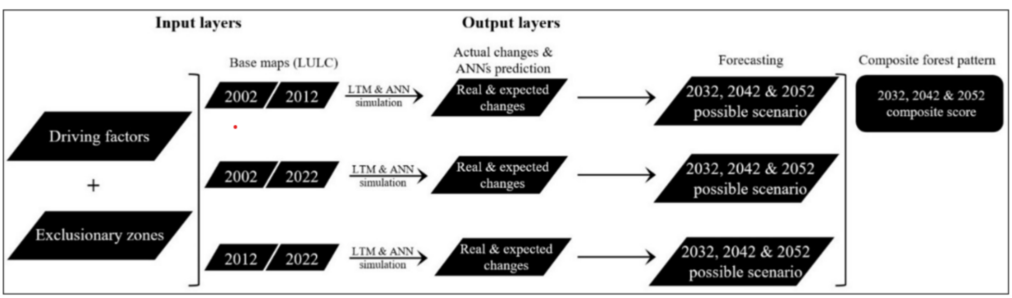

Figure 2 A flowchart for the LTM used to anticipate changes in forest cover.

Difference Vegetation Index (GNDVI), and Difference Vegetation Index (DVI), were calculated. In total, 90 STMs were used for LULC classification (Table 2).

A visual inspection of very high-resolution satellite imagery was carried out in Google Earth (GE) to generate a reference dataset, which provided a sufficient number of training and validation samples. To obtain multi-temporal reference datasets, the sample extraction process started with the earliest time milestone (2022). For the previous ones (2002 and 2012) a revision process was implemented. To do this, the 2022 reference dataset was overlaid with previous ones which were in the form of GE images and/or Landsat color composites. In the next step, all the samples throughout the study site were checked and updated. The subsets for training (70% of the samples) and validation (30% of the samples) were randomly selected from the reference datasets. Table 3 lists the characteristics of the reference datasets for 2022.

For land use classification, the training samples, STMs and random forest (RF) algorithm were used. RF is a tree-based machine learning algorithm (Breiman 1999) that has been widely used to classify remote sensing datasets (Pflugmacher et al. 2019). In previous studies, RF outperformed traditional parametric (such as maximum likelihood) and novel nonparametric machine learning algorithms (Valero Medina & Alzate Atehortúa 2019). In GEE, several hyperparameters can be tuned to improve the learning process, including but not limited to the number of trees and variables (www.developers.google.com). In this study, only the number of trees for the earliest time milestone (2022) was tuned, and an optimal value (ntree = 100) was also used to classify land use/cover for other time milestones. Default values were used for the rest of the tuning parameters. For the post-processing step, an iterative majority-filter tool was used in ArcGIS software on the classified output images to simplify the last land use maps (Baumann et al. 2015). Using validation samples and confusion matrices, the accuracy assessment of thematic land use maps was assessed (Geyer & DeWald 1973). Accuracy metrics such as the overall accuracy, kappa coefficient, producer and user accuracies (PA% and UA%), commission and omission errors (Ce% and Oe%) were calculated based on the data from confusion matrices. Then, land use maps of the time milestones (2002, 2015, and 2022) were reclassified into forest and non-forest classes with the aim to produce a land-use change map for each model (Figure 3).

Using the command prompt of Windows, the three models were developed to evaluate the forest change of Sardasht by using 14 identical input factors (variables) with the aim of outputting a forest change map. Following the training of ANN models, simulation cycles were run for each time period. The output layers (i.e., suitability and probability to change) were then converted to binary data based on cell position change (forest, non-forest) after all input layers had been standardized to a range from 0 to 1. The input variables (drivers) for calculating the expected changes of forest cover between the time periods (2002-2012, 2002-2022, and 2012-2022) were then used to train the ANNs. In the training phase, each ANN model was run up to 100,000 times; after that point, no appreciable decrease in the MSE between the output of the model and the given data was observed. Following the ANNs' training, preparation of the real change map and computing of the number of transitioned

Table 3 The details of the reference dataset for 2022: the number of samples and pixels for training and validation subsets.

Land use/ cover class	Training samples		Validation samples	
	No. of Samples	No. of Pixels (10 m)	No. of Samples	No. of Pixels (10 m)
Dense forest	135	4839	57	2073
Open forest	316	11384	135	4888
Built-up areas	25	1036	12	444
Croplands	340	1353	147	595
Rangelands	238	880	102	480
Waterbodies	245	875	105	375
Barren lands	28	1034	13	442

cells, the network testing was done based on the input layers; the cycle that had the best correlation between the simulated models and the actual change was retained to build the suitability and the change probability maps, as well as to validate the models (Pontius Jr & Schneider 2001).

Two validation statistics were used to evaluate the accuracy of ANNs: Percent Correct Metric (PCM) and Kappa Statistic (KS) values. These metrics were used to assess how closely the actual change and expected change maps across the time periods (2002-2012, 2002-2022, and 2012-2022) corresponded. In addition, using XLSTAT-R (ver. 2019) software the Receiver Operating Characteristic (ROC) by Area Under Curve (AUC) analysis was used to compare actual and probable transition maps, as supplementary means of evaluating the performance of ANN models (Gaur et al. 2020). These can only be used to compare pixels classified as binary maps (PCM and KS) or probabilities of change (ROC) (Tayyebi et al. 2011). In particular, the true positive against false positive rates (TPR vs. FPR) of a model are plotted against one other by considering all potential classification levels to create the ROC curve. The typical architecture of the ANN models used in this study is depicted in Figure 4, along with the connections between the neurons.

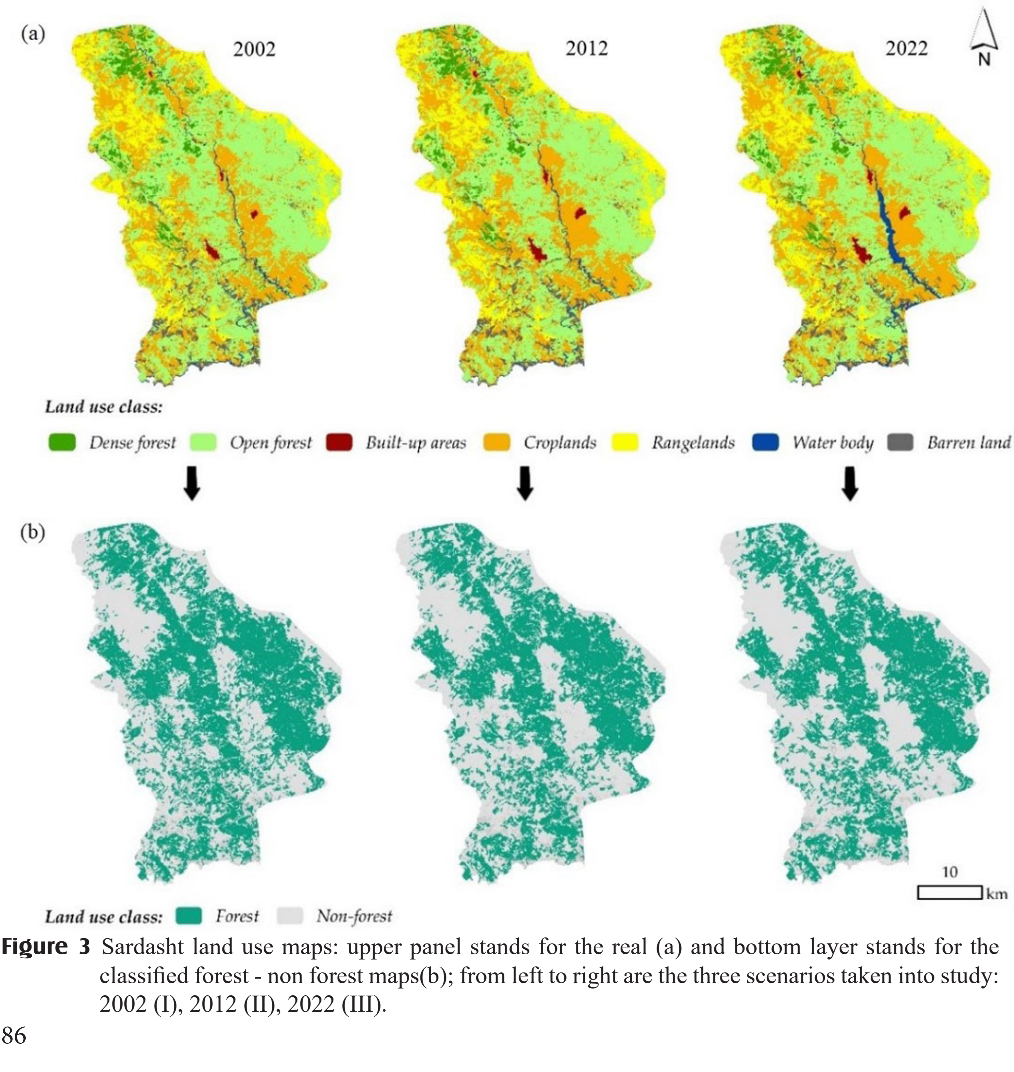

Figure 3 Sardasht land use maps: upper panel stands for the real (a) and bottom layer stands for the classified forest - non forest maps(b); from left to right are the three scenarios taken into study: 2002 (I), 2012 (II), 2022 (III).

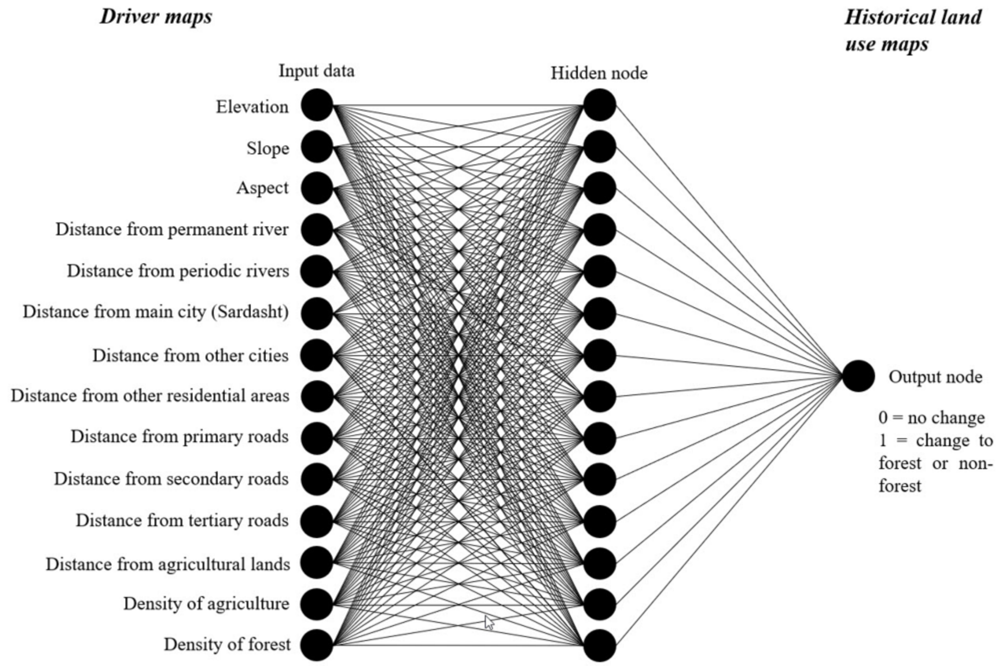

Figure 4 Architecture of the ANN used in this study.

Based on the above, for each scenario of probable changes (2032, 2042, and 2052) a score reflecting the changes was used. A score of 1 was given to the data indicating deforestation, and a score of 0 was given to data indicating the absence of deforestation. The three scenarios were then combined for each of the models developed for the considered time periods, and locations where all three, two, or only one scenario overlapped in terms of forecasting, received a grand score of 3, 2, and 1, respectively.

Results

Land use mapping and accuracy evaluation

Classification accuracy of the Landsat images was high for the created land use maps. The findings indicate that all three land use maps (2002, 2012, and 2022) were, globally, very accurate. The overall accuracy of the maps created for 2002, 2012, and 2022 was 89.48, 88.28, and 89.02%, respectively, with Kappa coefficients of 87.54, 86.74, and 85.70%. The values of PA and UA accuracies along with Ce an Oe are given in Table 4. For the majority of land use categories, the PA and UA accuracies were higher than 65%.

Table 4 Image classification accuracy evaluation for the studied years.

Land use class	2002				2012				2022			
	PA[1]	UA[1]	Ce[1]	Oe[1]	PA	UA	Ce	Oe	PA	UA	Ce	Oe
Dense forest	95.29	90.30	5.51	7.11	89.29	92.81	11.81	7.19	95.24	92.68	4.76	7.32
Open forest	86.61	87.22	10.28	11.40	93.30	82.45	7.98	17.55	86.9	88.27	13.10	11.72
Built-up areas	90.04	85.52	7.66	12.94	80.15	96.42	20.99	11.14	87.74	98.52	12.25	1.47
Croplands	90.39	92.44	8.71	7.47	91.38	92.66	8.62	7.34	87.5	89.07	12.50	10.93
Rangelands	88.22	91.24	12.98	11.41	87.48	91.62	13.81	8.37	91.31	89.39	8.68	10.61
Waterbodies	85.51	88.14	18.74	17.22	86.44	88.25	11.53	11.75	95.91	86.41	4.09	13.58
Barren lands	66.28	88.32	35.61	11.74	70.41	85.85	28.99	14.14	76.46	78.69	23.54	21.30

Note: PA and UA: Producer's (%) and User's (%) accuracies, Ce and Oe: Commission (%) and Omission (%) errors.

Change detection

Table 5 shows the trends of forest and non-forest changes in Sardasht during the studied years. During the 20 years of the studied time period (2002 to 2022), 4,350.52 ha of forests (dense + open forests) were lost, and forest lands decreased from 69,238.16 ha in 2002 to 66,490.92 and 64,887.64 ha in 2012 and 2022, respectively. This diminishing tendency of forest areas has resulted in a corresponding growth in non-forest land uses.

The results of actual changes have shown that 2,752.46, 4,355.26, and 1,602.80 ha of forest loss occurred during time periods of 2002-2012, 2002-2022, and 2012-2022, respectively (Figure 5).

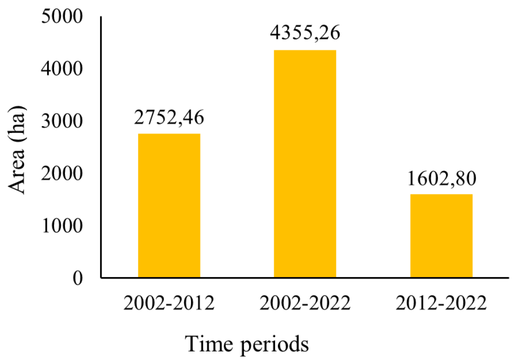

Figure 5 Changes (deforestation) which occurred in Sardasht forests (ha) in the studied time periods.

Table 5 Changes in forest and non-forest lands (ha) over the studied years.

Time milestone	Area	Land use class						
		Forest		Non-forest				
		Dense forest	Open forest	Built-up areas	Croplands	Range-lands	Barren lands	Water body
2002	ha	6130.09	63108.07	598	41529.75	19753.2	1430.74	5411.08
	%	4.44	45.74	0.43	30.10	14.32	1.04	3.92
	T[1] (ha)	69238.16		68722.77				
	T (%)	50.19		49.81				
2012	ha	5669.94	60820.98	906.44	44767.60	18968.43	1428.83	5398.71
	%	4.11	44.09	0.66	32.45	13.75	1.04	3.91
	T (ha)	66490.92		71470.01				
	T (%)	48.20		51.80				
2022	ha	5664.26	59223.38	974.09	45167.89	18944.89	2841.07	5145.35
	%	4.11	42.93	0.71	32.74	13.73	2.06	3.73
	T (ha)	64887.64		73073.29				
	T (%)	47.03		52.97				

Note: [1] T = Total.

Implementing the LTM

Training process was stopped after 100,000 cycles when the MSE of each ANN achieved a stable minimum (Figure 6). The results of ANN testing showed that, according to PCM and KS, the cycles of 50,000 (first scenario), 7000 (second scenario) and 800 (third scenario) had the highest values of PCM and KS (Table 6), respectively. Based on this level of accuracy over Sardasht region, the models were considered to be satisfactory. Therefore, these cycles were used as proper network cycles to generate the suitability map, probability change map, and for the simulation and evaluation of the models.

Figure 7 shows the suitability and probability change maps developed with the aim of modeling forest cover changes in Sardasht for each of the time periods. These two maps, which were created from the cycles with the highest Kappa and PCM, depict locations with a high likelihood of deforestation over the studied periods and have a significant impact on forecasting, reflecting the probability of change from forest to non-forest over the next 10, 20, and 30 years.

Table 6 Changes (deforestation) which occurred in Sardasht forests (ha) in the studied time periods.

Scenario	Training cycle	PCM (%)	KS
2002-2012	50000	58.60	0.57
2002-2022	7000	56.60	0.54
2012-2022	800	52.32	0.51

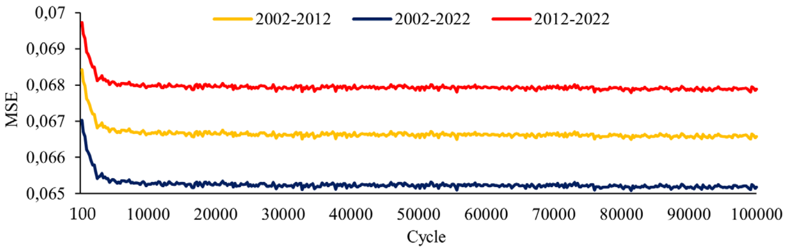

Figure 6 Difference of MSE returned by modelling deforestation in the studied time periods.

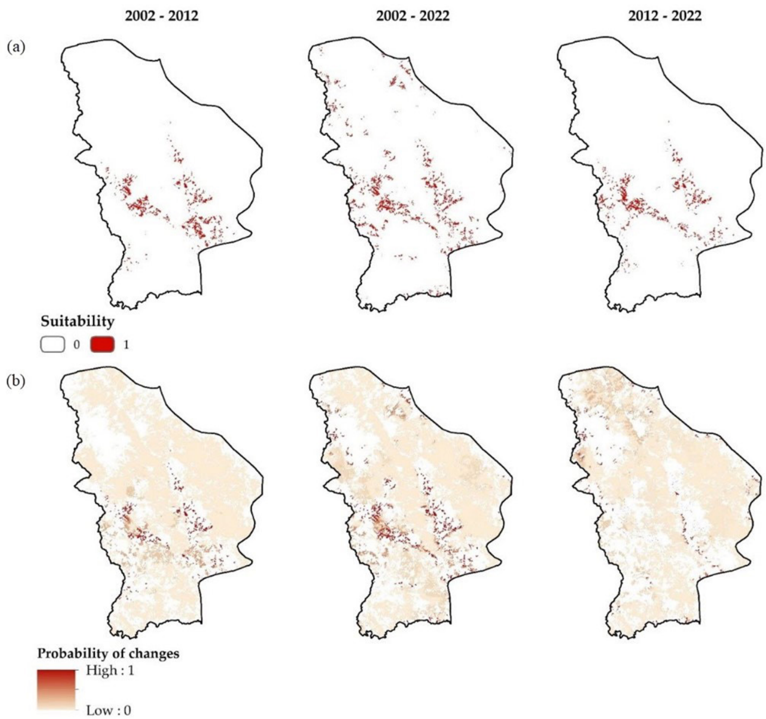

Figure 7 Suitability (a) and probability (b) change maps of deforestation models in Sardasht over time.

The LTM models performed well since all computed AUC values (ROC curves) returned values of more than 0.80 (Figure 8). The data in these three graphs are above the equality line, indicating a highly accurate positive rate. Based on these results, modelling obtained from the third scenario had the highest AUC value for deforestation modelling (0.860) (Figure 8). For all cut-off values measured from the modelling results, the coordinate points in these curves are connected using "1-specificity (FPR)" as the x-axis and "sensitivity (TPR)" as the y-axis. More points on the curves have migrated downward and to the left, indicating that deforestation models are performing properly and that tighter criteria are being used for them. In contrast, if loose criteria were used, more points on the curve would shift upward and to the right side of the curve.

After training, testing, simulating the changes, and evaluating the models, forest cover changes from Sardasht were predicted using all models for the years 2032, 2042 and 2052. The results of the models from Figure 9 and Table 7 also indicate an increase in deforestation trend in Sardasht over the next 10, 20 and 30 years, so the highest deforestation rate (9.46% of the total area) was estimated by the second scenario (2002-2022) and the lowest deforestation rate (1.16% of the total area) was estimated by the third scenario (2012-2022).

Spatial location alignment among anticipated forest cover changes appeared to fluctuate dramatically with different model input patterns at different time periods. Based on the results, there was low spatial overlapping between the models for 2032, 2042, and 2052 in the entire region. In the forest cover change models, 0.08% (110.55 ha), 0.15% (207.27 ha) and 0.33% (456.00 ha) of the entire area

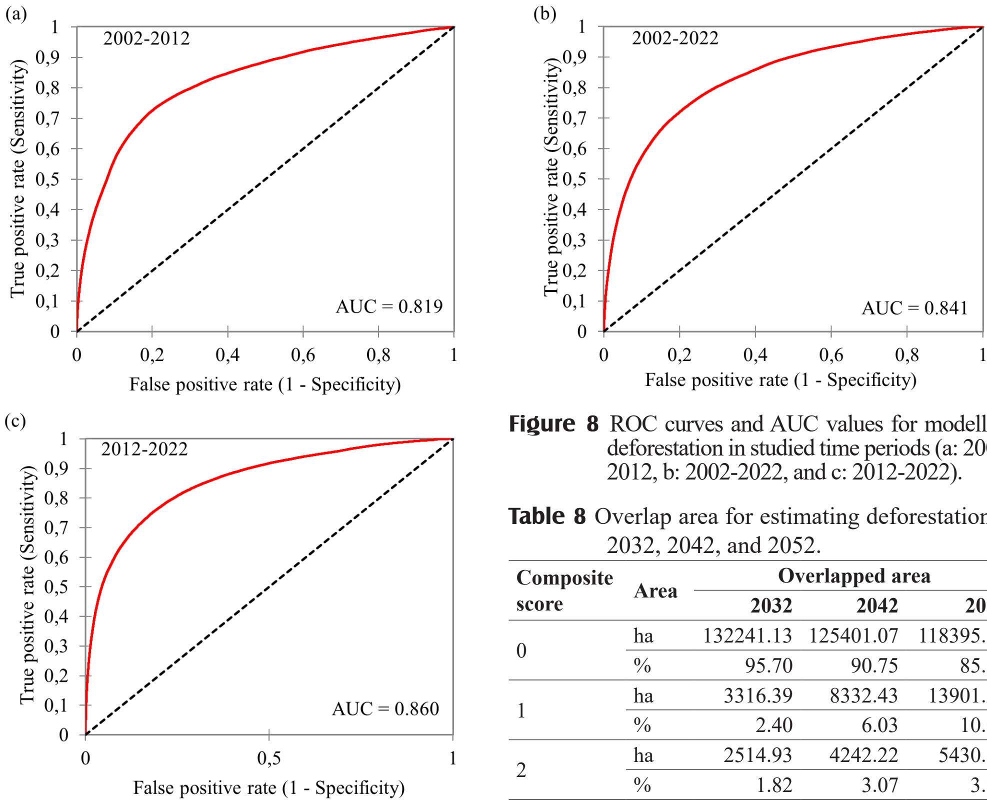

Figure 8 ROC curves and AUC values for modelling deforestation in studied time periods (a: 2002-2012, b: 2002-2022, and c: 2012-2022).

Table 7 Deforestation area for 2032, 2042 and 2052 based on the used scenarios.

Scenario	Area	Forecast year		
		2032	2042	2052
2002-2012	ha	2752.68	5505.35	8258.00
	%	1.99	3.98	5.98
2002-2022	ha	4355.26	8710.51	13065.77
	%	3.15	6.30	9.46
2012-2022	ha	1602.72	3205.59	4808.39
	%	1.16	2.32	3.48

for the years 2032, 2042, and 2052 were found to be common, respectively. Also, there was an overlapping of 1.82%, 3.07% and 3.93% for deforestation predicted for the years 2032, 2042, and 2052, for each combination of two probable scenarios, respectively (Figure 10), which indicates the relatively high potential of these areas to be subjected to deforestation in the future (Table 8). The overlap of these maps with the modelling input variables revealed that these locations are primarily located around croplands, roads, cities, and villages.

Table 8 Overlap area for estimating deforestation in 2032, 2042, and 2052.

Composite score	Area	Overlapped area		
		2032	2042	2052
0	ha	132241.13	125401.07	118395.19
	%	95.70	90.75	85.68
1	ha	3316.39	8332.43	13901.21
	%	2.40	6.03	10.06
2	ha	2514.93	4242.22	5430.59
	%	1.82	3.07	3.93
3	ha	110.55	207.27	456.00
	%	0.08	0.15	0.33

Discussion

Iran's Zagros forests have deteriorated dramatically during the last few decades. For a better management, accurate data and information regarding present types of land uses and their changes are required. Such changes are also expected to explain the implications of current conservation policies on increasing or decreasing the area of various land uses in order to properly manage them. It should also be mentioned that the relationship between conservation strategies and the changes in the Iranian forest cover is still poorly understood, owing to the adoption of conventional frameworks that are insufficiently sensitive to local human and physical geographies (López-Carr 2021).

To effectively manage land cover, policy

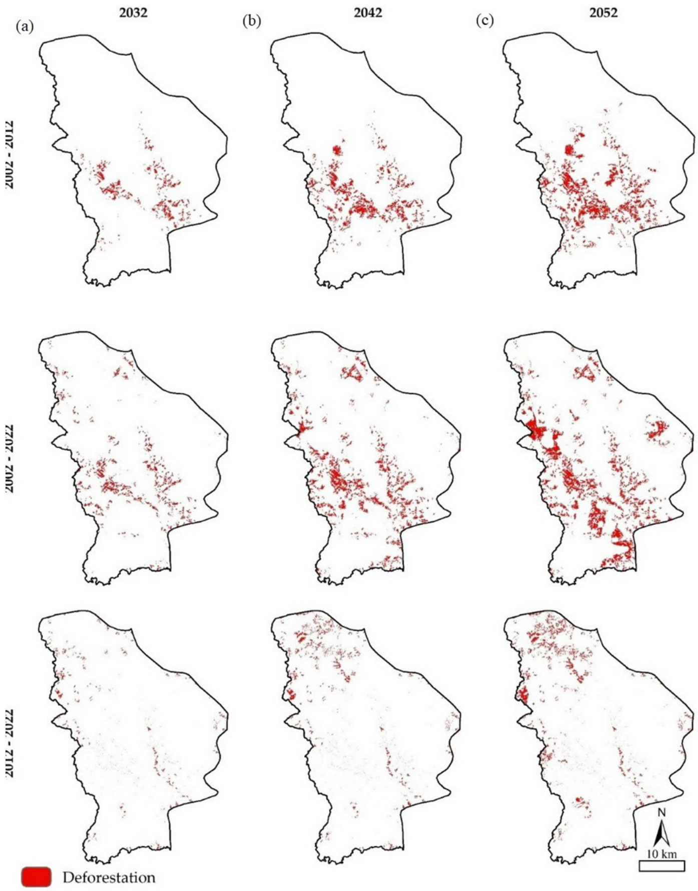

Figure 9 Possible patterns of deforestation by 2032 (a), 2042 (b) and 2052 (c) based on the studied scenarios.

makers must also have access to information on how current conservation policies affect the areas dedicated to forests, both positively and negatively. Our findings showed that the forest areas in the Iranian northern Zagros forests have shrunk after 20 years, despite the adoption of conservation policies such as the *Siyanat* plan; accordingly, 4,350.5 ha of forests have been lost and 4,355.6 ha have been added to the non-forest lands in the region (Table 5). Explanations on the development of this process could be those related to the insufficient effectiveness of conservation strategies, coupled with the pressures brought by the population growth, which have resulted in the increase of non-forested areas such as croplands and built-up areas, to meet the demand for food and housing within natural habitats. Other studies also revealed that these changes will lead to deforestation and to intensifying the fragmentation of the remaining forests in the region (Lambin et al. 2003; Mondal & Southworth 2010; Kabba & Li 2011; Riutta et al. 2014). An important aspect is that the changes of forest to other land use patterns frequently occurred near forest regions and existing croplands, surrounding Sardasht's major river, and close to populated areas (Kamusoko & Gamba 2015). Furthermore, Arekhi (2014) found that forest land loss occurred mostly near the forest areas due to their accessibility, livestock grazing, and tourism attractions in western Iran. Shooshtari and Gholamalifard (2015) pointed out that the most significant land use changes occurred on the edges of agricultural fields in the Neka Basin of northern Iran, demonstrating the importance of human activities in increasing deforestation rates.

Meanwhile, due to the poverty of rural people and their reliance on forests for living, the implementation of the conservation policies (i.e., *Siyanat* Plan) in Sardasht has not been flawless. The following were the most significant shortcomings of the *Siyanat* Plan: the local people were ignored during the goal-setting stages; facilities and incentives were not allocated to the rural people, preventing

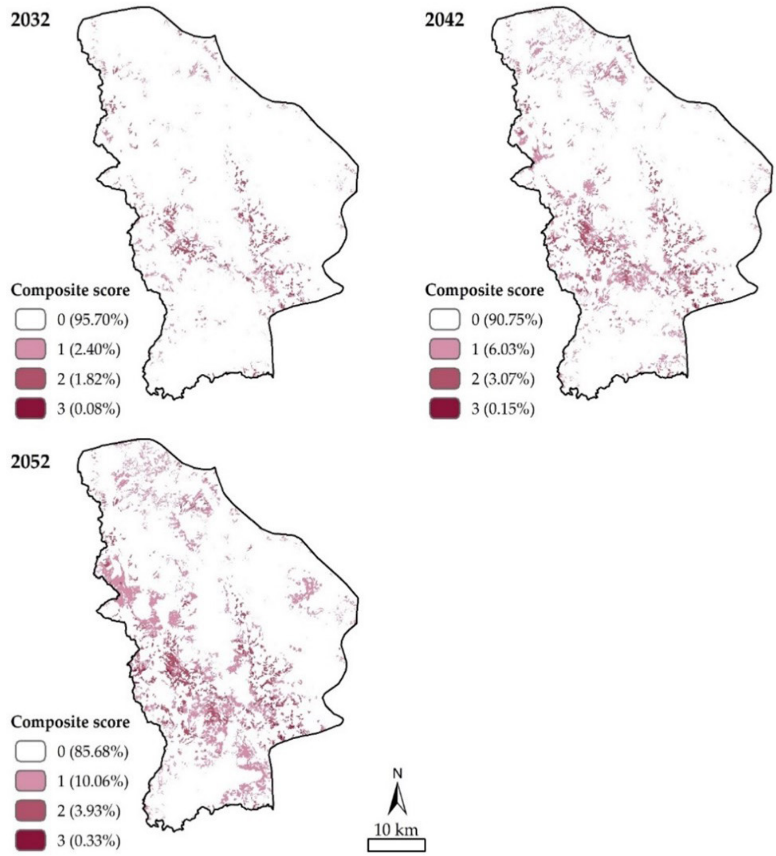

Figure 10 Overlap of all three scenarios for forecasting deforestation.

them from adjusting and converting their livestock and finding secondary careers; and the government did not adequately supervise the implementation of the related projects. According to the findings of Heidari Zahiri et al. (2015), environmental resources have a vital influence in the livelihoods of rural communities. Meanwhile, the forest claims 30% of the typical overall household income. If this source of income would be lost, the number of impoverished individuals would grow 1.8-fold, and their distance from the poverty line would increase 4.2-fold. These findings revealed that the *Siyanat* Plan's intermediate goals of improving forest inhabitants' living conditions, increasing their secondary substitution income, and eliminating their financial reliance on the woods could not be met. The presence of a vicious loop of poverty and environmental damage is frequently proved to be in opposition with the ideals of sustainable development (Reardon & Vosti 1995). Poor people exploit natural resources as a quick source of income, to breed animals, and as a source of energy, and convert forests to agricultural areas and other land uses. Population expansion aggravates the problem even further (Beygi Heidarlou et al. 2022).

The results of forest cover change modelling using LTM indicate a definite increase in forest degradation and deforestation activities in Sardasht over the next three decades. These outcomes forecast the likely implications of future developments therefore, conservation policies can be developed to minimize the negative effects of these changes. The proper application and development of these policies will increase decision efficiency and the ability to respond timely to changes (Heathcote 1998, Duncan et al. 2020). Other studies have found that when deforestation operations rise in the future, forested regions would suffer the greatest area losses (Pijanowski et al. 2002b, Tang et al. 2005).

The spatial overlapping results of deforestation forecasting models showed that, according to the three probability prediction scenarios used in this study, 0.33% of Sardasht forests loss converged in similar locations over the next 30 years; these areas are characterized by a high potential of deforestation. The majority of forest loss in Sardasht has happened near croplands (Beygi Heidarlou et al. 2020b). This represents the contribution of human activities to deforestation (Beygi Heidarlou et al. 2019). Hence, increasing monitoring programs in these areas can stop or reduce forest land losses.

According to the results of this study, the LTM model, which combines the capabilities of ANN and GIS, has the capacity to understand the patterns of forest cover changes and, as a consequence, to make accurate predictions. Results of calibration and validation of ANN models showed that forest cover change models developed for different temporal scenarios performed reasonably well by ROC analysis at shorter time periods and close to the end years of the study time period. Other studies have also shown that the ANNs performed better in short-time intervals (Brown et al. 1993, Areerachakul & Sanguansintukul 2010, Tayyebi & Pijanowski 2014,Tayyebi et al. 2014). In reality, there may be fewer spatial factors and interactions between them that affect LCLUC in short-time periods, but in long-time periods additional drivers that are not captured by models and modellers may possibly contribute to LCLUC (Tayyebi et al. 2014). However, few research has examined the efficacy of ANN modelling to detect change patterns in specific areas across different time intervals. Our findings are comparable with earlier research that consistently demonstrated a better performance of ANN when compared to conventional methods (Lek et al. 1996, Paruelo & Tomasel 1997, Lek-Ang et al. 1999, Mas et al. 2004).

ANN-based models can account for any nonlinear relationship between the explanatory and dependent drivers (variables) (Mas et al. 2004). In this study, the networks that were more sophisticated and included more input variables performed better. When fewer input variables are given to the network, the loss in generalization ability may be addressed (Kavzoglu & Mather 2000). As a result, choosing the right variables might be of first importance in producing results that are both relevant and accurate. They appeared to be tied to specific forest cover change patterns throughout the training period, have retained the general deforestation tendencies, and have effectively anticipated future deforestation.

The "black box" approach that ANNs use to describe the relationship between two sets of data (Mas et al. 2004) is a limitation in the use of ANN-based models (e.g., LTM). Although the LTM was capable of making faultless predictions, the functional form of the relationship between the 14 demographic, socio-economic and environmental variables and the output layers remains undisclosed. The network's weight matrices, on the other hand, have no clear significance. As a result, these matrices may help to identify the most important factors influencing changes in forest cover along with their functional form and model outputs (i.e., suitability and probability to change maps). While the LTM has shown to be a potentially helpful spatial analytic tool for academics and professionals (Pijanowski et al. 1995, Tang et al. 2005, Tayyebi et al. 2011, Pijanowski et al. 2014, Tayyebi et al. 2015), it still requires some substantial improvements before it can be widely used for planning and policy formulations in the forest management. It takes a long time to perform LTM modelling on Windows command prompt (e.g., one week for network training in this study). Additionally, adopting methods that provide finer granular information and increased spatial resolution, for example, can enhance accuracy (Newman et al. 2016). However, the running duration of the model is significantly increased (Beygi Heidarlou et al. 2022). The model has the following general drawbacks: the model only forecasts the places where a change in forest cover is expected to take place, and the simultaneous consideration of deforestation is not included in the model. Additionally, the model does not take into account changes in all land uses simultaneously; actually, the model should only have two land use types (e.g., forest and non-forest classes).

Conclusions

One of the most important dynamic components of ecosystems is Land-Cover and Land-Use Change (LCLUC). Human-induced changes to the land regularly influence patterns and processes in ecosystems, such as changes in forest cover. This study tested the GIS-based LTM's ability to forecast forest cover changes using as inputs demographic, socio-economic and environmental variables. Although forecasting changes using empirical forest cover change models do not guarantee total confidence regarding their future occurrence, the findings of this study for the 10, 20, and 30 years demonstrated that the ANN can draw plausible future patterns in forest cover change. The LTM model's results for anticipating changes in the forest lands cover over the research periods showed a comparable and upward trend in forest loss. In addition, the findings showed that, despite the implementation of several forest management and conservation plans in Iran, forest cover loss in the Zagros forests has continued. In other words, the forest transition was surpassed by the forest loss, making it to appear that conservation efforts to manage forests sustainably in Iranian Zagros forests have failed.

Acknowledgments

The authors declare that they have no conflict of interest.

Ethical statement

All ethical practices have been followed in relation to the development, writing, and publication of the paper.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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