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Detection of Land Use Changes in Forests Using Satellite Image Classification Based on Deep Learning: A Case Study of Sardasht Forests

Ziba Zarrin [a*], Yousef Khajavigodellou [b++] and Mohammad Javad Valadan Zoej [c#]

[a] *Department of Remote Sensing Engineering, K.N. Toosi University of Technology, Tehran, Iran.*
[b] *Department of Geography, Environment, and Spatial Sciences, Michigan State University, Michigan.*
[c] *Department of Photogrammetry and Remote Sensing, K.N. Toosi University of Technology, Iran.*

Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Awareness of changes in forest areas has always been one of the most crucial environmental considerations globally. Sardasht forests is located in the northern Zagros region and with an area of around 91,117 hectares constitute for 24% of Iran total forests. They play an important role in water supply, soil preservation, climate regulation and overall economic and social balance in the

++ *Ph.D. Student;*
# *Professor;*
**Corresponding author: E-mail: zz.zarrin@yahoo.com;*

country. Nevertheless, these forests are currently perceived as degraded due to the primary reason of tree cutting for fuel and livestock feed. In this study, remote sensing data of the study area including Landsat 5 TM satellite images from 2002, Landsat 7 ETM images from 2012, Landsat 8 OLI images 2020 and classification algorithms, maximum likelihood and artificial neural network were utilized. To examine the accuracy of each classification, ground truth points were randomly collected using GPS devices and by implementing control points, statistical parameters of error accuracy including Kappa coefficient and overall accuracy were calculated. The results show that the map generated using the artificial neural network algorithm has an overall accuracy of 98.32% with a Kappa coefficient of 0.9781 while the map produced by the maximum likelihood algorithm has an overall accuracy of 92.45% with a Kappa coefficient of 0.901. As a result, the artificial neural network algorithm demonstrates to be a more suitable method for producing land cover maps compared to the maximum likelihood algorithm.

Keywords: Forest land use changes; satellite images; deep learning; artificial neural network; maximum likelihood; sardasht.

1. INTRODUCTION

Forests, which span vast areas of diverse terrains, include a rich ecosystem of trees, plants, and various animal species such as mammals, algae, bacteria, and other living organisms. Covering about 30% of the Earth's surface, forests play a key role in the global ecosystem and climate [1].

The removal of trees over the years, driven by various reasons including natural disasters and human activities such as construction and energy production, has significantly increased. According to the National Institute for Space Research (NISR) report, deforestation worldwide rapidly accelerated in the 1990s. This has raised early warnings indicating that rainforests may disappear by 2030. A recent study by Isaienkov et al. (2020) highlighted the threats posed by human pressure on Ukrainian forests where illegal tree cutting increased to 100,000 m^3 in 2019.

Forests in Iran, with an area covering about 12.4 million hectares, constitute for 7.4% of the country's total area. The Sardasht forests is located in the northern Zagros region and with around 91,117 thousand hectares allocate 24% of Iran total forested area. They have a substantial influence on water supply, soil preservation, climate regulation and overall economic and social equilibrium nationwide. These forests, currently perceived as degraded, face significant challenges with the primary cause being tree cutting for fuel and livestock feed. The Sardasht forests accommodate nearly one-third of the entire country's population. There are over 190 species of trees and shrubs covering an area of 5.2 million hectares in these forests [2,3]. The degradation of the Sardasht forests has persisted for decades due to the relentless expansion of urbanization, forest fires and extensive mechanized agriculture (Salehi et al., 2020). Beyond this challenging scenario, monitoring and preventing deforestation typically involve laborious manual methods such as visual inspections and spectral profile assessments in forested areas. Hence, there is an urgent need to provide accurate and reliable information regarding forest cover changes to monitor any illegal deforestation activities and reduce the additional burden of manual monitoring operations as much as possible [4].

Remote sensing techniques utilizing temporal change data outputs provide powerful tools for quantifying and monitoring forest cover changes at both local and global scales [5,6]. Computer vision techniques applied to satellite imagery can automatically monitor forests and analyze the disappearance of tree cover on a much larger scale [7]. Advancements in AI-equipped technologies including sensors and drones in addition to algorithms can effectively identify forest changes and aid in halting any illegal activities. Because of its profound influence on human life, forest analysis has been broadly studied from different perspectives [8,9,6]. Several platforms for forest analysis using high-resolution satellite images have been thoroughly introduced such as planet and global forest watch (GFW) [10]. Recently, deep learning has attracted researchers' attention given its ability to extract distinct features from images including satellite images. So that, it has been used in different complex environments and tasks [11], showing advanced outcomes in land use and land cover classification and retrieval [12], object detection (Chen et al., 2018) and semantic segmentation [13]. Semantic image segmentation is a challenging and effective method and plays an important role in the analysis and understanding of images including applications in medical imaging (Ohabi and Taleb Ahmad, 2021; Cheng et al., 2021) and remote sensing [7,14,15]. There is a lack of studies that specifically examine the capabilities of deep learning-based semantic segmentation models for monitoring deforestation via satellite images. As a result, employing semantic image segmentation outputs with deep learning models based on spatiotemporal satellite images can provide an initiative for the development of effective forest cover change monitoring systems. This is especially important in regions with small forested areas experiencing high rates of deforestation such as the Sardasht forests in northern Zagros. Most importantly, there is presently no study using machine learning and artificial intelligence solutions for monitoring changes in the Sardasht forests. Besides, examining the deforestation of the Sardasht forests necessitates the collection of a sufficient number of high-resolution forest images that accurately depict tree cover in this area. This is attributed to the absence of an accurate and comprehensive information source for the Sardasht forests which could be used as standard datasets for any environmental analysis study dedicated to this area. Because of these challenges the present study investigates the detection of land use changes through the classification of satellite images based on deep learning in the Sardasht forests. The objective of this work is to evaluate the capability of Landsat satellite data for detecting both quantitative and qualitative changes in the Sardasht forests over three different years: 2000, 2010 and 2020 using the TM sensor.

2. MATERIALS AND METHODS

2.1 Study Area

Sardasht is situated at an average elevation of 1515 meters above sea level within the geographical coordinates of 35°57´36´´ to 36°28´12´´ North latitude and 45°13´48´´ to 45°42´00´´ East longitude with covering an area of 1381.83 km2 and constituting 3.8% of the total area of West Azerbaijan Province (Fig. 1). According to the latest population and housing census in 2016, the population of this county was 118,849 individuals with 68,162 in urban sector (including the cities of Sardasht, Rabat and Mirabad) and 50,687 in rural population (including 352 villages and settlements).

2.2 Research Data

In the present research, remote sensing data of the study area were used including TM sensor images from Landsat 5 satellite in 2000, ETM sensor images from Landsat 7 satellite in 2010 and OLI sensor images from Landsat 8 satellite in 2020. The objective of this study, focusing on assessing the trend of land cover changes in Sardasht forests located in northern Zagros, caused to the selection of images that were approximately close to each other in terms of lunar phases. Consequently, to avoid cloud and snow cover and enhance solar radiation intensity four images with a ten-day interval in July were chosen (Table 1). For accuracy assessment and geometric correction of forest land cover maps, 1:25,000 topographic maps from the National Cartographic Center were employed. Additionally, for data processing, classification and analysis, software such as Google Earth (To prepare educational points and control points), ArcGIS 10.1(Preparation of user maps), ENVI 5.1 (To process and digitize satellite images) were utilized.

2.3 Preprocessing and Image Preparation

In general, data preprocessing includes two fundamental stages: radiometric and geometric corrections [16]. Through examinations and alignment of communication pathways extracted from the topographic map of the National Cartographic Center with satellite imagery, it was observed that these images lacked a significantly noticeable geometric error. However, they exhibited radiometric errors. Radiometric corrections were implemented to mitigate or eliminate two major types of errors (atmospheric and instrumental). At first, radiometric correction was performed using calibration. Following that, to reduce the effects of atmospheric influences, which usually manifest as cumulative errors and cause excessive brightness in the image and diminishing clarity, a method involving reducing the numerical values of dark pixels was employed. For radiometric correction, the Calibration Radiometric tool and the FLAASH method for atmospheric correction in ENVI software were utilized due to the fact that supervised classification provides greater control by the user compared to unsupervised classification. For the creation of land use maps

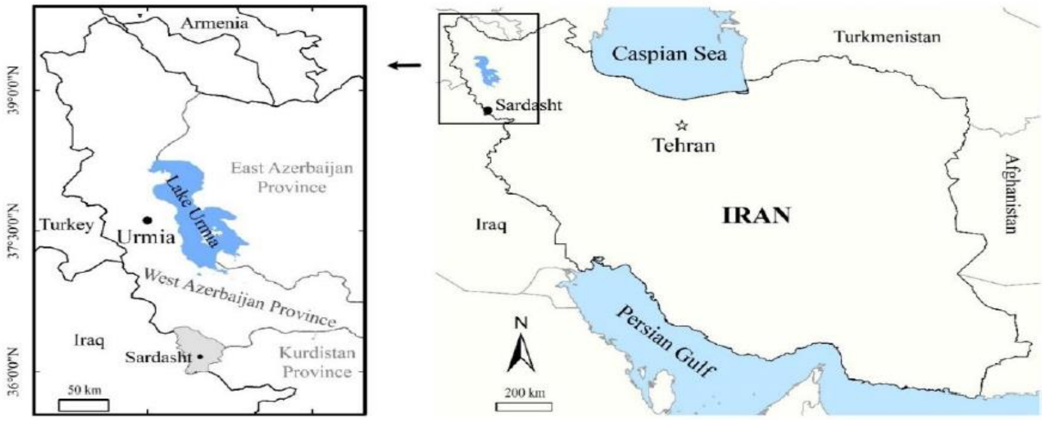

Fig. 1. Geographical location of study area (Sardasht County)

Table 1. Satellite image specifications used in the study

Sensor Type	Row and Pass	Photography Capture Date	satellite name
TM	168-33	10/7/2000	Landsat5
ETM+	168-33	30/6/2010	Landsat7
OLI	168-33	11/7/2020	Landsat8

the maximum likelihood classification and neural network methods were employed [17]. This involved categorizing land uses in the region into two general classes: forest, Nonforest. For each land use in each region training samples were prepared using field visits and Global Positioning System (GPS) device. These training samples were then divided into two categories. A portion of these training samples was selected for image classification using the support vector machine and neural network algorithms while the remaining portion was used to assess the accuracy of the results obtained from the mentioned classification algorithms (100 control points). It's noteworthy that the training and validation samples were considered consistent across all classification methods. Following the application of image corrections based on the studied algorithms using ENVI software, each algorithm generated a land use map for the study area using the training samples.

2.4 Artificial Neural Network Classification Method

In this study, a MLP (Multi layer perceptron) with one hidden layer, 7 input neurons, 9 hidden neurons and 7 output neurons were employed for the classification of data using the neural network method (Fig. 2). The number of input neurons corresponds to the number of bands in the satellite image while the number of output neurons represents the selected land cover classes. The error rate is related to the network training error and is calculated based on the square root of the average:

$$\text{Equation 1:} \quad \mathrm{RMS} = \frac{\sqrt{\sum_p \sum_k (t_{pk} - o_{pk})^2}}{P \times N}$$

In this study, to implement the neural network, a hidden layer and a different number of average training and testing pixels in each class and training rate were tested in order to select the optimal number of them to increase the classification accuracy. Also, the number of hidden nodes was automatically determined with the help of the software and based on the number of bands introduced in the input layer. Also, in order to choose the optimal network and perform the correct classification, different values were considered for network indicators such as learning and repetition rate and their accuracy was tested to identify the most suitable values for this study. Finally, the values for these indices were chosen to increase the accuracy and reduce the classification error.

2.5 Assessment of Accuracy of Classification

To evaluate the accuracy of satellite image classification and user class of created ground control points with a neural network the overall accuracy and kappa coefficient indices were used. The overall accuracy is resulted by

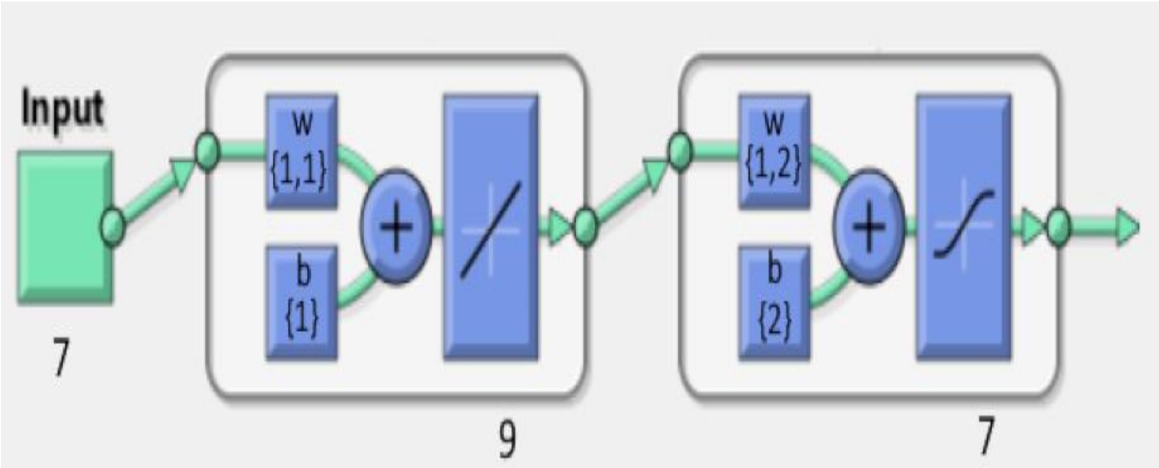

Fig. 2. Neural network design used in research

summing the elements on the main diagonal of the error matrix and dividing by the total number of pixels (Equation 2). The overall accuracy of the classification which represents the level of validity in the conducted classification and extracted land use maps from satellite images should be greater than 85% [18].

(Equation 2): OA = $1/N\Sigma\, p_{ij}$

The Kappa coefficient essentially measures the difference between actual agreement in reference data and automatic classification as well as agreement between reference data and random classification [19]. It is defined by Equation 3:

(Equation 3): $\mathrm{Kappa} = \mathrm{p0} - \mathrm{pc} * 100$

3. RESULTS AND DISCUSSION

After the selection of educational samples, a maximum likelihood classification was employed for land cover classification. This parametric approach utilizes training samples extracted from the region to estimate dispersion, co-dispersion and class probabilities. It tries the training samples to have a normal distribution considering the mean vector of the data and the laws of probability. Following the classification using the maximum likelihood method, a majority filter was applied to coherence the data and land cover map classes and forest surface levels for the years 2000, 2010 and 2020 (Fig. 3).

A map of land cover classification was then generated using an artificial neural network method. In this study, the MLP approach is employed. After obtaining the map (similar to the previous method) a majority filter with pixel dimensions of 3*3 was applied to enhance data coherence. The land cover classification map using the artificial neural network method was finally produced for the years 2000, 2010 and 2020 (Fig. 4).

Table 2 illustrates the dynamics of land use changes for both forest and non-forest along with the actual changes that occurred in Sardasht during the examined years (2020, 2010 and 2000). Over the 20-year period under consideration a reduction of 7898.58 hectares in forested areas has transpired. The forested land area decreased from 91335.15 hectares in 2000 to 87568.11 and 83436.57 hectares in 2010 and 2020, respectively. This decline continues indicating an ongoing trend of degradation wherein an additional 7947.45 hectares have been converted to non-forest lands.

In this study, for the accuracy assessment of the employed methods 20-30 ground points were selected as reference samples for each class. The positional coordinates of these samples were obtained using a GPS device. Kappa coefficient and overall accuracy of the produced maps were then calculated based on these reference samples. Table 3 presents the accuracy of the classification maps considering the suitability of the 2020 imagery.

Examining the accuracy of the classified maps indicates that the map generated using artificial neural network algorithm have an overall accuracy of 98.32% with a Kappa coefficient of0.978. In contrast, map produced by employing the maximum likelihood algorithm indicate an overall accuracy of 92.45% and a

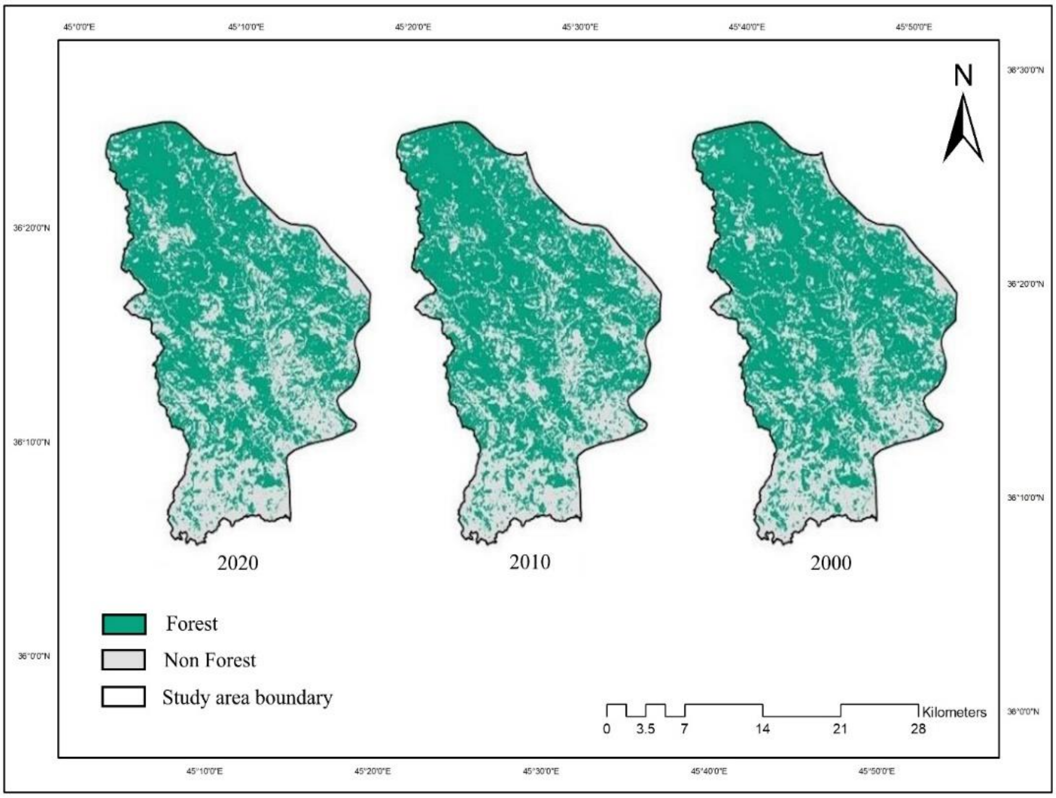

Fig. 3. Classification maximum likelihood method for year 2000, 2010 and 2020

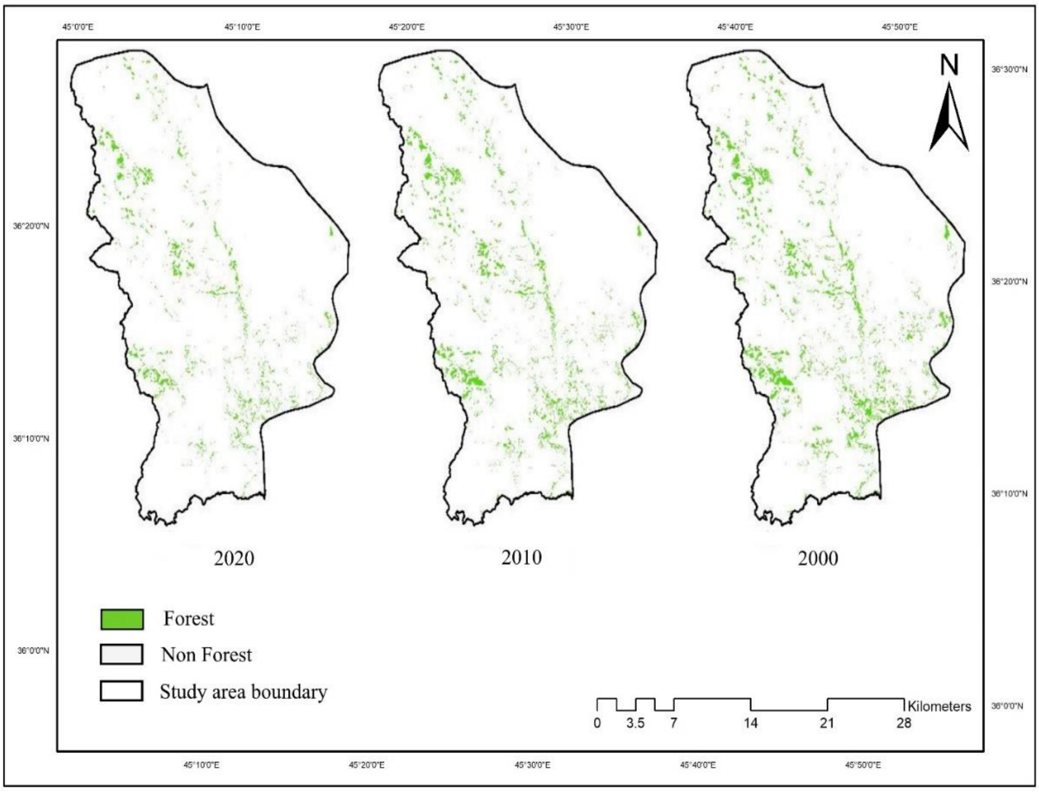

Fig. 4. Classification artificial neural network method for year 2000, 2010 and 2020

Table 2. Changes in the area of forest and non-forest land in hectares the based based on the ANN

Year	2020	2010	2000
Forest	83436.57	87568.11	91335.15
Non-forest	54986.58	50855.85	47039.13

Table 3. Determining the accuracy of maps resulting from satellite image classification in 2020

Method	Kappa Coefficient	Overall accuracy	User accuracy
Maximum Likelihood	0.901	92.45%	81.2066
Artificial Neural Network	0.9881	98.32%	87.521

Kappa coefficient of 0.901. As a result, the artificial neural network algorithm is a more suitable method for generating land cover maps compared to the maximum likelihood algorithm. Therefore, this approach considered as the foundation for analyzing changes in land cover and forested areas in Sardasht. According to conducted investigations, remote sensing techniques are highly precise tools for generating land cover maps and monitoring changes in forested areas (Al-doski et al,2020). In addition, to enhance the accuracy of production and ensuring their accuracy error assessment methods can be used. However, it is undeniable that the user's precision in selecting samples and reviewing findings against the ground truth is essential. The results of this research show significant changes in the forested land cover of Sardasht over the past 20 years (2000 to 2020). Notably, 7898.58 hectares of forest land have diminished while 7947.45 hectares of non-forest land have been added to the region's surface (Table 2) One of the reasons for this is the creation of roads into these forests to provide services to rural settlements. These roads, passing through the forests, have caused the destruction of a large amount of these rare species. Also, field investigations showed that a part of this process of forest land destruction was done by the villagers to increase the area of the fields, the villagers of this region to earn more money by destroying the forest lands cause the physical development of their fields towards the forests and this action every It causes severe destruction of these lands every year. The continuation of this trend and pressures resulting from population growth have led to extensive development of non-forest lands such as agricultural and residential areas to meet demands for food and housing within natural habitats. This change will finally cause to deforestation and intensify the fragmentation of the remaining forest habitats in the area.

In light of the results, although employing neural network algorithms yields higher accuracy compared to the maximum likelihood classification method, the latter with its 92.45% classification accuracy remains a desirable approach for assessing changes. Consequently, the observed changes over the 20-year research period in the region signify the transformation of forest lands into predominantly human-made land uses. A parallel study by Amir Entekhabi et al. [20] also investigated land-use changes and influencing factors in Talesh County using artificial neural networks. Their findings showed a declining trend in forest land use over a 14-year period in Talesh which align with the results of the current study. In another study, Arkhi [21] explored the spatial changes in land use using the LCM model in GIS environment and based on artificial neural networks and Markov chain analysis in the Sarableh region of Ilam province. According to his study results over the period from 1988 to 2011, 146,191 hectares of the region's forests have been degraded. The degradation has been predominantly one-sided with other existing land uses not converting to forests. Given the relative similarity in the study period's duration and the comparable rate of forest degradation in two regions despite differences in the types of forests, the assault on the country's natural forests and their significant degradation during the study period are noteworthy, primarily attributed to economic and social issues and the indigenous need for fuel and agricultural land over the study duration. In a similar study, Islam et al. [22] modeled land-use changes in the protected Chanani area in Bangladesh. The land classification with artificial neural network algorithms showed that in 2005 around 76% of the protected area (equivalent to 8,258 hectares) had vegetative cover and decreased by 15% to 41% (6,637 hectares) in 2015. Their study identified human factors both legal and illegal as reasons for forest degradation. In the current study, the increase in other land uses and forest degradation in favor of rangeland expansion can also be influenced by human factors. In Africa and Eritrea, the studies of Ghebrezgahher et al. [23] demonstrated the acceptable accuracy of interpreting forest and woodland cover based on landsat satellite images. They assessed a high rate of forest degradation and change into woody rangeland, aligning with the findings of the present study.

The research findings show a decline in the forested areas of the research region over the study period. According to the results and the significance and sensitivity of the Sardasht forests it is essential to enhance the conservation efforts for the forested masses in the area. In addition, due to the high rate of conversion of forest lands into rangeland in this region, implementing forestry operations in some rangeland areas with native species would be a judicious and valuable practice. This would not only contribute to better water and soil conservation in the region but also aid in maintaining the historical balance between the forest and rangeland in this area.

4. CONCLUSION

The aim of this research is the detection of forest land use changes to evaluate changes in Sardasht forests in northern Zagros through the classification of satellite imagery based on deep learning utilizing two classification algorithms: maximum likelihood and artificial neural network. The results of the study indicate that the map generated by the artificial neural network algorithm with an overall accuracy of 98.32% and a Kappa coefficient of 0.9781 outperforms the maximum likelihood algorithm. Generally, since the neural network algorithm operates based on its features and network structure and each neural network string works very precisely in data integration, this method not only reduces errors in the classification process but also facilitates accurate separation of classes in practical projects.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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