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Detecting pollarded stands in Northern Zagros forests, using artificial neural network classifier on multi-temporal lansat-8(OLI) imageries (case study: Armarde, Baneh)

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ABSTRACT

Local economy, based on animal husbandry in Northern Zagros forest leads to increase employing leaves and branches (pollarding) compared to the other parts of Zagros. Pollarding is a convenient method in forest utilization to supply fodder and it has been always trying to obtain its stable production by proper management skills. One of the most important forest management tools in a given forest is to provide up-to-date spatial maps of pollarded regions. The objective of this study was to investigate the capability of multi-temporal Landsat 8 OLI sensor for mapping pollarding areas of Northern Zagros forests. So that, we employed Landsat 8-OLI single and multi-date images acquired on 2014 and 2015. To assess the accuracy of output maps, a complete ground-truth of the study area was used to calculate the accuracy heuristics for the output maps. Different classification approaches were applied including minimum distance and maximum likelihood classifiers, artificial neural networks and fuzzy method. The classification accuracy was calculated on the basis of overall accuracy and kappa coefficient. The results indicated that artificial neural network and fuzzy classifier present the highest accuracy than the other classifiers. It was also found that utilizing the multi-temporal OLI imageries improves the accuracy over employing a single date. The results indicate that the multi-temporal imagery is moderately capable of mapping pollarded stands and classifying pollarding types, using ANN and Fuzzy classifiers.

Key words: OLI, Pollarding, Zagros forests, ANN.

INTRODUCTION

Forests are among the most important ecosystems on the earth, providing vast variety of goods and services, such as food, water, nutrient cycle, and protect biodiversity. Also human and animal lives depend largely on suitable management of forests (Karjalainen *et al.* 2009*)*. Therefore, an increasing fraction of the world's forests being intensively managed either by foresters or local people (Noormets *et al.* 2015*)*. In the northern Zagros forests, which located in the west part of Iran, there is a traditional conventional forestry, carried out with the participation of local people. In this traditional system, the villagers use the forest to feed their livestock, provide fuel wood and housing timber, and non-timber forest products (Hanara Khaliani *et al.* 2013). Due to the dependency of local economy on animal husbandry, fodders from tree foliage is more common in this area than in other parts of Zagros. Furthermore, there is a high population density in this region, hence, almost the entire forested areas are affected by forest grazing and forage utilization. In response to making a balance between the crucial requirements of local dwellers and forest conservation, a traditional forestry system has been developed on the basis of animal husbandry in which trees were pollarded to provide enough winter fodder for livestock (Ghazanfari 2003).

In the traditional pollarding practice (locally called Galazani (gælazæni), each rural household according to the common law owns a forested area which is divided into three sections (locally called Shan (ʃʌn)). They pollard oak trees (especially *Quercus libani* Oliv.) on one section each year to collect winter fodder of their livestock and fuel wood (Moradi *et al.* 2009). The Shan which is pollarded in the current year was called *Kurpe* (kɔ:rpə), the one pollarding in the second period was called *Kor* (kɔ:r) and the third pollarding area was *Khert* (kert).

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Implement the traditional forestry has been able to continually provide for the basic needs of local communities for a long time (Ghazanfari *et al.* 2004*)*. Classification of pollarded area and developing a separate plan for each unit is the most basic way to manage forest units.

One of the important tools of forest management is to have updated maps of forest stands and types (Stone 1998; Franklin 2001; Moradi *et al*. 2009). Updating thematic maps (i.e. pollarding areas) on a large scale through extensive fieldwork is time-consuming and costly. Therefore, space-borne remote sensing technology with multi-temporal, and multi-spectral imageries can offer an alternative to generate thematic maps of pollarding areas with descriptive characteristics (Ustin & Gamon 2010; Lawley *et al.* 2016). Remote sensing technology, thus, can provide comprehensive information on the status of forests to managers and planners. Since the 1970s, many researches have been investigating on this field.

Landsat satellite imagery is the most common and widely-used data for land cover mapping because of its moderate spatial resolution (Wulder *et al*. 2008; Knorn *et al.* 2009), multi-spectral and multi-temporal images and USGS' decision to provide free access to all Landsat data set (Knorn *et al*. 2009).

The use of Landsat data acquired at different dates (different months, seasons or years) could improve land cover classifications (Wolter *et al.* 1995; Oetter *et al.* 2001; Brown De Colstoun *et al.* 2003; Dorren *et al.* 2003; Yuan *et al*. 2005). Fassnacht *et al.* (2015) used Landsat 8 multi-temporal data for mapping degraded grassland on the Eastern Tibetan Plateau. Schultz *et al.* (2015) studied the Classification of Multi-temporal Landsat8 images for crop type mapping in Southeastern Brazil. Pourshakouri Aladeh (2005) used multiple SPOT5-HRG and Terra-Aster scenes acquired in the spring and fall to separate the northern border of Caspian forests. Conventional approaches for land cover classification have relied on statistical classifiers such as Minimum Distance (MD) and Maximum Likelihood Classifiers (MLC) (Brown De Colstoun *et al.* 2003; Kavzoglu & Mather 2003). These methods have some limitations such as related particularly to distributional assumptions (Kavzoglu & Mather 2003). Artificial neural networks (ANNs), usually produce classifications with higher accuracies from fewer training samples compared to traditional classification techniques (Carpenter *et al.* 1997; Kavzoglu & Mather 2003).

Moradi *et al.* (2009) studied the capacity of HRG data of SPOT5, and IRS-P6 satellites in mapping and distinguishing pollarded forest sites using conventional classification algorithms in Baneh Township, Iran. The results indicated that although IRS-P6 satellite images had a higher accuracy than SPOT5 using maximum likelihood classifier, however, the detection and classification of pollarded areas was not yet properly possible.

The objective of this study was to evaluate the performance of the conventional classifier approaches, i.e. maximum likelihood (ML), minimum distance (MD) against the advanced approaches, i.e. the fuzzy and artificial neural network (ANN) classifiers to map pollarding areas. In addition to the selected classifier approach, we assumed that inclusion of multi-temporal imageries could help to identify different pollarding areas.

MATERIALS AND METHODS

Study area

The study area covers approximately 373 ha and is located between 45°47’54’’ to 45°49’59’’ eastern longitude and 35°52’51’’ to 35°54’54’’ northern latitude, Armardeh, Baneh, Western Iran (Fig. 1). Its altitude ranges from 1420m above sea level (a.s.l.) at the valley bottom up to over 1780 m a.s.l. Climate of the area is affected by the high-pressure cold air mass of north Siberia and East Mediterranean air mass. The region, thus, has mild summers and cold snowy winters (Doostan & Alijani 2016). Dominant tree species in the study area include *Quercus brantii* Lindl, *Q. infectoria* Oliv, *Q. libani* Oliv. Local communities are highly dependent on the forest resources in many aspects (i.e. fuel wood harvesting, livestock grazing, non-wood utilization, and cultivation of crops under the forest canopy). Forest structure follows a coppice form with a naturally sparse canopy. The topography is complex with step slops in some areas.

Data

Multi-temporal Images, four Landsat-8 Operational Land Imager (OLI) scenes, were acquired between 2014 and 2015 to use in this study (

Table **1**). Landsat-8OLI Level 1 terrain-corrected (L1T) images were down loaded from United States Geological Survey National Center for Earth Resources Observation and Science website (USGS 2014)). The images were

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already geo-referenced in the Universal Transverse Mercator (UTM) coordinate system zone 38 N and WGS1984 datum.

These images were selected within spring (11 June 2014), summer (15 August 2014, 17 August 2015), and fall (21 November 2015) to capture the maximum variation in spectral reflectance to monitor pollarded forest areas in the northern Zagros. The landsat-8 data used in this study are listed in Table 1.

Table 1. Images used in this study.

No.	Acquisition Date	Path	Row
1	21 November2015	168	35
2	17 August 2015	168	35
3	15 August 2014	168	35
4	11 June 2014	168	35

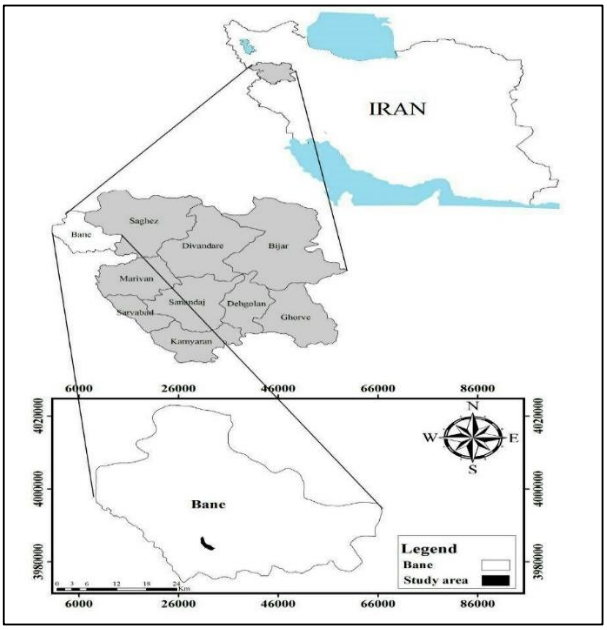

Fig. 1. Location of the study area in Iran, Kurdistan province, and Baneh city.

Ground truth maps

Two rounds of field works were carried out to collect ground-truth data during August-September 2015. A forested area which is conventionally pollarded every three years, and is representative of the whole forest in the region, was selected to generate the ground truth map. A first survey was conducted in the region before pollarding (August 2015). The second field survey was carried out after pollarding (i.e. in the second half of September 2015) to record the location of *Khert*, *Kor* and *Kurpe* sections as well as the locations of agricultural lands and residential areas using a Garmin GPS map 78S device with a precision of 3 to 5 meters. In total, an area of 374 ha was measured as a ground truth map. Fig. 2 shows the ground truth map of the study area.

Satellite imagery pre-processing

As mentioned before, landsat-8 images were ortho-rectified and geometrically corrected by USGS team (< 12m root mean square error (RMSE)).

We implemented the COST model to reduce the atmospheric effects on the all OLI images using TerrSet software (Chavez 1996). Sparse vegetation coverage challenges the satellite capability for extracting reliable information and inhibits the detection of vegetation less than 30% coverage.

Accordingly, it is tried to investigate vegetation indices able to reduce unintended effect of factors such as underlying soil. Therefore, two main categories of vegetation indices, i.e., ratio-based and soil-based indices were used (Fatehi *et al.* 2015). The Normalized Difference Vegetation Index (NDVI), the Soil-adjusted Vegetation Index (SAVI), and the Modified Soil-adjusted Vegetation Index (MSAVI) were calculated as described in Table **2**.

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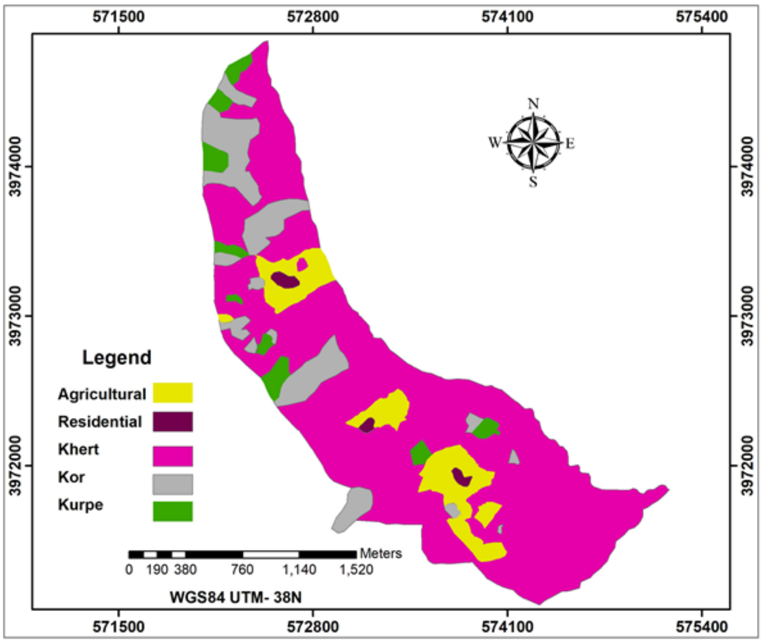

Fig. 2. The ground truth map of the study area.

Soil line parameters were used to calculate these indices (Satter white & Ponder Henley 1987; Baret *et al*. 1993). The Soil line parameters, i.e. the slope and intercept of the soil line, can be obtained by a regression analysis of a bare soil reflectance in the near-infrared (NIR) and red (R) wavelengths (Richardson & Wiegand 1977).

Furthermore, transformation approaches have been applied on the spectral bands to extract information about forest pollarding. The most commonly approaches are Principal Component Analysis (PCA) and Tasseled Cap Transformation (TCT). PCA is a commonly used statistical method for transforming spectrally the original remotely sensed dataset to produce uncorrelated, smaller (i.e. reduction of the dimensionality), and easier to interpret principal component images. This method is applied to a multispectral dataset to determine the amount of variance explained by each component. In general, the first component accounts for the most proportion of the variance, i.e., more than 90% of images' information is put in the first two or three components (Xu *et al.* 2003; Eastman Ronald 2006). Previous research has shown that TCT components are effective in vegetation characterization (Crist & Cicone 1984; Moradi *et al*. 2009).

The greenness component resulting from tasseled cap transformation is associated with vegetation, thus, it was used to classify Landsat 8-OLI images in this study. Additionally, Greenness represents the contrast between the visible and near-infrared bands; and is highly sensitive to the amount of green vegetation (Crist & Cicone 1984; Moradi *et al.* 2009). Equation 1 represents the overall equation of tasseled cap transformation for OLI data (Baig *et al*. 2014):

Relation 1 $$TCT = A_1(\rho OLI_2) + A_2(\rho OLI_3) + A_3(\rho OLI_4) + A_4(\rho OLI_5) + A_5(\rho OLI_6) + A_6(\rho OLI_7)$$

Table 2. Vegetation indices considered in this study (Red = 640-670 nanometer, NIR = 850-880 nanometer).

Vegetation Index	Equation	Reference
NDVI	$\mathrm{NDVI} = \frac{\rho\mathrm{NIR} - \rho\mathrm{RED}}{\rho\mathrm{NIR} + \rho\mathrm{RED}}$	Rouse *et al*. (1974)
SAVI	$\mathrm{SAVI} = \frac{\rho\mathrm{NIR} - \rho\mathrm{RED}}{(\rho\mathrm{NIR} + \rho\mathrm{RED} + \mathrm{L})} \times (1 + \mathrm{L})$	Huete (1988)
MSAVI1	$\mathrm{MSAVI1} = \frac{\rho\mathrm{NIR} - \rho\mathrm{RED}}{\rho\mathrm{NIR} - \rho\mathrm{RED} + \mathrm{L}}(1 + \mathrm{L})$ $\mathrm{L} = 1 - 2\mathrm{a.NDVI.WDVI}$	Qi *et al*. (1994)

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To select appropriate set of spectral bands, a procedure of histogram interpretation and signature comparison were followed using transformed divergence index. Table 3 indicated that the use of this band-sets resulted in better classification since the separability of the classes was better than other band combinations. The best combination of bands from spring (11 June 2014), summer (17 August 2015), and autumn (21 November 2015) images was also used for classification of multi-temporal images.

Image classification to map pollarded areas

The overall objective of image classification is accurately labeling the entire pixels in the image to a thematic class using a classification procedure. In general pixels are associated to a thematic class based on the spectral similarity (Rocchini *et al*. 2013). Accordingly, different thematic classes show different digital values regarding to radiation condition and their spectral reflectance behavior (Lu & Weng 2007). Different algorithms, i.e., minimum distance (MD), maximum likelihood (ML), fuzzy approach (FA) and artificial neural network (ANN) algorithms were used in this study to classify images. Every classification algorithm used the same training data in order to guarantee comparability between results.

The minimum distance and maximum likelihood classification approaches, also known as hard classification, may appropriate for mapping the classes that lie in a mosaic of discrete classes and presume that each pixel contain only one class. A heterogeneous forested area with a multiple tree species and open and pollarded canopy may highly challenge this assumption.

Fuzzy sets theory can present many imprecise and vague variables, concepts and systems in the form of mathematical equations and pave the way for reasoning, inference, control and decision-making under conditions of uncertainty (Ranjbar & Honarmand 2004; Soffianian *et al.* 2011). Fuzzy theory, basically, take in to account the heterogeneous nature of the real word. It is based on the fact that a detector records a signal reflected from heterogeneous materials such as soil, shadow, water, and vegetation found within a ground pixel. In the present study the implementation of the fuzzy theory may help to accurately classify image pixels contain a mix of classes which cannot be unambiguously associated with a single class.

An artificial neural network (ANN) is a computational machine inspired by structure of the biological nervous system. It is known that ANNs have a very flexible performance for any type of data. In general, an ANN is composed of the input, intermediate (hidden) and output layers. The input layer receives information from the environment and transmits it to the intermediate layer. Each neuron in the input layer is associated with all neurons in the intermediate layer so that data processing is carried out simultaneously. With single-date Landsat OLI data, for example, we used several nodes for including the best bands set (original bands, vegetation indices and other synthesized bands) (Gong *et al.* 1996; Erbek *et al.* 2004). Using multi-temporal remotely sensed data for classification requires large volumes of input nodes.

The hidden layer does the actual analysis of data in the network and are used for computations (Kavzoglu & Reis 2008). In the present study, a single hidden layer was applied. A single hidden layer usually is sufficient for map classifications (Lippmann 1987; Kavzoglu & Reis 2008). The number of neurons in the hidden layer is determined by trial and error. The output layer receives this analysis and returns it to the environment after division and calculation.

ANN is a powerful approach in extracting vegetation type information in complex mapping problems. This approach has a number of advantages compared to the traditional classification, notably that it does not need linear relationships and normally distributed training datasets. The disadvantage of ANN is that it is difficult to determine exactly how the ANN came up with a certain solution due to its complex nature; therefore, the ANN is often accused of being a black box. However, it is crucial to evaluate the potential of ANN approach to map land-cover in different areas. Multilayer Perseptron (MLP) has been the most widely used supervised ANN classifiers in land use/land cover classifications (Zhang & Foody 2001; Kavzoglu & Mather 2003; Kavzoglu & Reis 2008; Hu & Weng 2009). So, in this study the MLP with a back propagation learning algorithm was applied using TerrSet program.

Accuracy assessment

The Accuracy of the output maps were assessed using an independent ground-truth map obtained from an extensive field work. We developed error matrix based on the agreement between produced maps and ground-

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truth map (Foody 2002; Yuan *et al.* 2005). The produced maps were evaluated in term of overall accuracy, user accuracy, producer accuracy, and kappa coefficient (Foody 2002; Knorn *et al.* 2009).

RESULTS

In this study, four different supervised classification methods were used for mapping pollarded area in the Zagros forests, Iran, with single and multi-temporal Landsat8 OLI data.

Single-date OLI imagery

Regardless of the classifier methods, our results indicate that the image acquired on August with an overall accuracy of 73.44% performed better than other date (i.e. June, and November) (Table 4). In this case, there was some substantial confusion between *Kurpe* and *Kor* category. In contrast, the results obtained for the Khert forest are quite good (Khert have producer's and user's accuracies of 85.62% and 94.16%, respectively) (Table 4, Fig. 3). Using only the June and November scenes, the overall classification accuracy was 72.35% and 70.79% over the same ground truth map, respectively, somewhat worse than using only the August scene. Also, by comparing the results of different band combinations, it was observed that band combination of B4, B5, B7, Greenness and NDVI had the highest results.

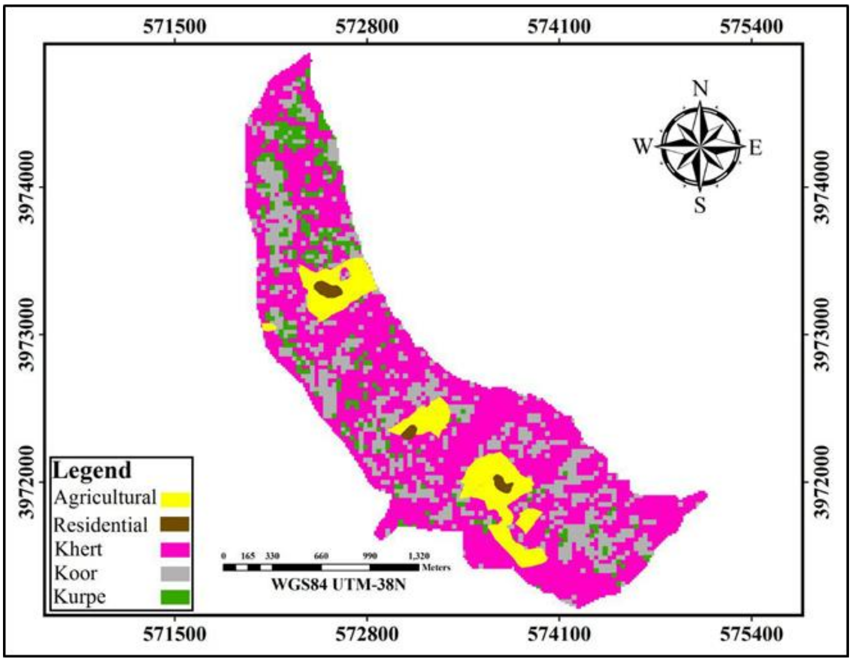

Fig. 3. The map of classification with artificial neural network algorithm for the images dated 15 August 2014.

Table 3. Input band sets for classifiers (i.e.MD, ML, FC and ANN) and acquisition date.

Date	Spectral bands and spectral indices
November 2015	B4, B5, B7, SAVI, MSAVI1
August 2015	B2, B3, B4, B5, B7
August 2014	B4, B5, B7, Greenness, NDVI
June 2014	B4, B5, B7

Multi-temporal OLI imageries

The overall accuracy and Kappa coefficient of classification when using multi-dates in the classification were increased to 75.27% and 0.39 respectively over the single-date alone (Table 5).

Among the analyzed multi-temporal images, the combination of images dated 11 June 2014, 15 August 2014 and 17 August 2015 with the band combination of B4, B5, B7, SAVI and MSAVI1 showed the highest accuracy. Fig. 4 illustrates the map of classification with artificial neural network algorithm for multi-temporal image combination related to the above three dates.

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Comparing four algorithms of classification

Classification was conducted with four algorithms for the three *khert*, *kor* and *kurpe* forest classes using single and multi-date data scenes. Minimum distance and maximum likelihood classifier, representing conventional classification methods, as well as MLP neural network and Fuzzy class, representing supervised modern algorithms, were applied. Since we used similar training dataset to perform the different algorithms, it can provide a possibility to implement a direct comparison among four approaches. According to the results, ANN was found to be better than other classifiers for both single and multi-date images with an overall accuracy of 73.44% and 75.27% respectively (Table 4- 5). For single date images, it shows an increasing accuracy of 15%, 7%, and 1% respectively. The overall accuracies for multi-temporal images increased 20.25%, 11.2 and 0.1%, respectively, using the ANN classifier rather than minimum distance, maximum likelihood and Fuzzy classifiers. The Fuzzy classification results were better than the maximum likelihood and minimum distance classification (overall accuracy of 72.51% for single-date and 75.15% for multi-date dataset) (Table 4 -5). The maximum likelihood algorithm was also better than minimum distance classifier for both single and multi-date images with an overall accuracy of 65.47% and 64.07% respectively (Table 4- 5).

Table 4. Classification results obtained from applied approaches considering a single date OLI data (15 August 2014).

Classifier	**Accuracy**	**Khert**	**Kor**	**Kurpe**	**Accuracy**
Maximum likelihood	Producer accuracy (%)	60.80	41.30	44.27	Overall accuracy (%) – 58.70 Kappa coefficient – 0.12
	User accuracy (%)	93.78	9..89	13.70	
Minimum Distance	Producer accuracy (%)	70.18	45.26	20.83	Overall accuracy(%) – 65.47 Kappa coefficient – 0.11
	User accuracy (%)	91.26	10.07	13.52	
Artificial Neural Network	Producer accuracy (%)	85.62	43.42	13.30	Overall accuracy (%) – 73.44 Kappa coefficient – 0.18
	User accuracy (%)	94.16	18.81	14.04	
Fuzzy	Producer accuracy (%)	91.56	31.11	5.02	Overall accuracy(%) – 72.51 Kappa coefficient – 0.16
	User accuracy (%)	90.44	16.22	20.61	

Table 5. Classification results obtained from applied approaches considering a single date OLI data (15 August 2014).

Classifer	**Accuracy**	**Khert**	**Kor**	**Kurpe**	
Maximum likelihood	Producer accuracy (%)	57.22	20.24	60.23	Overall accuracy (%) – 55.02 Kappa coefficient - 0.16
	User accuracy (%)	87.36	9.27	25.43	
Minimum Distance	Producer accuracy (%)	68.64	57.53	41.21	Overall accuracy (%) – 64.07 Kappa coefficient – 0.26
	User accuracy (%)	88.87	14.83	49.82	
Artificial Neural Network	Producer accuracy (%)	81.16	50.47	54.25	Overall accuracy (%) – 75.27 Kappa coefficient – 0.39
	User accuracy (%)	90.59	18.73	74.63	
Fuzzy	Producer accuracy (%)	87.49	24.76	30.30	Overall accuracy (%) – 75.15 Kappa coefficient – 0.25
	User accuracy (%)	83.67	17.83	56.17	

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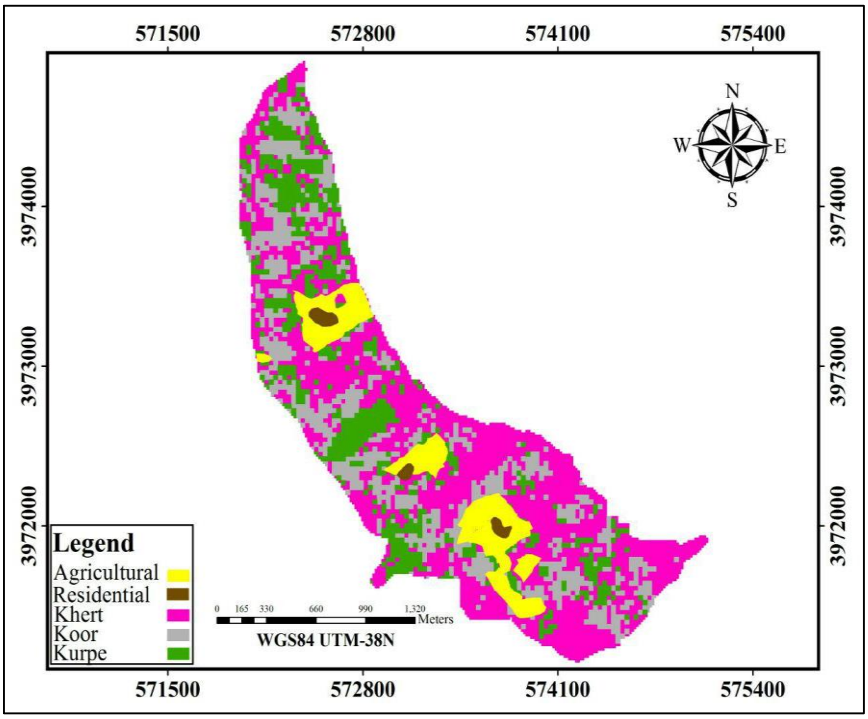

Fig. 4. The map of classification with artificial neural network algorithm for of images dated 11 June 2014, 15 August 2014 and 17 August 2015.

DISCUSSION

Human presence and activities may have negative consequences on the forest extend and its structural and functional attributes. The demand for harvesting wood and non-wood products has been the starting point of humans' relationship with forests. Zagros oak forests are facing a reduction in area due to several reasons such as illegal firewood cutting activities, expansion of agricultural lands, overexploitation of non-woody forest products (Rezayan & Erfanifard 2016). For millennia, pollarding has been used by rural people to utilize forest as a vital resource, particularly, in the northern Zagros oak forests. Henareh Khalyani *et al.* (2013) showed considerable loss in forest area in Zagros oak forests. They also detected a less connectivity loss for northern Zagros forests. They came to the conclusion that in the northern Zagros the traditional form of the forest management should be supported as a method that preserves forest connectivity. Therefore, the need to map, first, pollarded areas, then; to have updated maps of pollarded areas are of critical importance.

To map pollarded area VIs including, NDVI, SAVI, and MSAVI1 were used in addition to the original spactral bands. These vegetation indices are combinations of red and near infrared bands, which reflect important information on vegetation, because of the absorption of red wavelengths by chlorophyll and the strong reflection of the near infrared by leaf cellular structures (Bannari *et al.* 1995; Zhou *et al.* 2016) .

Given that the studied area is an open and relatively sparse forest cover, SAVI and MSAVI1, indices were used to minimize soil influences on canopy spectra. The results indicate that SAVI and MSAVI1 are of main spectral data set, according to their structural sensitivity to soil backscatter of open forest under-story. It is the condition over majority of the study area (Table 3). These results are consistent with the results of Bazrafkan *et al.* (2015) and Ahmadi Sani *et al.* (2008). The greenness component of Tasseled Cap Transformation (TCT) improved the performance of the classification. It can be contributed to the sensitivity of greenness component to variation of green vegetation in a pixel (Crist & Cicone 1984; Moradi *et al*. 2009).The greenness component of TCT is a combination of all OLI spectral bands and contain more information than the VIs, which contain only two bands (Bannari *et al.* 1995; Zhou *et al.* 2016).

The generated pollarded maps using four approaches, i.e., minimum distance, maximum likelihood, neural networks, and fuzzy algorithms showed that the artificial neural network and fuzzy algorithms obtained higher overall accuracy as well as higher kappa coefficient compared to other two algorithms. This efficiency is due to nonlinear and non-parametric feature of these classifiers.

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Artificial neural network operates on the basis of data structures and attributes (Mendoza *et al*. 2004). This has been confirmed by Bazrafkan *et al.* (2015); Ahmadi Nadoushan *et al*. (2009); Joshi *et al.* (2006); Chagas *et al.* (2013). As mentioned above, many studies have reported that ANN algorithm performs more accurately than the other techniques. It can be attributed to its capability dealing with complexity of feature space, i.e., having a complex topography, which is the case in our study area. Furthermore, once the thematic classes have high rate of similarity in the training dataset and training dataset, and also, do not follow a statistical distribution, ANN can improve the classification performance (Petropoulos *et al*. 2010). Selection of training samples is a crucial and challenging task in implementing the traditional and hard classification algorithms. Basically, training samples must follow a normal distribution. Our results showed that the ML approach provided the better results compared to MD approach. This is consistent with the results reported by Bazrafkan *et al.* (2014), Mendoza *et al.* (2004), Davis *et al.* (2002), De Laet *et al.* (2007), Jia & Richards (1994) and Kadmon & Harari-kremer (1999). The Generated map obtained by applying ANN and Fuzzy algorithms had higher accuracy in separating pollarded forest classes and, more generally, in preparing land cover maps based on multi-date images, compared to single-date imagery. Our results showed that the multi-date data has higher potential to separate the thematic classes by providing different spectral information for the classes at different times. The results obtained by Roy & Ravan (1996), Thakur *et al.* (2014), Pourshakouri Aladeh (2005), Jayakumar *et al.* (2000), Joshi *et al.* (2004), Pandey *et al.* (2006) and Fassnacht *et al.* (2015) on the employing multi-temporal data also confirm the results of the present study. The results showed a significant difference between overall accuracy and Kappa coefficient, due to the spectral interference of training classes. The same results were reported by Moradi *et al*. (2009).
The spectral similarity between two pollarded classes (i.e. *Kurpe* & *Kor*) and soil background resulted in low user accuracy for all applied classification approaches, hence, the probable relatively low kappa values in the present study. In contrast, *Khert* thematic class showed the highest producer and user accuracies which may be related to the development and regrowth rate of forest canopy after pollarding. The *Khert* class is in its three or longer years of recovery after pollarding. Therefore, canopy is fully recovered from the branches and leaves cutting and reflected signal from the canopy is sensitive enough to map this thematic class correctly. In addition, canopy cover for *Kor* and *Kurpe* classes is smaller and more heterogeneous, which in turn, can impact the classification accuracy Using multi-temporal images improved the spectral separability rate between less developed canopies (i.e. *Kurpe* & *Kor*), understory and soil background due to the ability to capture spectral information over different phonological stage.
Our results show an improvement, i.e. 10% in overall accuracy, to map pollarding area compared to the Moradi *et al.* (2009) who studied at the same area. They used the different satellite data, i.e. SPOT5 HRG and IRS-P6 LISS-III and implemented the maximum likelihood approach. It emphasizes on utilizing multi-date imagery of same sensor, for example, the Landsat 8-OLI multi-date data, rather than different sensors, as well as generating the proper vegetation indices along with applying approaches with capability to deal with nonlinear system such as ANN, where traditional approaches fail to map thematic classes correctly.
Generally, in land cover classification using satellite images, mixed pixels reduce the accuracy of classifications because of spectral confusion (Domac & Suezen 2006 ; Zhou *et al.* 2016) .
It could be concluded that the technical improvements (i.e. using more advanced classifiers or high-resolution imagery) cannot solve all problems of land cover mapping from remotely sensed data but will improve the results (Xie *et al.* 2008).

CONCLUSION

Mapping pollarding areas using single date imagery, multi-temporal imagery and nonparametric approach has shown promising results. By considering a 65% overall accuracy as an acceptable result for separating the pollarding areas (Moradi *et al.* 2009), both ANN approach and fuzzy classification are capable to map *Kor*, *Kurpe*, and *Khert* thematic classes with acceptable accuracy.
With the objective of understanding the impact of multi-temporal date on the classification performance, we observed a combination of multi-temporal and nonparametric proposed approaches (i.e. ANN) gained higher accuracy than single date. It was found that multi-temporal data of Landsat 8-OLI, as the latest Landsat product processed with artificial neural network algorithm has an ability to identify homogeneous units, separate and map the pollarded areas in the study region.

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Background reflectance from soil, high within-class variance due to the structure of forest canopies was the most contributing factor to the classification problem (Carpenter *et al.* 1997).

It could be concluded that providing different spectral information at different times, multi-date data can better separate the classes and yield more accurate results rather than single-date images.

REFERENCES

Ahmadi Nadoushan, M, Sofianian, A & Khajehaldin, SJAD 2009, Land cover mapping of Arak city using artificial neural network and maximum likelihood classifiers, *Physical Geography Research Quarterly*, 69: 83–98.

Ahmadi Sani, N 2008, Potentiality of ASTER images for forest density mapping in Zagros (Case study: Marivan forests). *Iranian Journal of Natural Resources*, 61: 603–614.

Baig, MHA 2014, Derivation of a tasselled cap transformation based on Landsat 8 at-satellite reflectance. *Remote Sensing Letters*, 5: 423–431.

Bannari, A 1995, A review of vegetation indices. *Remote Sensing Reviews*, 13: 95–120.

Baret, F, Jacquemoud, S & Hanocq, JF 1993, The soil line concept in remote sensing. *Remote Sensing Reviews*, 7: 65–82.

Bazrafkan, AM, PB & Fathi, P 2015, Capability of Liss III data for forest canopy density mapping in Zagros forests (Case study: Marivan Forests), *Iranian Journal of Forest*, 6: 387–401.

Bazrafkan, A, Pir Bavaghar, M & Fathi, P 2014, Capability of Liss III data for forest canopy density mapping in Zagros forests (Case study: Marivan Forests), *Iranian Journal of Forest*, 6: 387–401.

Brown De Colstoun, EC 2003, National Park vegetation mapping using multitemporal Landsat 7 data and a decision tree classifier, *Remote Sensing of Environment*, 85: 316–327.

Carpenter, GA 1997, Art neural networks for remote sensing: vegetation classification from landsat tm and terrain Data. *IEEE Transactions on Geoscience and Remote Sensing*, 35: 308–325.

Chagas, C, daS, Vieira, CAO & Fernandes Filho, EI 2013, Comparison between artificial neural networks and maximum likelihood classification in digital soil mapping. *Revista Brasileira de Ciência do Solo*, 37: 339–351.

Chavez, PSJ 1996, Image-Based Atmospheric Corrections-Revisited and Improved. *Photogrammetric Engineering & Remote Sensing*, 62: 1025–1035.

Crist, EP & Cicone, RC 1984, A physically-based transformation of Thematic Mapper data---The TM Tasseled Cap. *IEEE Transactions on Geoscience and Remote sensing*, 22: 256–263.

Davis, PA 2002, Evaluation of airborne image data for mapping riparian vegetation within the Grand Canyon. US Geological Survey, 470p.

Domac, A & Suezen, ML 2006, Integration of environmental variables with satellite images in regional scale vegetation classification. *International Journal of Remote Sensing*, 27: 1329–1350.

Doostan, R & Alijani, B 2016, Climate Change of Iran : A Synoptic Approach. *Journal of geography and regional developement*, 13: 21–26.

Dorren, LKA, Maier, B & Seijmonsbergen, AC 2003, Improved Landsat-based forest mapping in steep mountainous terrain using object-based classification, *Forest Ecology and Management*, 183: 31–46.

Eastman Ronald, J 2006, IDRISI Andes Guide to GIS and Image Processing, *Clark Labs, Clark University*, 284p.

Erbek, FS, Özkan, C & Taberner, M 2004, Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing*, 25: 1733–1748.

Fassnacht, FE, LiL & Fritz, A 2015, Mapping degraded grassland on the Eastern Tibetan Plateau with multi-temporal Landsat 8 data - where do the severely degraded areas occur? *International Journal of Applied Earth Observation and Geoinformation*, 42: 115–127.

Caspian J. Environ. Sci. Vol. 17 No. 1 pp. 83~96
DOI: 10.22124/cjes.2019.3347
Received: June 27. 2018 Accepted: Nov. 24. 2018
Article type: Research

Fatehi, P 2015, Estimation of Alpine Forest Structural Variables from Imaging Spectrometer Data. *Remote Sensing*, 7: 16315–16338.

Foody, GM 2002, Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80: 185–201.

Franklin, SE 2001, *Remote sensing for sustainable forest management*, CRC Press, 424p.

Frazier, RJ 2014, Characterization of aboveground biomass in an unmanaged boreal forest using Landsat temporal segmentation metrics. *ISPRS Journal of Photogrammetry and Remote Sensing*, 92,: 137–146.

Ghazanfari, H 2003, *Evaluation of growth and changes in diameter distribution of Quercus libani and Quercus infectoria stands to present forest adjustment pattern in Baneh region (Case study: Hawarakhol)*. University of Tehran, 82p.

Ghazanfari, H 2004, Traditional Forest Management and its Application to Encourage Public Participation for Sustainable Forest Management in the Northern Zagros Mountains of Kurdistan Province, Iran. *Scandinavian Journal of Forest Research*, 19: 65–71.

Gong, PPuR & Chen, J 1996, Elevation and Forest-Cover Data Using Neural Networks. *Photogrammetric Engineering & Remote Sensing*, 62: 1249–1260.

Hanara Khaliani, J 2013, Financial estimation and design of forestry incentive programs aimed at improving customary forest management (Case study: Baneh forests, northern Zagros). *Iranian Journal of Forest*, 5: 295–308.

Henareh Khalyani, A 2013, Deforestation and landscape structure changes related to socioeconomic dynamics and climate change in Zagros forests. *Journal of Land Use Science*, 8: 321–340.

Hu, X & Weng, Q 2009, Estimating impervious surfaces from medium spatial resolution imagery using the self-organizing map and multi-layer perceptron neural networks. *Remote Sensing of Environment*, 113: 2089–2102.

Jayakumar, S, Arockiasamy, DI & Britto, SJ 2000, Estimates of current status of forest types in Kolli Hill using remote sensing. *Journal of the Indian Society of Remote Sensing*, 28: 141-151.

Jia, X & Richards, JA 1994, Efficient maximum likelihood classification for imaging spectrometer data sets. *IEEE Transactions on Geoscience and Remote Sensing*, 32: 274–281.

Joshi, C 2006, Remotely sensed estimation of forest canopy density: A comparison of the performance of four methods. *International Journal of Applied Earth Observation and Geoinformation*, 8: 84–95.

Joshi, PK, Kumar, M & Agrawal, D 2004, Geospatial network analysis for path optimisation in solid waste management - a case study of Haridwar (India). *Journal of the Indian Society of Remote Sensing*, 32: 387–392.

Kadmon, R & Harari-kremer, R 1999, Studying Long-Term Vegetation Dynamics Using Digital Processing of Historical Aerial Photographs. *Remote Sens. Environ*, 68: 164–176.

Karjalainen, E, Sarjala, T & Raitio, H 2009, Promoting human health through forests: overview and major challenges. *Environmental Health and Preventive Medicine*, 15: 1-8.

Kavzoglu, T & Mather, PM 2003, The use of backpropagating artificial neural networks in land cover classification. *International Journal of Remote Sensing*, 24: 4907–4938.

Kavzoglu, T & Reis, S 2008, Performance Analysis of Maximum Likelihood and Artificial Neural Network Classifiers for Training Sets with Mixed Pixels. *GIScience & Remote Sensing*, 45: 330–342.

Knorn, J 2009, Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. *Remote Sensing of Environment*, 113: 957–964.

De Laet, V, Paulissen, E & Waelkens, M 2007, Methods for the extraction of archaeological features from very high-resolution Ikonos-2 remote sensing imagery, Hisar (southwest Turkey). *Journal of Archaeological Science*, 34: 830–841.

Caspian J. Environ. Sci. Vol. 17 No. 1 pp. 83~96 Received: June 27. 2018 Accepted: Nov. 24. 2018
DOI: 10.22124/cjes.2019.3347 Article type: Research

Lawley, V 2016, Site-based and remote sensing methods for monitoring indicators of vegetation condition: An Australian review. *Ecological Indicators*, 60: 1273–1283.

Lippmann, R 1987, An introduction to computing with neural nets. *IEEE ASSP Magazine*, 4: 4–22.

Lu, D & Weng, Q 2007, A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, 28: 823–870.

Mendoza, EH 2004, Land use/land cover mapping in Brazilian Amazon using neural network with aster/terra data. In *Proc. Geo-Imagery Bridging Continents*. Citeseer, 2004: 123–126.

Moradi, A 2009, The ability of SPOT-HRG and IRS-LISSIII data to identify and separate pollarding classes in north Zagros (Case study: Pollarded forests of Baneh in Kurdistan). *Iranian Journal of Forest and Poplar Research*, 17: 463–450.

Noormets, A 2015, Effects of forest management on productivity and carbon sequestration : A review and hypothesis q. *Forest Ecology and Management*, 355: 124–140.

Oetter, DR 2001, Land cover mapping in an agricultural setting using multiseasonal Thematic Mapper data. *Remote Sensing of Environment*, 76: 139–155.

Pandey, VK 2006, Delineation and parameterization of banikdih watershed using remote sensing and avswat model. *Journal of the Indian Society of Remote Sensing*, 34: 143–152.

Petropoulos, GP 2010, A Comparison of Spectral Angle Mapper and Artificial Neural Network Classifiers Combined with Landsat TM Imagery Analysis for Obtaining Burnt Area Mapping. *Sensors* , 10: 1967-1985.

Pourshakouri Aladeh, F 2005, *Separating the northern border of Caspian forests using multi-temporal satellite images (Case study: Kalachai forests)*, University of Tehran, 93p.

Ranjbar, H & Honarmand, M 2004, Integration and analysis of airborne geophysical and ETM+ data for exploration of porphyry type deposits in the Central Iranian Volcanic Belt using fuzzy classification. *International Journal of Remote Sensing*, 25: 4729–4741.

Rezayan, F & Erfanifard, Y 2016, Estimating biophysical parameters of Persian oak coppice trees using UltraCam-D airborne imagery in Zagros semi-arid woodlands. *Journal of Arid Environments*, 133: 10–18.

Richardson, AJ & Wiegand, CL 1977, Distinguishing vegetation from soil background information. *Photogrammetric engineering and remote sensing*, 43(12): 1541–1552.

Rocchini, D 2013, Uncertainty in ecosystem mapping by remote sensing. *Computers & Geosciences*, 50: 128–135.

Roy, PS & Ravan, SA 1996, Biomass estimation using satellite remote sensing data—An investigation on possible approaches for natural forest. *Journal of Biosciences*, 21: 535–561.

Satterwhite, MB & Ponder Henley, J 1987, Spectral characteristics of selected soils and vegetation in Northern Nevada and their discrimination using band ratio techniques. *Remote Sensing of Environment*, 23(2): 155–175.

Schultz, B 2015, Self-guided segmentation and classification of multi-temporal Landsat 8 images for crop type mapping in Southeastern Brazil. *Remote Sensing*, 7: 14482–14508.

Soffianian, AR 2011, No Title. *Journal of RS and GIS for Natural Resources*, 2: 1–11.

Stone, MG 1998, Forest-type mapping by photo-interpretation: A multi-purpose base for Tasmania’s forest management. *Tasforests*, 10:15–32.

Thakur, T, Swamy, SL & Nain, AS 2014, Composition, structure and diversity characterization of dry tropical forest of Chhattisgarh using satellite data. *Journal of Forestry Research*, 25: 819–825.

USGS 2014, No Title. Available at: ear.

Ustin, SL & Gamon, JA 2010, Remote sensing of plant functional types. *New Phytologist*, 186: 795–816.

Wolter, PT 1995, Improved forest classification in the northern Lake States using multi-temporal landsat imagery. *Photogrammetric Engineering and Remote Sensing*, 61: 1129–1143.

Caspian J. Environ. Sci. Vol. 17 No. 1 pp. 83~96
DOI: 10.22124/cjes.2019.3347
Received: June 27. 2018 Accepted: Nov. 24. 2018
Article type: Research

Wulder, MA 2008, Landsat continuity: Issues and opportunities for land cover monitoring. *Remote Sensing of Environment*, 112(3): 955–969.
Xie, Y, Sha, Z & YuM 2008, Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology*, 1: 9–23.
Xu, B, Gong, P & PuR 2003, Crown closure estimation of oak savannah in a dry season with Landsat TM imagery: Comparison of various indices through correlation analysis. *International Journal of Remote Sensing*, 24: 1811–1822.
Yuan, F 2005, Land cover classification and change analysis of the Twin Cities (Minnesota) metropolitan area by multitemporal Landsat remote sensing. *Remote Sensing of Environment*, 98: 317–328.
Zhang, J & Foody, GM 2001, Fully-fuzzy supervised classification of sub-urban land cover from remotely sensed imagery: Statistical and artificial neural network approaches. *International Journal of Remote Sensing*, 22: 615–628.
Zhou, J 2016, Comparison modeling for alpine vegetation distribution in an arid area. *Environmental Monitoring and Assessment*, 188: 408-420.

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شناسایی توده‌های گلازنی‌شده در جنگل‌های زاگرس شمالی با استفاده از طبقه‌بندی شبکه عصبی مصنوعی بر روی تصاویر چند زمانه سنجنده OLI ماهواره لندست ۸ (مطالعه موردی: آرمرده، بانه)

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چکیده

وابستگی اقتصادی جامعه محلی در زاگرس شمالی به دامداری موجب استفاده زیاد برگ و سرشاخه‌های درختان یا به اصطلاح گلازنی نسبت به دیگر قسمت‌های زاگرس شده است. گلازنی یک الگوی دیرینه بهره‌برداری از جنگل برای تامین علوفه بوده و برای استمرار این تولید همیشه تلاش بر این بوده است که با یک مدیریت مناسب این تولید ادامه داشته باشد. یکی از ابزارهای مهم مدیریت بر این جنگل‌ها داشتن نقشه‌های به‌هنگام از محوطه‌های گلازنی شده است. برای رسیدن به این هدف از تصاویر یک زمانه و چندزمانه سنجنده OLI ماهواره لندست ۸ مربوط به سال‌های ۲۰۱۴ و ۲۰۱۵ استفاده شد. برای ارزیابی صحت نتایج حاصل از طبقه‌بندی داده‌های ماهواره‌ای، نقشه واقعیت زمینی به‌صورت برداشت کامل از منطقه مورد مطالعه تهیه شد. الگوریتم-های مختلف طبقه‌بندی شامل حداقل فاصله، حداکثر احتمال، شبکه عصبی مصنوعی و فازی به کار گرفته شد. ارزیابی صحت طبقه‌بندی براساس صحت کلی و ضریب کاپا محاسبه شد. نتایج نشان داد که طبقه‌بندی کننده‌های شبکه عصبی مصنوعی و فازی نسبت به دیگر الگوریتم‌ها صحت بالاتری ارائه دادند. علاوه بر این، استفاده از تصاویر چندزمانه نسبت به تصاویر تک زمانه باعث بهبود میزان صحت نتایج طبقه‌بندی می‌شود. نتایج نشان داد که تصاویر چندزمانه با استفاده از الگوریتم‌های شبکه عصبی مصنوعی و فازی قابلیت متوسطی برای تهیه نقشه توده‌های گلازنی‌شده و طبقه‌بندی واحدهای گلازنی دارند.

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