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Accuracy of pixel-based classification: application of different algorithms to landscapes of Western Iran

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Abstract Scenarios for monitoring land cover on a large scale, involving large volumes of data, are becoming more prevalent in remote sensing applications. The accuracy of algorithms is important for environmental monitoring and assessments. Because they performed equally well throughout the various research regions and required little human involvement during the categorization process, they appear to be resilient and accurate for automated, big area change monitoring. Malekshahi City is one of the important and at the same time critical areas in terms of land use change and forest area reduction in Ilam Province. Therefore, this study aimed to compare the accuracy of nine different methods for identifying land use types in Malekshahi City located in Western Iran. Results revealed that the artificial neural network (ANN) algorithm with back-propagation algorithms could reach the highest accuracy and efficiency among the other methods with kappa coefficient and overall accuracy of approximately 0.94 and 96.5, respectively. Then, with an overall accuracy of about 91.35 and 90.0, respectively, the methods of Mahalanobis distance (MD) and minimum distance to mean (MDM) were introduced as the next priority to categorize land use. Further investigation of the classified land use showed that good results can be provided about the area of the land use classes of the region by applying the ANN algorithm due to high accuracy. According to those results, it can be concluded that this method is the best algorithm to extract land use maps in Malekshahi City because of high accuracy.

Keywords Remote sensing · Land use classification · Landsat imagery

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Introduction

Land use is a specific area that citizens use by different management processes to utilize the property for their purposes (Makwinja et al., 2021). Land cover means the biophysical characteristics of the surface and lateral subsurface of the planet. It involves four different variables, namely, water, land, air, and human activity (Osaliya, 2021). Analyses of land use shifts may also be a valuable method for analyzing improvements in habitats and their environmental consequences at various spatial and temporal scales (Egidi et al., 2021; Kii et al., 2019; Velli et al., 2019). Among many applications of remote sensing science, assessing the trend of changes in land use/land cover has an important place (Betru et al., 2019; Chiang et al., 2021; Mao et al., 2019; Valdez et al., 2019; Wolaver et al., 2018; Yang et al., 2020; Yao et al., 2020; Zhang et al., 2020). This assessment is important because the earth's surface is constantly affected by the ongoing changes of cumulative effects of a series of chaotic factors, the development of ecosystems, and changes in human culture (Gergel & Turner, 2002).

Remote sensing science has important and special applications in various research and scientific branches, including fisheries, meteorology, forestry, scattering, distribution of wildlife species, and management of protected areas (Leyequien et al., 2007; Priede & Miller, 2009; Buchanan et al., 2013; Reyes-Acosta & Lubczynski, 2013; Marian et al., 2013; Martínez-López et al., 2014; Liu et al., 2017). Since one of the main purposes of satellite image processing is to provide thematic and efficient maps, selecting the appropriate algorithm for classification plays a large role (Haut et al., 2019; Xu et al., 2019). For this reason, researchers have done extensive efforts to develop advanced methods and techniques of classification to improve classification accuracy, including object-oriented, artificial neural network approaches, blurred reasoning, tree judgment, and smart systems (Li et al., 2020). According to features of image processing, to extract information from satellite images in these algorithms, they can be divided into two main groups that are: (A) classification algorithms based on numerical values of visual elements or pixels (pixel-based) and (B) image object-based classification algorithms (object-oriented).

Object-oriented classification utilizes both spectral and spatial information for analysis. The approach includes the categorization of pixels based on their spectral properties, texture, color, tone, and spatial relationship with the neighboring pixels. This approach is a classification algorithm that can be used to process a high-resolution image. With the advancement of computer technology, various classification algorithms have been used to identify land cover classes, including the artificial neural network (ANN) (Ge et al., 2020), vector support machinery (SVM) (Ge et al., 2020), maximum likelihood classification (ML) (Otukei & Blaschke, 2010), minimum distance to mean (MDM) (Lim et al., 2009), Mahalanobis distance (MD) (Krishnaswamy et al., 2009), binary encoding (BE), and spectral angle map (ASP). Many recent studies have contrasted some of the algorithms used to characterize satellite photos in various areas of the world for assessing land use and land cover. Wang et al. (2022) used three algorithms, including fuzzy, neural network, and minimum distance, based on the QuickBird satellite image classification for identifying three different land cover classes such as vegetation, urban area, and water. Results revealed that the accuracy of classification using neural networks compared with the other two algorithms in the study area is higher. Deval and Joshi (2022) contrasted the accuracy of three techniques of image classification, namely, supporting vector machine, maximum likelihood classifier, and artificial neural network, in a tropical area showing low to medium growth. This research was conducted using Koh Tao's 15-m ASTER view with spatial resolution in Thailand. Results demonstrated that the vector network system algorithm has the highest accuracy compared to the other two algorithms. Ghosh and Joshi (2014) used WorldView 2 images on bamboo patches in the lower Gangetic plains in parts of South 24 Parganas, West Bengal, India, to compare support vector devices and random forest algorithms. Results presented that the support vector machine algorithm has a higher producer accuracy by 84% compared with the random forest algorithm. Wahidin et al. (2015) determined the accuracy values of coral rock habitat classification on the island of Morotai in the Northern Province of Maluku, Indonesia, built on object-based classification algorithms such as vector machine support, random tree, and decision tree support. Outcomes showed that the most overall precision and Kappa values on coral reef ecosystem mapping were given by Help Vector Machine algorithms. Sanhouse-García et al. (2016) used the controlled classification system per pixel based on maximum probability and minimum distance algorithms based on the Bhattacharya algorithm using CBERS-2 photos from the Monagas and Delta Amacuro states of Venezuela in the municipalities of Sotillo and Casacioma and contrasted them among themselves. The results showed that among the algorithms used, the Bhattacharya algorithm, has the best classification performance with an overall precision of 83.93 percent and a Kappa index of 0.81%. Reyes et al. (2017) compared the accuracy of K-nearest neighbors and help vector machine for classification using medium-resolution images (Landsat TM) in the province of Pontodora in Spain, which has a diverse landscape with various coexistence components, including mixed trees, hardwoods and conifers, piers, natural meadows, fertile areas, water levels, barren soils, and urban and industrial areas. The best results with a kappa coefficient of 0.80 and an error rate of 85.31% were reported for the help vector machine. Shaharum et al. (2018) extracted and contrasted the precision of Krau Wildlife Reserve (KWR) in protected areas utilizing Landsat 8 and controlled spectral angle mapper classification algorithms. They used pan sharpening and cloud patching methods to boost LULC classification accuracy. Five grades of dense woodland, less thick woodland or farmland, built-up land, bare soil, and water were listed in the region under research. The results showed that the artificial neural network algorithm with an overall accuracy of 98% has the highest accuracy compared to the other two algorithms. Toosi et al. (2019) tested four tracked classification algorithms based on Landsat time series photos to classify mangrove cover in southern Iran and contrasted them. In this study, two classification algorithms were used in the biased analysis, namely, random forest and regularization, and two help vector methods (radial and linear). Their results showed that four algorithms provided a good overall precision of 81 to 93% and a Kappa index of 0.81 to 0.92, but visual analyses of forecasts indicated that Random Forest worked better. Ge et al. (2020) compared numerous algorithms to classify the LUCC of the Dengkou Oasis, China, using Landsat 8 Operational Land Imager (OLI) picture data with spectral indices and driver variables generated from a simulated terrain model to classify 7 specific land cover groups, namely, k-nearest neighbor, random woodland, help vector machine, and artificial neural network. Results demonstrated that the artificial neural network has the highest overall accuracy with 97.16% compared with other algorithms. An examination of the studies revealed that different algorithms have different results under different conditions and regions and that an algorithm cannot be considered a more accurate algorithm without performing a comparison. In addition, in most studies, the comparison of algorithms is limited to only a few specific algorithms, and on the other hand, these algorithms are rarely compared in arid and semi-arid regions. Hence, the main objective of this research was to extract land cover classes in Malekshahi City in Iran by applying nine different algorithms, including support vector machine classification (SVM), maximum likelihood (ML), artificial neural network (ANN), minimum distance to mean (MDM), parallel surfaces (PS), Mahalanobis distance (MD), spectral angle map (SAM), spectral information divergence (SID), and binary encoding (codes) (BE), as well as determining the best algorithm for land cover classification in this region.

Materials and methods

Study area

Malekshahi City is located in the northeast of Ilam Province with geographic coordinates of 33 degrees and 30 min to 33 degrees of North latitude and 46 degrees and 50 min to 46 degrees and 20 min of East longitude with an area of 1739 km^2. The Malekshahi tribe is the biggest Kurdish tribe in Ilam. The average rainfall of the region is 750 mm, and the temperature is 16.4 (Yaghobi et al., 2019). Malekshahi city is a part of the arid and semi-arid regions of the Zagros Mountains. Zagros is the largest and main habitat of different species of oak in Iran, and for this reason, this area is very important. Also, the forests of Zagros are one of the important ecosystems of the country, which play an important role in preserving water and soil, and the oak forests are one of the characteristics of this region. Zagros forests spread over 11 provinces of the country with an area of 6 million hectares and constitute 40% of Iran's forests. Their altitude ranges from 253 to 2770 m above sea level. The main land covers in this city are forest, agricultural, and residential areas. The location of the case study is shown in Fig. 1.

Methodology

In the present study, to compare different algorithms, ETM + satellite images from June 26, 2014, were adopted. The images were converted into a UTM coordinate system using ENVI software version 4.8 and using a polynomial conversion for interpreting and processing data. Coordinates of ground control points on the topographic map with a scale of 1:

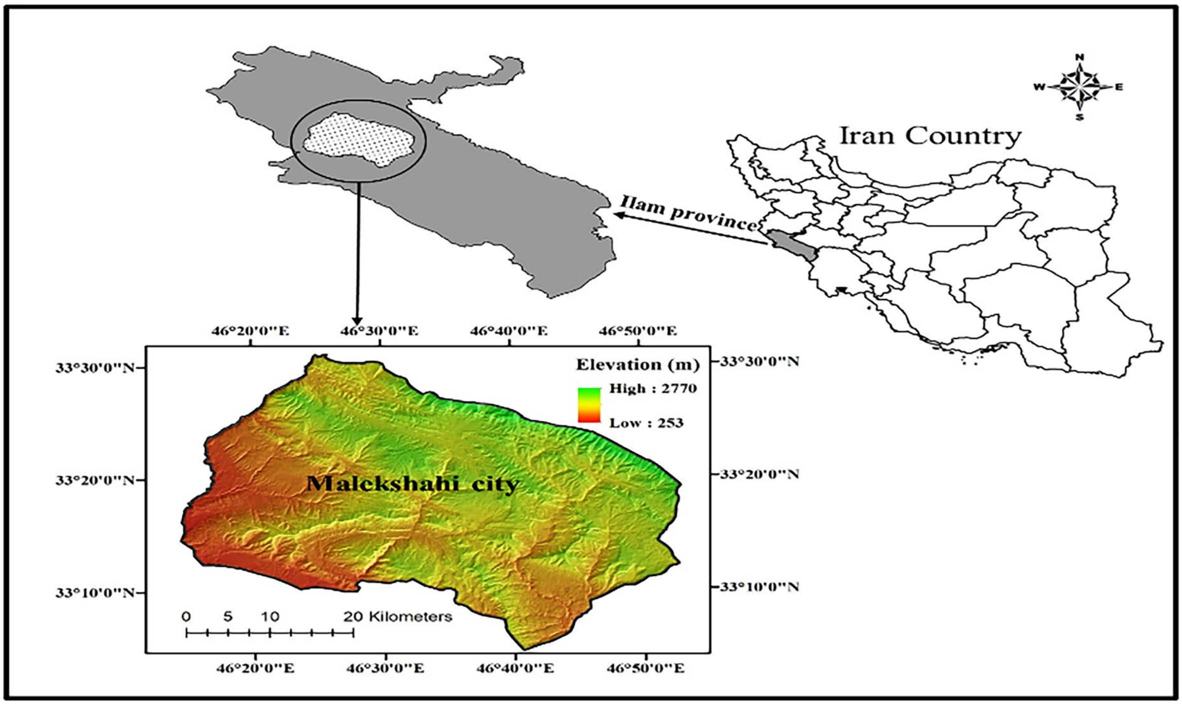

Fig. 1 Map of Iran showing the location of Ilam province and schematic diagrams of the study area

50,000, aerial photos with a scale of 1: 20,000, and ground reference points were collected using GPS. Geometric correction of these images, proper distribution of control points, and the rate of root mean square error (RMSE) were obtained by approximately 0/5 pixels. The geometric matching operation was done using topographic maps with a scale of 1: 50,000 to use 25 ground control points obtained in the field in the study area. The images used in this research were corrected geometrically and radially for classifying land cover maps. Thus, for the validation of the accuracy of the extracted land cover maps, a random sampling method was applied for data classification. These samples were collected based on a local land use map and visiting the area under study. This local map has been prepared by the Natural Resources and Watershed Management Organization of Iran for all provinces in the form of a vegetation map. Therefore, a local vegetation map of the studied area was received from this organization. For checking the accuracy of the image classification using validated images, the accuracy was measured using the error matrix approach as well as certain statistical metrics like total accuracy, kappa coefficient, accuracy of the manufacturer, and consumer precision. Accordingly, several pixels were selected as training samples. Those pixels as a ratio of the total image represent 1 to 5 percent of pixels (Richards & Jia, 1999). For extracting the land cover map, nine different algorithms utilized included SVM, ML, ANN, MDM, parallel surfaces PS, MD, ASP, SID, and BE (Fig. 2). The field of research was then divided into three major land use classes including forest class (which includes all rangelands and forest fields), agriculture class (which includes rainfed farmland, irrigated farmland, and gardens), and residential area (which includes all residential areas such as cities and villages).

Classification algorithms

Classification algorithm of maximum likelihood classification: One of the standard algorithms in image classification is the maximum likelihood algorithm, which is founded on the principle of probability (Nasiri, 1997). In this algorithm, the mean vector, variance–covariance matrices, and statistical probability are used for each class. Various

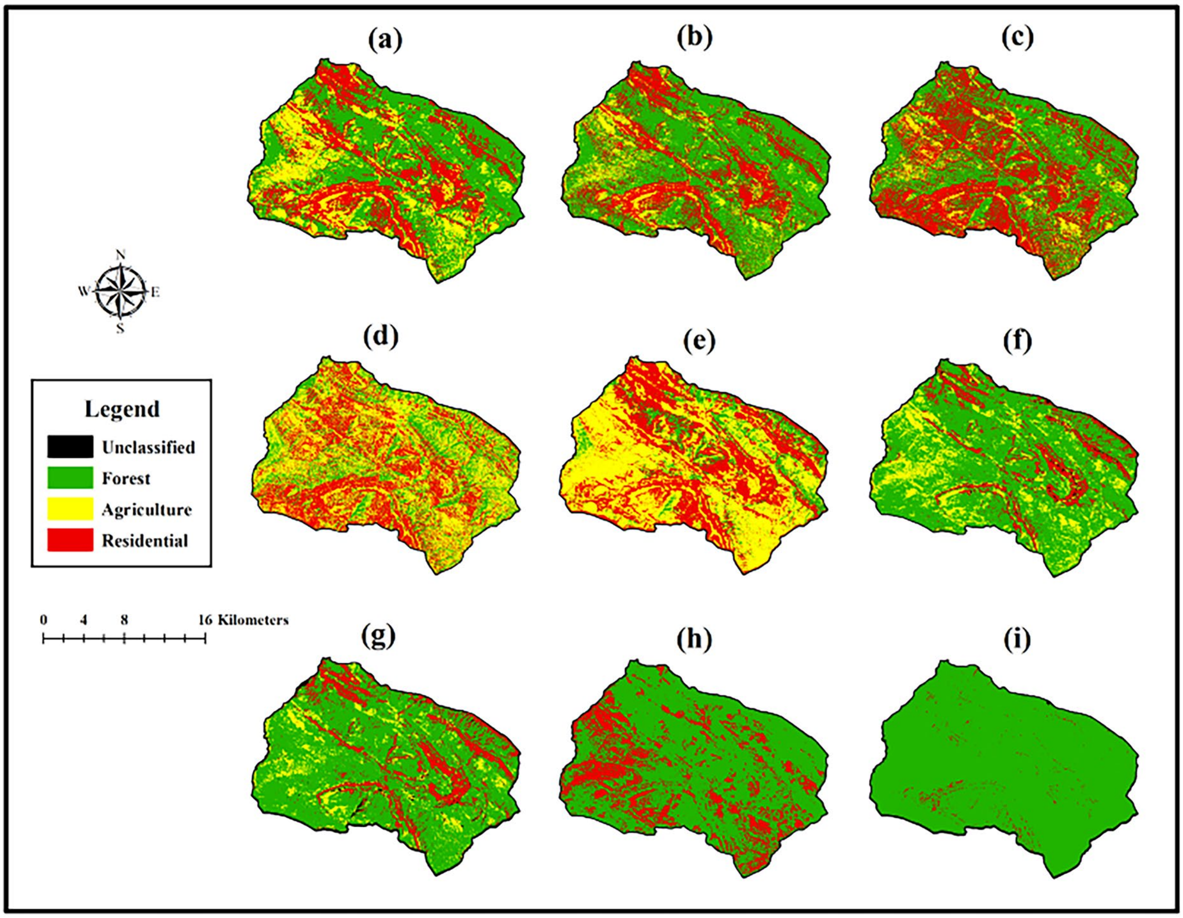

Fig. 2 Map of the land use extracted by the algorithm of ANN (**a**), the algorithm of MDM (**b**), the algorithm of MD (**c**), the algorithm of SVM (**d**), the algorithm of ML (**e**), the algorithm of SID (**f**), the algorithm of SAM (**g**), the algorithm of BE (**h**), and the algorithm of PS (**i**)

investigations have been done using the maximum likelihood classification algorithm in previous studies (Ali et al., 2018; Hagner & Reese, 2007; Singh & Singh, 2020).

Classification algorithm of minimum distance to mean: In this technique, at first, the mean of all classes that have already been separated from each other was determined using the method of determining climate zones, and then, the Euclidean distance of reflection of each pixel is calculated from the mean of all classes. This type of classification is mathematically simple and computationally efficient, but its theoretical basis is not as strong as the classification of maximum likelihood (AlizadehRabie, 1993; Tso & Mather, 2009).

PC algorithm This algorithm is one of the most widely employed algorithms for the classification of digital images. The algorithm is based on the decision rule using Boolean logic. Training results are used to conduct classification in N spectral bands. Brightness values of each pixel in the image in which the training data is obtained are possible for the c class, k band, and m class (Mahdavian Cheshmeh Gol & Niazi, 2014).

Support vector machine algorithm A new technique based on statistical learning theory named supporting vector machine is used for classifying remote sensing data (Dixon & Candade, 2008; Yao et al., 2008). In this method, for a non-linearly separable dataset that includes points from two different categories, all points in the first category may be segregated from those in the second category by performing an infinite number of hyperplanes, and a hyperplane which is the strongest with the widest range between the two categories is selected by following a subset of training samples known as support vectors (Cracknell & Reading, 2014).

ANN algorithm Artificial neural network solves some problems of classification algorithm of maximum likelihood using a nonparametric approach. Although the ANN algorithm may be used with high accuracy to classify satellite images, a number of studies have shown that users of this algorithm have difficulties in selecting various factors during the implementation of learning (Wilkinson, 1997). There are various forms of ANN algorithms for land use classification and land cover classification. There is a multilayer perceptron neural network, which is normally formed of one input layer and one or more output layers in order to receive, process, and display information (Wijaya, 1995). Due to the training algorithm of MLP networks of back-propagation, in this study, a multilayer perceptron network was used. There are three main phases in the ANN classification algorithm. The first phase includes the educational process using the input data that includes three bands of 2, 3, and 4 and the learning samples. The second phase includes the validation process; at this phase, the accuracy of the network is determined (Yuan et al., 2005). The final phase is the classification phase in which maps of land cover and land use based on the educational process are provided (Oommen et al., 2008). Perceptron multi-layered networks are often taught by the back-propagation method.

MD algorithm MD algorithm is another algorithm for image classification. This algorithm is very similar to MDM, but using a covariance matrix in the MD method is the main difference. This method assumes that the histogram of bands is normal (Richards & Jia, 1999).

SAM algorithm Another algorithm for the classification of satellite images is SAM, which is based on spectral classification. The method is used when the data is calibrated according to reflection and it is almost non-sensitive against the effects of light and Albedo (Zhang & Li, 2014).

SID classification algorithm Another algorithm of classification is the SID algorithm. In this algorithm, divergence size is used to match the pixel with a given spectrum. In addition, in this algorithm, the lower the divergence, the higher the possibility of the similarity of pixels (Chang, 2004).

BE algorithm Binary encoding algorithm is a very simple method among classification algorithms of images. In this algorithm, data and spectra are encoded between zero and one, according to which, a bond is higher or lower than the mean spectrum (Mazer et al., 1988).

Model validation

The estimation of accuracy is important to understand results and apply those tests to decision-making. The most important accuracy calculation parameters include total accuracy, product accuracy, consumer accuracy, and the kappa coefficient (Lu et al., 2004), which were used to evaluate the accuracy of classification conducted from the mentioned parameters. The validation method proposes to fix the quality of the extracted map for 2014 concerning the local land use for the same year. Model validation can be reached mainly in two different methods: the statistical approaches and the visual methods. In the present study, the first method was used. For validating the model, the extracted map for 2014 was examined against the local map for the same year via the Kappa index which is calculated based on Eq. 1 (Cohen, 1960). This method weighs the agreement between the two maps that can have any number of categories.

$$K = \frac{p_a - p_e}{1 - p_e} \tag{1}$$

where $p_a = \frac{1}{n}\sum_{i=1}^{k} nii$ (the relative observed agreement between the two maps) and $p_a = \frac{1}{n}\sum_{i=1}^{k} nii$ (the probability of chance agreement).

The research region was separated into three primary classes, including forest class, agricultural class, and residential area, after training samples were gathered from three distinct sections, including satellite images, Google Earth, and field visits. Later, data for 2014 was retrieved using the nine alternative techniques indicated above for land cover categorization.

Based on the findings, the artificial neural network method was able to extract the size of three layers of land cover at a sufficient level and display the extent of the forest layer well, taking into account that the study region is surrounded by Zagros forests. The forest class has also been effectively separated from the other two classes by MD and MDM algorithms. The area of the residential class in different algorithms is ranging such that it varies from 18 to 616 km^2 in PS and ML algorithms, respectively. The results concerning the agriculture class have conditions similar to the residential class; hence, the lowest and the highest areas are extracted in the PS and ML algorithms, respectively. Accordingly, it can be concluded that the lowest and the highest areas for forest class have been extracted in the ML and PS algorithms, respectively.

Table 1 Coefficients of accuracy of 9 supervised classification algorithms in the area under study

96.5	0.94	92.3	100	Forest	ANN
		100	90.48	Agricultural	
		100	100	Residential	
91.35	0.89	85.19	95.83	Forest	MD
		100	85.71	Agricultural	
		93.31	92.31	Residential	
90.1	0.89	88.66	95.83	Forest	MDM
		95	90.48	Agricultural	
		92.32	92.31	Residential	
44.48	0.36	62.12	100	Forest	SVM
		100	41.63	Agricultural	
		75	32.31	Residential	
37.5	0.31	100	42.4	Forest	ML
		35.2	28.32	Agricultural	
		23.9	51.74	Residential	
32.08	0.24	100	34.3	Forest	SID
		100	20.5	Agricultural	
		13.2	100	Residential	
29.21	0.19	12.77	100	Forest	SAM
		100	26.67	Agricultural	
		34.62	100	Residential	
24.43	0.1	65	100	Forest	BE
		0	0	Agricultural	
		100	100	Residential	
20.96	0.12	59.38	79.17	Forest	PS
		0	0	Agricultural	
		80.77	100	Residential	

Results

After classification, some statistical indicators, including the error matrix, the accuracy of the producer, the accuracy of the user, overall accuracy, and the kappa coefficient, were calculated by conducting field operations, using aerial photos with a scale of 1:20,000 and satellite images of Google Earth, and random sampling of the surface of the study area, as shown in Table 1. The highest value for overall classification accuracy and kappa index for the year 2014 was 96.5 and 94.0% in the ANN algorithm, respectively. In contrast, the lowest value for those indexes was 20.9 and 10.0% in PS and BE algorithms, respectively. Based on Table 1, the kappa index is acceptable not only for the ANN algorithm but also for MD and MDM algorithms. On the other hand, this index is unacceptable for the rest methods because of its low value. The reason that the ANN algorithm has higher accuracy than other algorithms is that this method is a non-parametric/non-linear algorithm.

Comparing the area of land cover classes in different algorithms

According to Fig. 3 obtained from the calculation of the area of different land uses in the study area, it was determined that the ANN algorithm, the rate of the area of forest, and agricultural and residential lands provide acceptable results that are resulted from high accuracy (90%) of classification of this algorithm. In the MD and MDM algorithms, due to the same accuracy as the ANN algorithm, the obtained areas are similar to the mentioned algorithm. In contrast to the rest of the land cover classes, the rate of the area of agricultural and residential land uses had a significant difference compared with the two previous algorithms. In BE and PS algorithms, due to the very low accuracy of both classifications, the total area of the region is only devoted to forest and agricultural land uses.

Discussion

Timely and accurate information on land cover is required for decision-makers and researchers at all levels. With research and field observations and the use of satellite data, land cover maps can be produced with minimum time and cost (Alawamy et al., 2020). These tools will help to portray natural and artificial

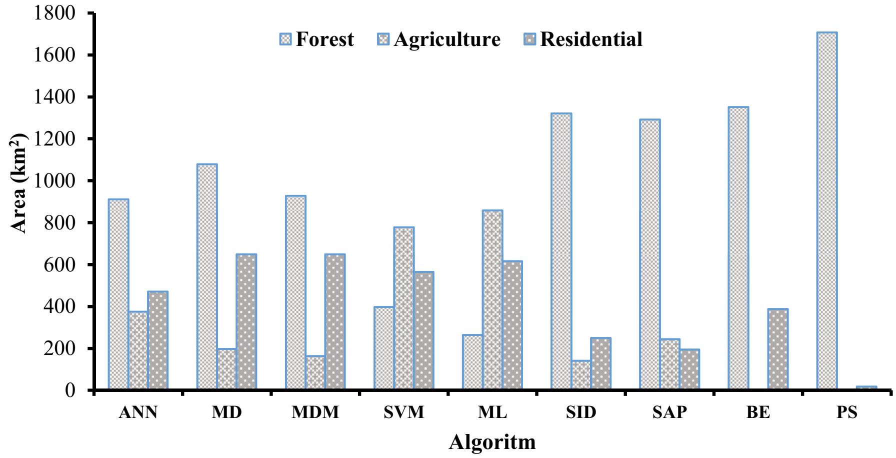

Fig. 3 Area of land cover classes based on nine supervised algorithms in the study area

phenomena on the surface of the earth without human intervention, and they can be accountable for past confusions. One of the major remote sensing applications is detecting and investigating improvements in land use (Zhang et al., 2019). The possibility of identifying and investigating dynamic and changing phenomena using repetitive features of remote sensing data at different times is created in the environment. According to the purpose of this study, which is to determine the best algorithm for the study area, at first, the geometric and radiometric corrections were done on the images, and then, the 9 supervised classification algorithms were used. The results showed that the ANN algorithm with a kappa coefficient of approximately 94% and an overall accuracy of approximately 96.5% has the greatest coefficient and overall accuracy among the 9 supervised classification algorithms. The MD and MDM algorithms have an overall accuracy of approximately 91.35 and 90.10%, respectively.

According to the results of the area of land uses using 9 categorization techniques, using the ANN algorithm, it was found that the extent of forest, agricultural, and residential land uses was 910.97, 375.57, and 470.62 km2, respectively. Considering that the studied area has an extensive forest cover, this algorithm can show the extent of the forest area with an accuracy of over 90%. In fact, the results are in line with the findings of Mahdavian Cheshmeh Gol and Niazi (2014) who showed that the ANN algorithm has more efficiency in deriving land use maps with accuracy equal to 82.32 compared to ML and MDM algorithms. Akbari et al. (2013) showed in their comparison of the two MD and ANN algorithms in Sabzevar that the second technique has more accuracy than the ML algorithm, which has a kappa coefficient of 90% and an overall accuracy of 94.23. The second method has a kappa coefficient of 97%. In addition, Zeshan et al. (2021), by applying the ANN algorithm, showed that thick woods had significantly decreased from the year 2000 to 2020. On the other hand, the amount of barren land had significantly increased (up to 547.39 km^2) and urban land usage had witnessed a sharp increase. However, a considerable decrease will occur in the area of dense forests in the simulated years.

Soffianian et al. (2011) used the ANN algorithm with NDVI plant index as auxiliary data in Hamedan Province and found a kappa coefficient and overall accuracy of 86% and 88%, respectively. This indicated that the ANN algorithm has high potential in providing land use maps and cropping patterns with high accuracy. Duro et al. (2012), by using object-based classifications, created an attractive visual representation of land cover classes. There was no advantage to preferring one image analysis approach over another for the purposes of mapping broad land cover types in agricultural environments using medium spatial resolution earth observation imagery.

Li et al. (2015) declared that SVM outperformed RF in classifying urban tree species. Ghosh and Joshi (2014) reported that RF classification performed worse than SVM classification for mapping bamboo. Zhang and Li (2014), however, found that RF produced higher overall accuracy than SVM for mapping coastal vegetation. Le Louarn et al. (2017) showed that RF slightly outperformed SVM for urban tree species classification. These results showed that when employing different remote sensing images with different classification purposes, machine learning algorithms performed differently.

Mas (2003) graded ground usage and land use using ANN and a back-propagation algorithm in the Terminus Wetland in the southeast of Mexico. The results indicated that the overall accuracy of this algorithm was 80% with six classes of land cover. This corresponds with the results of the current research, which selected the ANN method with the back-propagation algorithm as the best method. This research provides an entry point for land cover as part of the discussion on a more sustainable and adaptive ground use and control of land use for the region under research. Thus, the results presented in the investigation should be interpreted as a suggestion to discuss and make a better decision to apply the appropriate approach for identifying and determining land cover classes (Mas, 2003).

Conclusion

The purpose of this investigation was to classify and determine land cover classes based on nine different supervised classification algorithms. To extract the classes, the Landsat imagery for the year 2014 was used. Firstly, the images were radially and atmospherically corrected using ENVI 4.8. A large number of recent investigations applying accuracy assessments use kappa coefficient (K) based indices and overall accuracy as an indication of the validity of the classification algorithm. However, recent developments in accuracy assessment methodology have pointed out the effect of the kappa indices (Aksoy & Kaptan, 2021; Arumugam et al., 2021). Then, based on the extracted land cover maps, the ANN method was selected as the best method among the 9 supervised classification algorithms with the kappa coefficient and overall accuracy of approximately 94% and 96.5%, respectively. With an overall accuracy of around 91.35, 90.10, and 84.48%, respectively, MD, MDM, and SVM were chosen as the following priority to categorize land use. According to the results obtained from the area of the land cover classes with nine different classification algorithms, it was specified that using the ANN method, the area of forest, agricultural, and residential land cover classes were 910.9, 375.57, and 470.62 km2, respectively. Given that the study area is surrounded by a forest area, this classification method can well show the extent of forest class in the whole region with an accuracy of over 90%. Land cover maps resulting from satellite imaging have a significant role to play in the state and national land cover evaluation. This study reveals that the ANN algorithm has many advantages compared to other classification algorithms and has higher classification accuracy. Hence, it is a good alternative to the usual classification algorithms, and it has separation potential and higher capability for providing a land cover map in the urban area.

Author contribution S. A. and A. D.: Conceptualization, methodology, software, Writing—original draft, and Visualization. S. Kh. and H. A.: Reviewing, editing, and validation.

Availability of data and material Raw data were generated at the Gorgan University of Agricultural Sciences and Natural Resources. We confirm that the data, models, and methodology used in the research are proprietary, and derived data supporting the findings of this study are available from the first author on request.

Computer code availability Not applicable**.**

Declarations

Conflict of interest The authors declare no competing interests.

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