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APPLICATION OF SENTINEL-2A DATA AND PIXEL-BASED ALGORITHMS FOR LAND COVER MAPPING IN ILAM-IRAN

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Abstract

The western forests and rangelands of Iran in Zagros Mountain are valuable ecosystems for protecting the water and soil resources and providing the habitat for endemic fauna and flora. These ecosystems have widely destroyed by human interferences in the recent years. The land cover mapping using an accurate method is the first step to prevent the further destruction of these ecosystems. The aim of this study was to generate a land cover map of Ilam (Western Iran) using Sentinel-2A data at 10 m spatial resolution using the best suited classification algorithm. For this purpose, the supervised classification of Sentinel-2A image was performed by seven pixel-based algorithms (Maximum Likelihood, Minimum Distance, Spectral Angle Mapper, Spectral Correlation Mapper, Mahalanobis Distance, Neural Network and Support Vector Machine). For accuracy assessment of the land cover maps, the stratified random points were created and controlled in the field. After checking out the current land cover of each point in a plot area at the field, the real land cover of each one was compared with the defined land cover of the same point based on classification maps. Finally, the accuracy of the algorithms was evaluated by accuracy indices. The results showed that Support Vector Machine algorithm had the highest accuracy in classification of Sentinel-2A image with overall accuracy 79% and Kappa Index 0.70. This algorithm usually shows a good efficiency for land cover mapping in the heterogeneous regions like the study area. The analysis of the land cover map obtained from this algorithm showed that the dense, semi-dense and sparse forests have covered 319.64 ha, 361.44 ha and 1832.36 ha of the study area, respectively. The human-made land covers such as agriculture and understory agriculture have widely extended in the study area and have covered 658.42 and 4504.64 ha, respectively. The results of this study could be used as a baseline for managers to monitor land cover changes in the region. For the optimum management of the study area, land cover mapping using SVM algorithm in the certain temporal intervals is recommended to discover the forests change and to control the agriculture development.

Key words: Ilam, Land cover map, Pixel-based algorithms, Sentinel-2A satellite image

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1. Introduction

The broad-leaved forest (mainly oak forests) located in the Zagros Mountain in the west of Iran, named "Zagros forest", with an area about 6.07 million hectares is a millenary forest created more than 5500 years ago (Forests, Rangelands and Watershed Organization of Iran, 2016). Previous reports stated that Zagros forests in the Western Iran are the oldest oak forests in the world (Soheili and Naji, 2017). So, these forests in Iran are natural treasures not only because their high plant and animal biodiversity, but also because the cultural heritage they represent. Plant and animal biodiversity in these forests and rangelands are unique in Western Iran, which makes it one of the most important biodiversity hotspots for threatened mammal species are located in the west of Iran (Farashi et al., 2017). Furthermore, Zagros forests and rangelands have many environmental values, as trees, shrubs and rangelands in this ecosystem have a fundamental role in water and soil conservation (Fattahi, 1994). These ecosystems have many economic and touristic values as well, since many plants in Zagros area have medicine applications (Da-Cheng et al., 2013) and the beautiful views in the mountainous ecosystem have turned this area into a tourist attraction. Therefore, ensuring the conservation of the Zagros forests and rangelands is decisive to maintain the current state and value of this natural area.

In the recent years, these forests and rangelands, especially in Ilam province-Western Iran, have been damaged by climate change, drought events (especially in oak forests), fire occurrence and human interferences, such as the living dependence of the residents, provision of the fuel wood, grazing and, agricultural development (Fattahi, 2001; Khalili et al., 2018; Sadeghi et al., 2017). At present, the productive potential of these ecosystems has been lost because of mentioned reasons and lack of comprehensive management plan for these forests (Derikvandi et al., 2009). Management and planning in these forests has been associated with many problems which lack of the required information has strengthened this issue (Mahdavi and Fallah Shamsi, 2012). Therefore, knowledge of qualitative and quantitative changes in these forests and rangelands is necessary to manage these ecosystems and to solve the current problems (Amini et al., 2008).

The extraction of temporal and spatial information from current situation of Zagros forests will be very useful for conservation planning and management. In this case, the land cover mapping can provide the valuable information in these ecosystems. The digital satellite imagery as the spatial information sources have many advantages to other conventional sources including the wide coverage, reduction of the field works and costs and provision of the updated data (Mahdavi and Fallah Shamsi, 2012).

So far, the various satellite images have widely applied for land use/land cover mapping in different areas of the world (Cakir et al., 2008; Chauhan and Nayak, 2005; Erbek et al., 2004; Melesse and Jordan, 2003; Rakesh Kumar et al., 2014; Stefanov et al., 2001). In addition, different algorithms have been developed for satellite image classification to provide land use or vegetation cover map on a global scale (Hansen et al., 2000; Hansen et al., 2013).

About Western Iran, some studies have performed for land cover mapping using different satellite images and various algorithms (Arkhi et al., 2014; Eskandari and Moradi, 2012, 2020; Fathizad et al., 2015; Mahdavi et al., 2017; Mahdavi and Fallah Shamsi, 2012; Mirzayizadeh et al., 2015; Niazi et al., 2011). Despite of these studies performed in the Western country, the land cover mapping in 10 m spatial resolution and novel pixel-based algorithms have not been performed in these forests and natural ecosystems; While Sentinel-2 satellite images have successfully been applied for different purposes and mapping around the world in the recent years. Sentinel-2 data has been very useful satellite image for land use/land cover mapping in different areas around the world (Mustafa et al., 2018; Phan et al., 2017; Topaloglu et al., 2016), achieving superior results for this purpose by applying the Support Vector Machine algorithm (Mustafa et al., 2018; Topaloglu et al., 2016). Regarding crop type mapping at different sites and various scales, Sentinel-2 has also been proven successful by using a Random Forest classifier (Immitzer et al., 2016; Inglada et al., 2015). In case of forest monitoring and management, Sentinel-2 image has successfully been applied for tree species mapping (Immitzer et al., 2016), vegetation mapping (Jedrych et al., 2017), forest type mapping (Puletti et al., 2017), forest succession (Szostak et al., 2018), and estimation of defoliation of needle-leave stands (Hawrylo et al., 2018). Results of these studies have shown that Support Vector Machine algorithm led to high accuracies for vegetation mapping and forest monitoring (Hawrylo et al., 2018; Jedrych et al., 2017) and also Random Forest classifier for tree species discrimination (Immitzer et al., 2016).

The results of the mentioned studies have confirmed that Sentinel-2 data have the high efficiency for land cover and forest mapping in natural areas especially in forest ecosystems. Therefore, despite of extensive destruction of Ilam forests and rangelands in the recent years, a comprehensive research is necessary for land cover mapping in these forests using moderate resolution (10 m) satellite image such as Sentinel-2A. Furthermore, selection of the best pixel-based algorithm for forest classification will be very useful for management of these sensitive ecosystems.

This study is the first application of Sentinel-2A data for land cover mapping in Zagros sensitive forests of Iran which is aimed to determine the current natural and human land covers by the most accurate pixel-based method in 10 m spatial resolution. Although some studies have been done for land cover mapping by Sentinel-2 data around the world, efficiency and ability of these data for land cover mapping in the sensitive ecosystems of Iran has not been performed before this study. The results of this study will be so valuable because land cover mapping by the best algorithm in 10 m resolution in a part of Zagros forests (Ilam province) can be used as a baseline to manage the natural and human land covers and to monitor the land cover changes in Ilam for the future.

2. Material and methods

2.1. Data

Sentinel-2A is a wide-swath, high-resolution, multi-spectral imaging mission developed by ESA (European Space Agency) as part of the Copernicus Programme, supporting the Copernicus Land Monitoring such as land cover, soil characteristics, water bodies and coastal areas (ESA, 2015). Sentinel-2A has 13 spectral bands with the spatial resolution from 10 to 60 meters (Table 1).

For this research, Sentinel-2A Level-1C image for study area (July 28, 2017) was downloaded from ESA website https://scihub.copernicus.eu (ESA, 2015).

The maps of Ilam province and Zagros site in this province was provided from Forest, Rangeland and Watershed Organization of Iran. In addition, 1:25000 sheets map was prepared from National Mapping Organization of Iran to select the study area. Then the sheets covered the Zagros site in Ilam province were separated (Fig. 1).

2.2. Study area

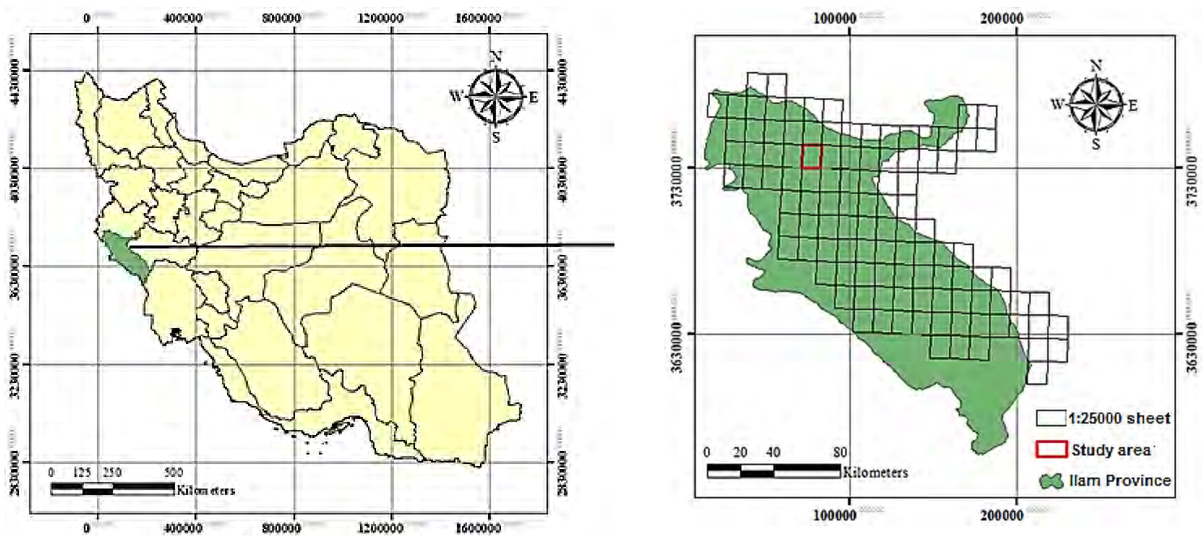
The study area was included one sheet which was a part of forest area in Ilam province (Fig. 1). This sheet was selected to test the accuracy of pixel-based supervised classifications of Sentinel-2A image for land cover mapping, which was included all the predictable land covers (dense forest, semi-dense forest, sparse forest, rangeland, garden, agriculture, understory agriculture, bare soil and rock) (Fig. 2). To select this sheet and to check all the land covers, 1:25000 sheets map was imported to Google Earth Pro.7 and land covers of all the sheets were investigated. Then, existence of all land covers inside each sheet was considered and the proper sheet which was included all the land covers was selected as the study area. Then, Sentinel-2A satellite image of this sheet with an area about 16000 ha was separated in GIS (Fig. 3). This sheet (study area) has been located between 627439 to 639055 East longitude and 3735317 to 3721467 North latitude at Zone 38 (Northern hemisphere) of UTM WGS 1984 coordinate system.

2.3. Research method

The type of Sentinel-2A satellite image used in this study was Level-1C which geometric and radiometric corrections have been performed on the image (ESA, 2015). Therefore, after selecting the proper sheet as the study area, just minor corrections were performed on Sentinel-2A image to reveal the more contrast among different land covers. Then, a layer stack of the bands 2, 3, 4 (blue, green, red) and 8 (NIR) with 10 m spatial resolution was performed to get a color satellite image of the study area (Fig. 3).

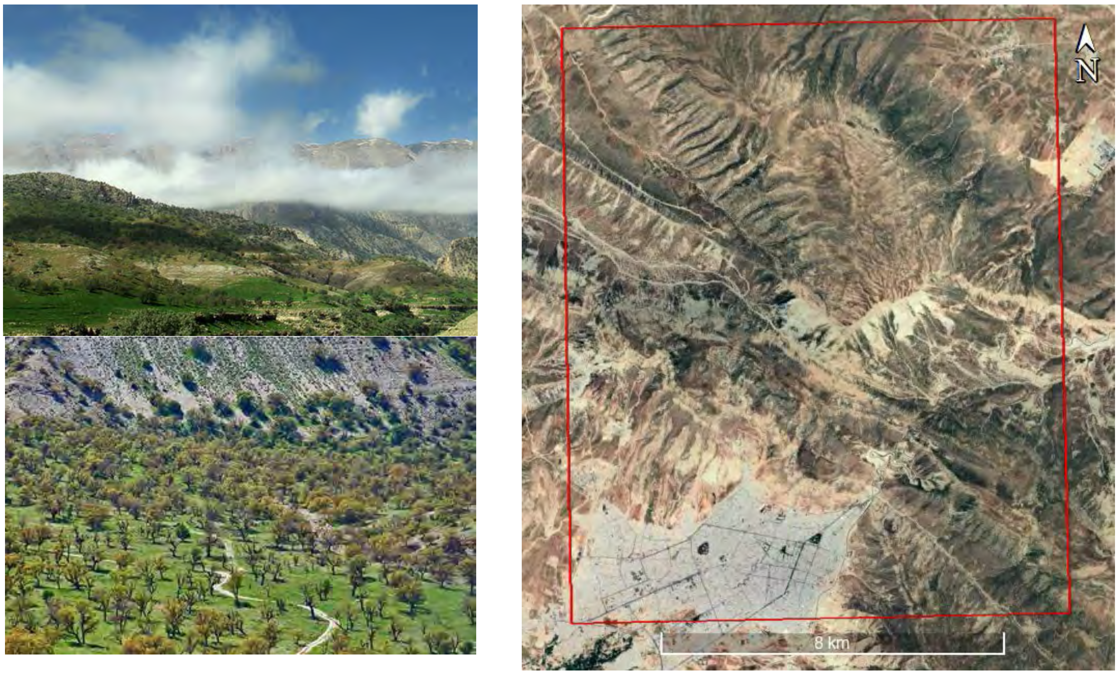
Table 1. The spectral bands of Sentinel-2A satellite image

Band Number	*Band Name*	*Wavelength Mean (nm)*	*Spatial Resolution (m)*
B01	Coastal aerosol	443	60
B02	Blue	490	10
B03	Green	560	10
B04	Red	665	10
B05	Vegetation Red Edge	705	20
B06	Vegetation Red Edge	740	20
B07	Vegetation Red Edge	783	20
B08	NIR	842	10
B08a	Narrow NIR	865	20
B09	Water Vapor	945	60
B10	SWIR– Cirus	1375	60
B11	SWIR	1610	20
B12	SWIR	2190	20



(a) (b)

Fig. 1. Location of the study area in Iran (a) and in Ilam province (b)



(a) (b)

Fig. 2. Landscape of the study area in the nature (a), and in Google Earth (b)

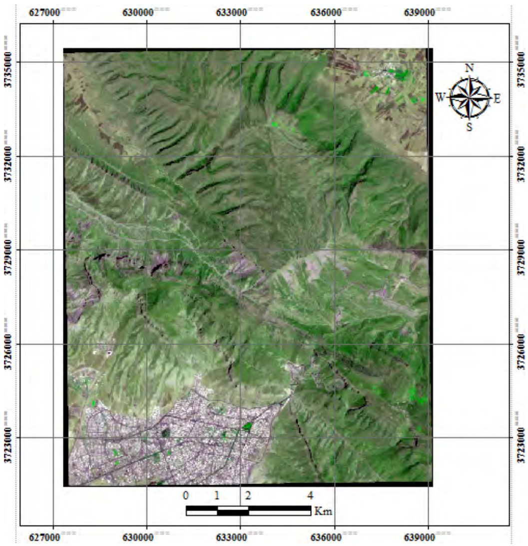


Fig. 3. Sentinel-2A satellite image of the study area (Layer stack of the bands 2, 3, 4 and 8)

2.3.1. Supervised classification of Sentinel-2A image

In this study, after pre-processing of Sentinel-2A image, the pixel-based supervised classification of the image was performed by seven pixel-based algorithms in Envi 5.3: Maximum Likelihood (ML), Minimum Distance (MD), Mahalanobis Distance (MaD), Spectral Angle Mapper (SAM), Spectral Correlation Mapper (SCM), Neural Network (NN) and Support Vector Machine (SVM). These algorithms were selected due to their qualities to adapt to the heterogeneous structure of study area, the spatial resolution of satellite image (10 m) and their ability to perform land cover classification. Although the Random Forest algorithm has also shown a good efficiency in tree species mapping in some studies (Immitzer et al., 2016), but it was not applied in this study; because the main purpose of current study was to find out the most accurate pixel-based algorithm which is available in Envi 5.3 software. Furthermore, the object-based classifications were not applied in this study, because the shape of different land covers didn't follow a systematic geometric format (except agricultural lands); while object-based classifications usually use for small urban areas with geometric land covers where the high resolution imagery is available for a limited area. Considering the wide extent of the study area (16000 ha), inaccessibility to high resolution imagery, non-geometric land covers and natural inherent of the study area, we just used the pixel-based algorithms in this study.

For pixel based classifications, ten areas of interest (AOI) as pixel-based training areas were selected for each class of land cover (dense forest, semi-dense forest, sparse forest, rangeland, garden, agriculture, understory agriculture, rock and bare soil). Then, pixel-based supervised classifications were implemented on Sentinel-2A image in Envi 5.3 software. After image classification by different algorithms, "Clump" and "Eliminate" commands were implemented on each classified land cover map in order to remove all the small pixels inside the big land covers. Then, the final land cover maps were constructed. The applied algorithms are described below.

2.3.1.1. Maximum Likelihood (ML)

The most common supervised classification algorithm used in applications of remote sensing is the Maximum Likelihood, which is a parametric statistical method (Lillesand et al., 2004; SEOS, 2018). It computes a probability density function taking into account the spectral distribution of the data to determine the probability of a pixel belonging to a specific class (SEOS, 2018). This method assigns all unclassified pixels to the class of highest probability (Lillesand et al., 2004; Mustapha et al., 2010).

2.3.1.2. Minimum Distance (MD)

In Minimum Distance algorithm, pixels are usually classified to the closest category. The minimum distance classifier, computes the Euclidean Distance (ED) between the pixel values (xp,yp) and the mean values for the classes, and then allocates the pixel to that class with the shortest Euclidean distance (Chuvieco, 2016; SEOS, 2018).

2.3.1.3. Mahalanobis Distance (MaD)

The Mahalanobis distance algorithm performs the classification of the pixels very similar to Maximum Likelihood algorithm, but it considers that all class co-variances are equal, and therefore, it is a faster method. So the advantage of the Mahalanobis classifier over the maximum likelihood procedure is that it is faster and yet retains a degree of direction sensitivity via the covariance matrix C; which could be a class average or a pooled covariance. All pixels are classified to the closest Region Of Interest (ROI) class unless a distance threshold is specified, in which case some pixels may be unclassified if they do not meet the criteria (Park, 2008).

2.3.1.4. Spectral Angle Mapper (SAM)

The Spectral Angle Mapper (SAM) algorithm is based on an ideal assumption that a single pixel of remote sensing images represents one certain ground cover material, and can be uniquely assigned to only one ground cover class. The SAM algorithm is a simply based on the measurement of the spectral similarity between two spectra (Rashmi et al. 2014). The SAM is a spectral algorithm for classifying the pixels which considers the spectral similarity between image and reference data via calculation of angle between spectral characteristics. Then it trains the pixels in space dimension (Kruse et al 1993; Hunter and Power, 2002).

2.3.1.5. Spectral Correlation Mapper (SCM)

The Spectral Correlation Mapper (SCM) method is a derivative of Pearsonian Correlation Coefficient that eliminates negative correlation and maintains the SAM characteristic of minimizing the shading effect resulting in better results. The SCM varies from –1 to 1 and cos (SAM) varies from 0 to 1. The SCM algorithm method, similar to SAM, uses the reference spectrum defined by the investigator, in accordance with the image to classify (Carvalho and Meneses, 2000).

2.3.1.6. Neural Network (NN)

The most popular Neural Network classifier in remote sensing is the multilayer perceptron. Feed forward or Multilayer Perceptrons (MLP) may have one or more hidden layers of neurons between the input and output layers (Mustapha et al., 2010). They have a simple layer structure in which successive layers of neuron are fully interconnected, with connection weights controlling the strength of the connections. The input to each neuron in the next layer is the sum of all its incoming connection weights multiplied by their connecting input neural activation value (Tedesco et al., 2004; Mustapha et al., 2010). This method is independent of statistical parameters of a particular class and accepts qualitative and quantitative data to be introduced as input data.

2.3.1.7. Support Vector Machine (SVM)

Support Vector Machines (SVM) algorithms are the non-linear binary classifiers and aim to find a threshold which divides the dataset to the predefined classes using training samples (Huang et al., 2002). The optimal separation is applied to minimize misclassifications, which usually occur in the training step (Hawryło et al., 2018, Mountrakis et al., 2011;). Considering the principles of structural risk minimization (Vapnik, 1995; Vapnik and Vapnik, 1998), SVMs aim at minimizing the upper bound of the expected generalization error through maximizing the margin between the separating hyperplane and the data. The concept of margin plays a key role in SVM algorithm as it indicates the generalization capability of SVMs (Burges, 1998; Huang et al., 2010). The main advantage of SVMs is the ability to transform the model to solve a nonlinear classification problem without any prior knowledge (Mustafa et al., 2018).

2.3.2. Accuracy assessment of pixel-based algorithms for land cover mapping

The accuracy of the land cover maps was assessed by field work. First, a set of random points was created in the software and then, "Accuracy Assessment" command was used to evaluate the accuracy of the classified land cover maps in this research. For this purpose, 100 stratified random points were created (Fig. 4). The stratified random distribution (Stratification method) was used to assign a sufficient number of points to each class of land cover (Zobeiri, 2008). In this method, the number of points assigned to each class is based on the area of that class and the points are randomly distributed in each class. Based on the previous studies, the stratification method has shown more accuracy than other methods for forest inventory to estimate the forest area in Zagros forests (Fallah et al., 2012). A stratified random sampling has also been recommended in other studies for reference data collection, because the reference data should cover the full range of the study area and all the land covers (Karlson et al., 2015). Therefore, this method was applied in this research for reference data collection.

Finally, all the random points with certain geographical coordinate were imported to Arc map 10.4. In the field work, these points were found by GPS (Garmin GPSMAP 64 Sc) and their current land covers were determined at the pixel area (10*10 m). It means that the current cover of each random point was checked in a square area with dimension of 10*10 meter which was accordant to pixel size (10*10 m) in Sentinel-2A satellite image (Fig. 5).

Later, the field land cover class and the classified land cover class were compared to assess the accuracy of the pixel-based classification algorithms. The accuracy metrics were included the Overall Accuracy (*OA*) and the Kappa Index (*k*) (Congalton and Green, 2008, Fleiss et al., 1969). Overall Accuracy is calculated as Eq. (1):

$$OA = \frac{\sum_{i=1}^{j} n_{ii}}{n} \tag{1}$$

Kappa Index (*k*) is obtained from Eq. (2) (Cohen, 1960, Fleiss et al., 1969; Jenness and Wynne, 2007):

$$k = \frac{n\sum_{i=1}^{j} n_{ii} - \sum_{i=1}^{j} n_{i+}n_{+i}}{n^2 - \sum_{i=1}^{j} n_{i+}n_{+i}} \tag{2}$$

n: number of the reference pixels (real pixels) in error matrix
n_{ii}: sum of the pixels in the main diamond (correct classification) in error matrix
n_{i+}: number of pixels in row i of error matrix
n_{+i}: number of pixels in column i of error matrix
j: number of classes

The value of Kappa Index (*k*) ranges from 0 to 1, where 0 means no agreement between reference data and classified data and 1 means full agreement between the reference data and classified data (Cohen, 1960; Yang et al., 2019).

3. Results

3.1. The land cover maps by pixel-based algorithms

The land cover maps of the study area obtained from supervised classification of Sentinel-2A image by different pixel-based algorithms have been shown in Fig. 6. Furthermore, the areas of different land covers in the land cover maps by different algorithms have been shown in Table 2.

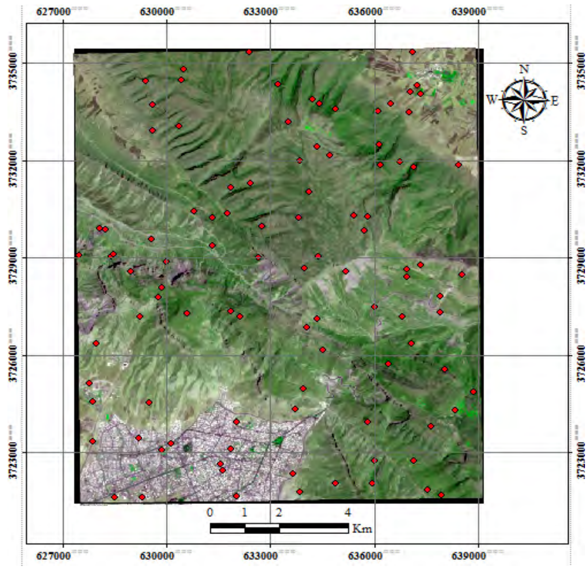


Fig. 4. The random points for accuracy assessment of classification algorithms

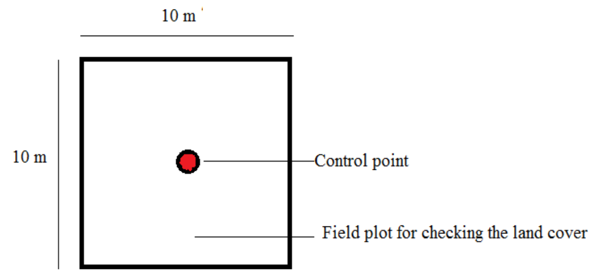


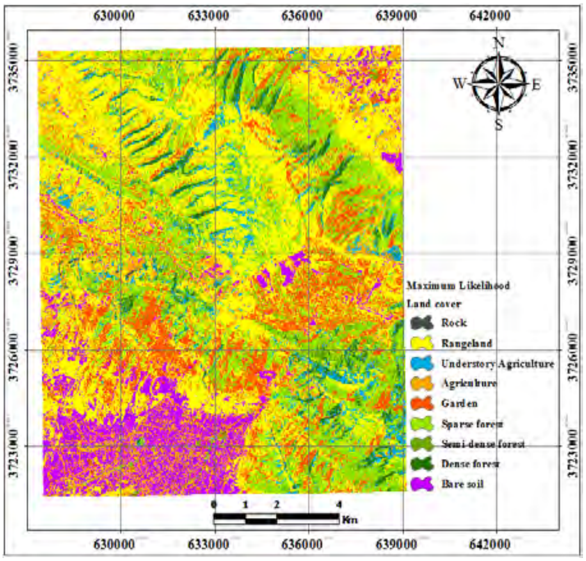
Fig. 5. The control point and the field plot for checking the land cover

3.2. Accuracy assessment of pixel-based algorithms for land cover mapping

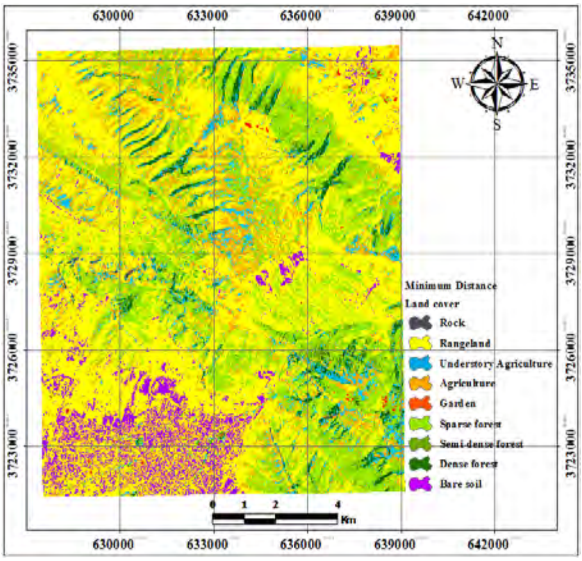
The accuracy assessment of pixel-based algorithms by Overall Accuracy and Kappa Index has been shown in Table 3. The ground truth validation and Kappa Index for each land cover classes based on SVM algorithm has also been shown in table 4.

4. Discussions

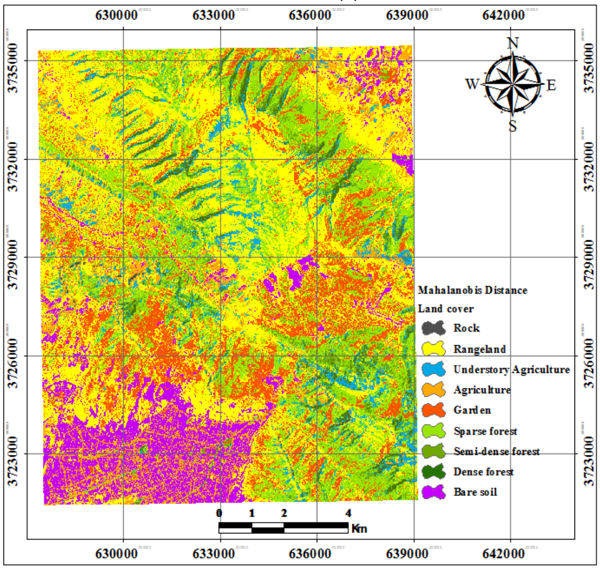
The land cover map is one of the most important information for natural resources management especially in the sensitive ecosystems (Niazi et al., 2011). Regarding to extensive destruction of Ilam sensitive forests in the recent years, this research was performed for land cover mapping in a part of these forests using Sentinel-2A satellite image in 10 m spatial resolution. Furthermore, another purpose of this study was to compare the accuracy of pixel-based algorithms to provide the land cover map using the most accurate method in whole of Ilam province. Therefore, a main objective of this study was to generate a land cover map with the highest spatial resolution available using free data as there was no previous knowledge of land cover distribution in the study area.


Maximum Likelihood
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

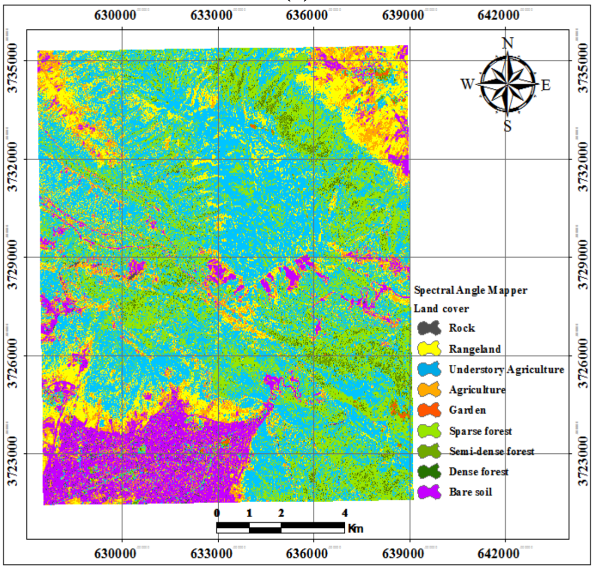
(a)


Minimum Distance
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

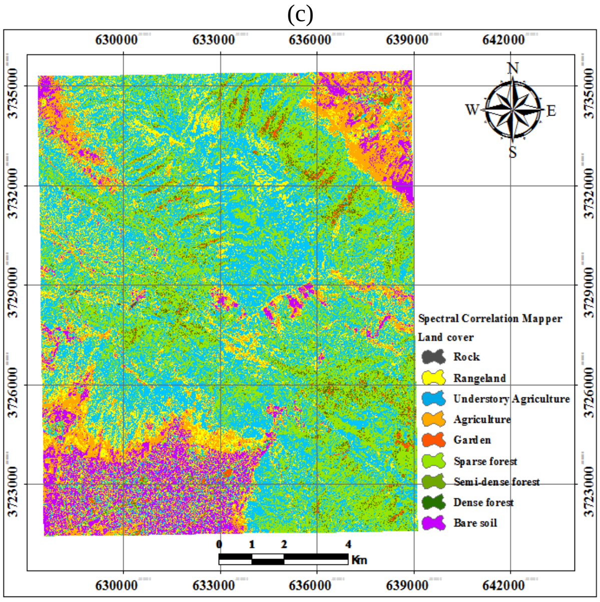
(b)


Mahalanobis Distance
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

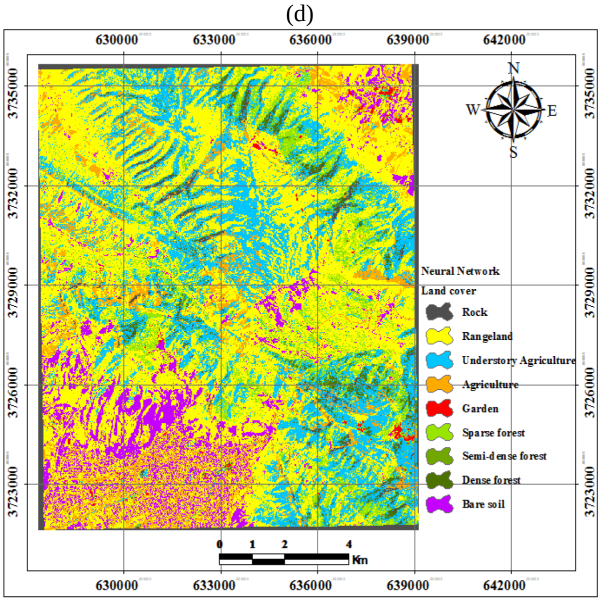
(c)


Spectral Angle Mapper
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

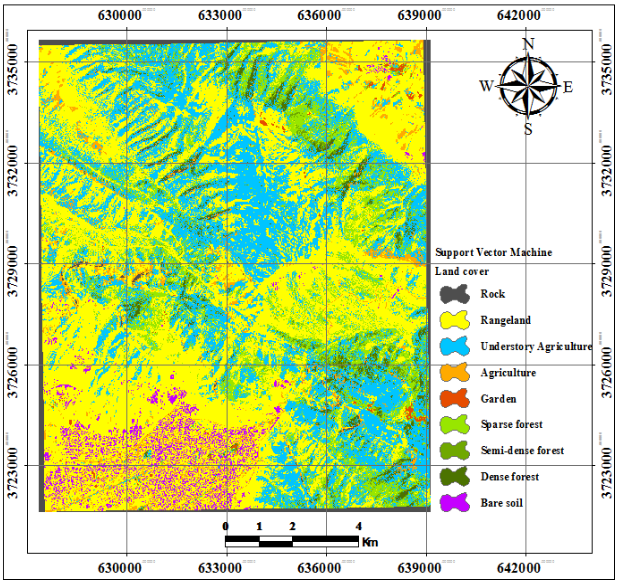
(d)


Spectral Correlation Mapper
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

(e)


Neural Network
Land cover
Rock
Rangeland
Understory Agriculture
Agriculture
Garden
Sparse forest
Semi-dense forest
Dense forest
Bare soil

(f)



(g)

Fig. 6. The supervised classification of Sentinel-2A image by pixel-based algorithms: (a) Maximum Likelihood, (b) Minimum Distance, (c) Mahalanobis Distance, (d) Spectral Angle Mapper, (e) Spectral Correlation Mapper, (f) Neural Network, (g) Support Vector Machine

Table 2. The areas of different land covers in the land cover maps by pixel-based algorithms

	Pixel-based algorithm						
Area of land cover (ha)	***Maximum likelihood***	***Minimum distance***	***Mahalanobis distance***	***Spectral angle mapper***	***Spectral correlation mapper***	***Support vector machine***	***Neural Network***
Dense forest	361/13	387/32	331/18	294/05	373/38	319/64	376/58
Semi-dense forest	529/45	438/47	588/95	237/15	31/8	361/44	77/08
Sparse forest	3579/81	3836/83	3446/68	3693/71	4486/09	1832/36	1275/88
Rangeland	5788/1	7658/12	5539/45	2152/42	2137/99	7352/78	7211/36
Garden	2359/35	30/41	2638/33	34/35	188/48	62/32	82/62
Agriculture	1185/31	2084/09	1198/67	1528/91	1897/02	658/42	1415/25
Understory Agriculture	749/86	714/24	748/08	6401/71	5754/98	4504/64	3514/77
Rock	13/93	23/67	13/72	88/67	4/42	517/59	649/21
Bare soil	1518/37	912/16	1580/25	1654/34	1208/99	473/96	1480/4
Total	16085/31	16085/31	16085/31	16085/31	16085/31	16085/31	16085/31

Table 3. The accuracy assessment of pixel-based algorithms

	Accuracy assessment index	
Pixel-based algorithm	***OA (%)***	***k***
Maximum Likelihood	71	0.62
Minimum Distance	65	0.49
Mahalanobis Distance	70	0.61
Spectral Angle Mapper	38	0.27
Spectral Correlation Mapper	41	0.29
Support Vector Machine	79	0.70
Neural Network	62	0.45

Table 4. Ground truth validation and Kappa Index of different classes based on SVM algorithm

Land cover	***Area of land cover based SVM (ha)***	***Number of ground plots (reference data)***	***Number of correct classified plots***	***k***
Dense forest	319/64	2	2	1.000
Semi-dense forest	361/44	3	2	0.831
Sparse forest	1832/36	11	9	0.801
Rangeland	7352/78	42	36	0.612
Garden	62/32	1	1	1.000

Agriculture	658/42	4	2	0.412
Understory Agriculture	4504/64	28	21	0.513
Rock	517/59	4	2	0.411
Bare soil	473/96	5	4	0.801
Total	16085/31	100	79	0.70

We used the 10 m spatial resolution bands of Sentinel-2A sensor. That choice implied the analysis was limited to 4 bands covering visible and NIR spectral regions. Therefore, the spectral dimensions introduced to the classification algorithms were reduced in comparison with other studies using Landsat data for instance (Cakir et al., 2008; Yousefi et al., 2014; Heydarian et al., 2014; Rakesh Kumar et al., 2014; Topaloglu et al., 2016). This limitation may be affecting the performance of some of the classification algorithms applied which are completely based on spectral characteristics, such as Spectral Angle Mapper and Spectral Correlation Mapper. In this regard, the SVM proved superior to the other methods since it showed higher accuracies despite that limitation.

Based on the results of this study, this algorithm with Overall Accuracy 79% and Kappa Index 0.70 (Cohen, 1960, Fleiss et al., 1969), had the most accuracy in image classification and land cover mapping in Ilam province (Table 3). Results of some other studies performed in heterogeneous areas of Iran (Davoudi Monazam et al., 2014; Mirzayizadeh et al., 2015; Yousefi et al., 2014) and around the world (Mustafa et al., 2018; Pal, 2005; Hawrylo et al., 2018; Jedrych et al., 2017; Topaloglu et al., 2016) also showed the highest precision of SVM method in land cover mapping in natural ecosystems. This algorithm has high efficiency in image classification especially in heterogeneous areas. Fig. 2b shows the heterogeneity in the nature of study area, very well. This Figure shows that the land covers are completely mixed in the study area. It has been proved that Support Vector Machine algorithm has presented a good accuracy in land cover mapping in the heterogeneous areas of Iran (Davoudi Monazam et al., 2014; Mirzayizadeh et al., 2015; Yousefi et al., 2014) with very mixed land covers just like the study area. On the other hand, a main challenge in the current study was no previous knowledge of the land covers in study area in format of a digital map. The only available data for the study area were the field data and the high-resolution imagery of Google Earth Pro (available for 2017).

They were very valuable data for assessing the accuracy of land cover maps produced in current study. Accuracy assessment of land cover map by these reliable data proved the superior precision of SVM algorithm for land cover mapping of the study area in this research. The most important advantage of SVM algorithm is that it applies an optimal separation of pixel clusters to minimize misclassifications usually occurring in the training phase (Hawryło et al., 2018; Mountrakis et al., 2011). As the study area has vey heterogeneous structure (Fig. 2b), SVM has shown a high accuracy in land cover mapping in the study area.

For accuracy assessment of land cover maps in this study, Kappa Index was used (Cohen, 1960). Kappa Index is a useful quantitative index to discover the agreement or disagreement degree between two observations of the same class (land cover) (Cohen, 1960). Comparison of Cohen Kappa (Cohen, 1960; Fleiss et al., 1969) for each class (land cover) is a standard method to compare the classification accuracy of different land covers which has frequently been applied in the previous studies (Yang et al., 2019) and it was used in this study, as well. The results of Kappa Index (Cohen, 1960) for each land cover class based on SVM method (Table 4) showed that this algorithm has classified the dense forests (Kappa Index: 1) more accurate than the semi-dense forest (Kappa Index: 0.83) and the sparse forest (Kappa Index: 0.81).

In addition, garden with the highest Kappa Index (Kappa Index: 1) has been classified very well. A main problem of using optimal imagery in areas with an open tree canopy cover is that the soil contributes to the spectral signal and therefore renders the relationship between the tree cover and the remote sensing data less predictable (Franklin and Strahler, 1998; Karlson et al., 2015). When dense vegetation cover (close crown cover) is classified on the image, there is no effect of soil contributes on vegetation reflectance; while soil contributes in the background of image affects vegetation reflectance in the sparse vegetation cover with an open crown cover (Karlson et al., 2015). So the classification of the dense vegetation will be more accurate than the sparse vegetation (open crown cover). For reducing the effect of soil contributes on vegetation reflectance in image classification, the use of vegetation index such as NDVI-SAVI is recommended for vegetation mapping in the future studies.

About other land covers, the bare soils (areas with no vegetation cover) have classified well with Kappa Index 0.80. Rangelands have not classified very accurate (Kappa Index: 0.61); because a wide extent of the study area has been covered by sparse rangelands where the soil contributes in the background affects the grassland reflectance in the classification procedure. Agriculture (Kappa Index: 0.412), understory agriculture (Kappa Index: 0.513), and rock (Kappa Index: 0.411) have been classified with the lowest accuracy based on SVM algorithm.

After SVM, Maximum Likelihood with overall accuracy 0.71 and Kappa Index 0.62 had the most accuracy in land cover mapping in Ilam province. Borzafkan et al. (2015), Erbek et al. (2004), Heydarian et al. (2014), Mahdavi and Fallah Shamsi (2012), Mustapha et al. (2010) and Stefanov et al. (2001) also showed that Maximum Likelihood method had the most precision to detect the forest area which is accordant with the results of current study.

The analysis of the land cover map obtained from SVM algorithm showed that from the total area of the study area (16085.31 ha), the dense forest has covered 319/64 ha, the semi-dense forest has covered 361/44 ha, and the sparse forest has covered 1832/36 ha of the study area. In addition, areas of rangelands and gardens have been 7352/78 ha and 62/32 ha, respectively. Agriculture has covered 658/42 ha and understory agriculture has covered 4504/64 ha of the study area. Furthermore, 517/59 ha of the study area has been covered by rock and 473/96 ha by bare soil (Fig. 6g and Table 2). Based on these results, human-made land covers occupy a large area of the study area. Agriculture (farmlands and understory agriculture) covers more than 5000 ha of the study area which is a serious threat for the forests of study area. Results of some studies have proven that the pressure of human on natural ecosystems will cause some environmental dynamics (Petrişor et al., 2010). Based on previous studies, the human-made land uses such as agricultural lands have improperly developed in the forests of western Iran (Eskandari and Moradi, 2020).

Therefore, a proper management of the Zagros forests in Ilam province is essential regarding to the increasing area from dense forests to sparse forests in the study area. The land cover map provided in this research can be used as the basic data to manage these forests. For management of the remained forests, a protective plan should be performed. The dense forests (319/64 ha) are very important in terms of fauna and flora biodiversity. Thus, they should be protected as a habitat for endemic fauna and flora in Zagros Mountains. The semi-dense forests (361/44 ha) also should be managed by proper environmental plans for water and soil conservation. The sparse forests (1832/36 ha) are the most sensitive ecosystems in the study area. If they won't be protected, they may be converted to agricultural lands or bare soils in the near feature.

The results of some studies have shown that forest area is decreasing in Iran (Jadidi et al., 2019). Therefore, these forests should be rescued by plantation and forestation. Finally, it is suggested that the land cover mapping to be continued in the study area in the certain interval time series using Sentinel-2A data and SVM method. The periodic land cover maps facilitate the change detection in the land covers during the time and accelerate the management of the forests for the future. Remote sensing and geographic information system can significantly help to predict the future land covers and identify the future threats in the study area in the spatial and temporal scale (Nath et al., 2020).

5. Conclusions

This research was performed to compare the pixel-based classification algorithms to produce an accurate land cover map in a part of Ilam province using Sentinel-2A data. The results of this study showed that Support Vector Machine algorithm had the highest accuracy for land cover classification in the study area. The SVM algorithm adapted better to the limited input spectral information, the land cover classes and the within class variability than other commonly used method such as Neural Networks classifier. SVM algorithm usually shows a good efficiency for land cover mapping in the heterogeneous regions such as study area. The analysis of the land cover map obtained from this algorithm showed that human-made land covers such as agriculture and understory agriculture have covered a wider area of Ilam than the forested area. Continuous and consistent land cover mapping of the study area using Sentinel-2A data will offer the managers and policy makers the information they need to protect the natural resources of Ilam. For the optimum management of the study area, land cover mapping using SVM algorithm in the certain temporal intervals is recommended to discover the forests change and to control the agriculture development.

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