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LAND-USE/LAND COVER CLASSIFICATION ANALYSIS USING PIXEL BASED METHODS: CASE OF TAROM CITY, IRAN

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A B S T R A C T

This research inspects the convenience of Landsat-8 imagery in generating Land-use Land Cover (LULC) maps based on RGB and NIR bands dates back to August 8th, 2017, and at the same time to reveal which type of LULC in Tarom basin can be utilized with maximum accuracy considering the comparison of results with ground samples. Besides necessary preprocessing, land-use classification was done after atmospheric corrections (via FLAASH Algorithm). LULC maps were generated using three pixel-based supervised classification methods, Maximum Likelihood (ML), Support Vector Machine (SVM), and Artificial Neural Networks (ANNs). Results proved that imagery precision based on Kappa statistics and overall accuracy for ML classification method were 0.88 and 91.55, respectively. The acquired outcome indicated that Landsat-8 OLI data, present satisfying LULC classification in the waterbody, mountain and rock, bare land, vegetation, and forest classes. In addition, as the results indicated, it can be stated that all three methods of classification in a region of considerable heterogeneity in terms of elevation (between 280-3000 m), land-use and vegetation such as Tarom, can have significant results. In comparison with the other two methods, classification with the ML method had higher speed and lower complexity for execution in achieving the required maps.

1. INTRODUCTION

A modern country must have sufficient information on a multitude of interrelated complex aspects of its activities in order to make decisions. A modern country to have an advanced management system should have proper detailed data on different aspects of socio-economic activities. One of these cited aspects is known as land-use and land cover (LULC), which has become important in recent years. These two mentioned terms are often used interchangeably, but it should be noted that each of them has a unique definition and meaning. Land-use refers to human methods and

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purposes in utilizing land with different usages and resources. Among which agriculture, wildlife, and recreation can be outlined. Also, the observed biological, physical, or biophysical envelopment of the surface of the earth is called land cover (e.g., waterbody, vegetation, soil, and urban infrastructure. When these terms used together as LULC, it refers to the categorization of natural elements and human activities on the earth. Regarding this, it can be clearly understood that, on a daily basis, existing lands will undergo changes in the types of land-use and land covers.

In order to get over the issue of casual development, desertification, erosion, destruction of wildlife, and marshes, we need accurate data of the pattern of LULC in the study area. LULC is interdependent, so when people start to use lands for human activities, the cover of those lands changes and this process influences its properties (De Sherbinin, 2002). In addition, as Young (1998) believes, the identical section of land can just be used for one objective at a time; so this limitation leads to competition among diverse activities which depends on the availability of lands. One of the important data for controlling the development of the region and land-use dependent activities is the information on the pattern of the existing land-use.

Cultivable lands are becoming a scarce resource due to the increasing hustle of agriculture and population growth. Hence, possession of adequate data can lead to optimal use and management of the available resources to meet the essential needs.

With the help of satellite imagery, we can observe the earth from up above, and the effect of our activities on natural resources and use obtained data to assess the changes and utilize it for future management purposes. The multi-temporal high-resolution data and the remote sensing (RS) technology, has been broadly used to gather information on existing LULC and for mapping LULC over time. To create these maps, the RS data can be obtained from various types of satellites such as Landsat, Sentinel, and Spot series. Periodic, acquisition of free, fast, rapid, and accurate data is possible; for example, in the case of Landsat 8, it is every16 days (Topaloglu, *et al.*, 2016).

2. RS AND LULC MAPS

Satellite data can play an effective role in the development of LULC maps due to its specific characteristics, including the wide coverage, repeatability, diversity of LULC, and continuous uptime capabilities. As mentioned before, producing LULC maps has gained significance for land management, convenient planning of resources and climate-related researches in recent years (Turner, *et al.*, 2001, Mejía and Hochschild, 2012). Owning information about the changes in LULC over time, grant us precise data on sustainable resource management. (Mejía and Hochschild, 2012). Remote sensing tech is a robust instrument in order to have constant management of natural resources and land scout (Cetin, 2009; Van, *et al.*, 2017). Acquired satellite data are converted into a land-use map by the utilization of this technology. There are various kinds of the algorithm used in the abovementioned conversion process, which has become much more accurate in time and their technological advancements.

Landsat-8 OLI is a recently operational new generation earth observation satellite. Therefore, in the presented research, the OLI and TIRS sensors data (acquired from Landsat-8 satellite) were used as a data source. It should be mentioned that in addition to Landsat data, there are other satellite dataset resources such as Sentinel and Spot. Numerous studies have been made to determine which imagery has better and accurate results in generating the land-use maps (Jia, *et al.*, 2014; Liu, *et al.*, 2015; Elhag and Boteva, 2016; Pirotti, *et al*., 2016; Marangoz, *et al*., 2017).

Akar and Güngör (2012) used the Random Forest Algorithm (RFA) to evaluate the classified land-use maps from multispectral images. To assess the performance of RFA, the results are compared with the results obtained from other classification methods such as Maximum Likelihood Classification (MLC) and Support Vector Machine (SVM). Manandhar, *et al*., (2009), by using a post-classification enhancement on Landsat images, determined the accuracy of LULC maps. These researchers applied the MLC method to classify the Landsat imagery for 1985, 1995, and 2005 data. Their results showed that the MLC, as a widely used classifier, could not yield satisfactory results in Built-up areas.

Duarte, *et al*., (2016), made the comparison of three supervised classification methods (MLC, MD, and ANN) using Unmanned Air Vehicle (UAV) data in Viçosa-MG, Brazil.

They reported that the classification that best delimited the different features present in the image was the classification by Artificial Neural Networks. In order to prove the classification efficiency statistically, the validation was carried out through the Kappa index and visual analysis. Zomlot, *et al*., (2017), used trajectory analysis to improve LULC maps. They also tried to assess the impact of LULC changes on the amount of groundwater resupply in the Flanders region, Belgium.

Their results showed that the amount of groundwater recharge decreased by about 35% in this region due to urbanization. Sekertekin, *et al*., (2017), studied pixel-based classification analysis of LULC using two kinds of imagery (Sentinel-2 and Landsat-8) in Zonguldak area, Turkey. Their findings showed that the LULC images conducted by MSI sensor of Sentinel-2 data are more accurate than LULC images by OLI sensor of Landsat-8 in sea and waterbody classes.

Increase in the wastewater of the industrial regions in Tarom Basin, growth of the vegetated regions- which were previously in the form of bare land or grasslands in hillsides- and population growth have caused socio-economic damages to this region. Due to water transfer from the main river passing from the area Ghizil-Ozan through stable or mobile water pumps, a significant number of the abrupt regions and highlands in Tarom province, which were previously utilized as grasslands are severely affected and have been changed into gardens or have got agronomic uses. Typically, two types of trees (i.e., olive and pomegranate) in length with the cultivated species (i.e., garlic and celery) are planted in most parts of this region and are irrigated by Ghizil-Ozan River. However, since water transfer is done through illegal piping systems and pumps an exact amount of water withdrawal cannot be provided. In comparison with other fruit trees of the area, olive with extensive compatibility and 12600 ha has the most amount of area under cultivation. The results of the temperature compatibility model conducted in 10 hydrometric stations. In olive-growing areas, and a control station indicated that Tarom is one of the best areas for expansion of growing olive. For the reasons mentioned above, land-use change from grasslands and bare lands to the olive orchard are obvious in locations where water can be transferred from the river, and it has got an ascending trend. Thus, land-use maps should be created annually by means of satellite imageries. Planting fruit trees on bare land may increase the afforested area, and protect the land against flood or erosion but where, when, and how much abandonment and tree farming have occurred remains unclear. By using three pixel-based methods (MLC, ANN, and SVM), OLI sensor data have been transformed into the land-use map in the current study.

3. STUDY AREA

The study area, is Tarom basin (between 48˚ 19’ and 49˚ 24’ N latitudes and 48˚ 63’ and 49˚ 09’ E longitudes) which covers an area of about 5220 km^2 with the annual average precipitation and temp of 357 mm and 12.05 °C respectively alongside the altitude variation of 280 to 3000 m, conterminous with Zanjan province from the south and Ardebil province from the north Figure 1). The region is covered with a great number of vicissitudes and, due to the mountainous structure, most of the areas have thin soil cover. In addition, in districts where farming or planting is possible, numerous exploitations and land-use change have occurred. Also, due to propitious weather, cultivation of different types of olive in the height of 400-1200 m, and the cultivation of pomegranate or other species in low heights seems possible. Thus, the map projection of LULC appears to be beneficial in this region.

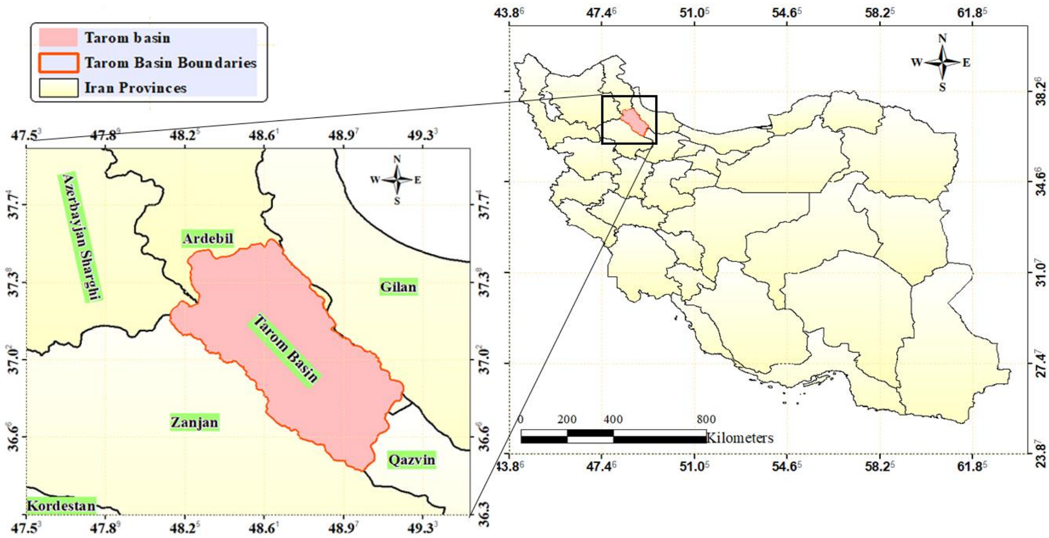

Figure 1: Study Area Tarom, Iran

It should be mentioned that Tarom province had experienced extreme changes in LULC over the past ten years, regarding the fact that it is one of the agriculturally strategic lands in the region. Evaluating the Ecologic Potential for Urban-Rural Development of Tarom's Basin showed that about 14.36 percent of the total area acquires grade one appropriate potential, and approximately 10.12 percent acquires the grade two potential appropriate for urban-rural development (Badroghnezhad, *et al*., 2017). Various important factors such as propitious environmental conditions, accessibility of water-which are derived from Ghizil-Ozan river- and presence of lands wherein cultivation seems possible (due to land-use change) has made this province a proper case study for assessing the changes in LULC and compare these changes over the selected time period. Besides these factors, environmental sensitivity, increasing number of cultivated areas, loss of grasslands and converting grasslands into olive, pomegranate or in some cases quince or apple orchards are among the reasons behind choosing this province for detecting land-use changes. On the other hand, Tarom is one of the propitious regions in cultivating different types of vegetation (e.g., garlic, celery, and potato) which due to the climate are typically under cultivation during the year.

3.1 DATA

In this study, the_Landsat-8 OLI data, (pass 166 and row 34 and 35), acquired on August 8th, 2017 and were taken from the USGS website (http://earthexplorer.usgs.gov) and used as the data source. Due to the maximum amount of greenness in plants and harvesting products such as olive, the proposed date was chosen.

From the downloaded datasets, four common spectrums of Red, Green, Blue, and NIR were selected to use in the classification process. Full detailed information for enthusiasts are available in Sekertekin, *et al*., (2017).

3.2 PRE-PROCESSING OF SATELLITE IMAGES

Since the fundamental purpose of RS technology is to recognize and segregate the earthborn phenomenon, the most significant step in analyzing the data achieved from various estimates is the process of classification of satellite imageries. Prior to the classification procedure, preprocessing operations (atmospheric and radiometric corrections) were done on the downloaded data sets (Song, *et al*., 2001). Eventually, four mentioned bands (RGB and NIR) gathered in one data set by layer stacking command. By considering the fact that two simultaneous imageries could cover the area under investigation, at first, the multispectral bands were mosaicked together and then the same process was repeated for thermal bands.

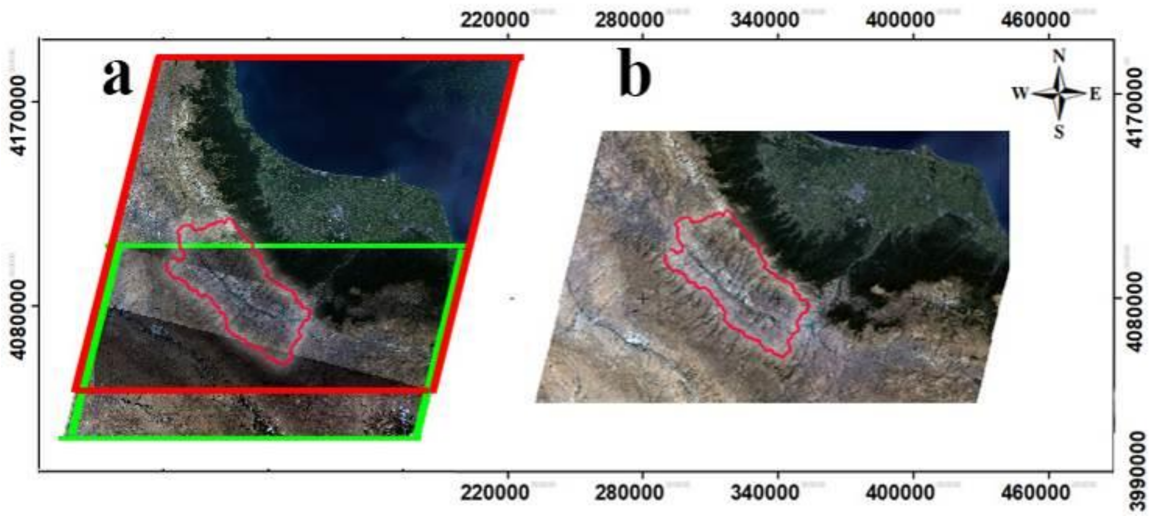

Figure 2: Spectral Bands before (a) and after (b) mosaicking.

3.3 MOSAICKING IN ENVI

Mosaicking technique combines two aforementioned data sets into a single georeferenced composite image the covering complete study area. Since the two imageries covered the area under investigation, the multispectral and thermal bands of the imageries were merged (mosaicking). We used a seamless Mosaic tool (in ENVI software), for combining multispectral RGB (Figure 2(a) and 2(b)) and thermal Band (NIR) of two images (Figure 3(a), and 3(b)). It should be noted that the red and green polygons shows the imagery for 166*34, and 166*35 row and paths respectively.

This mosaicked composite image, as shown in Figure 4, stacked and clipped by the study area boundaries through "Subset data from ROI" tool. Different methods exist for providing land-use maps that have their pros and cons. In addition, any of these methods have different preprocessing stages, which makes the results more accurate Zhou, *et al*., 2018; Zhu, *et al*., 2016; Song, *et al*., 2001). For instance, in land segregation by the ML method, using the FLAASH algorithm for primary processing is recommended.

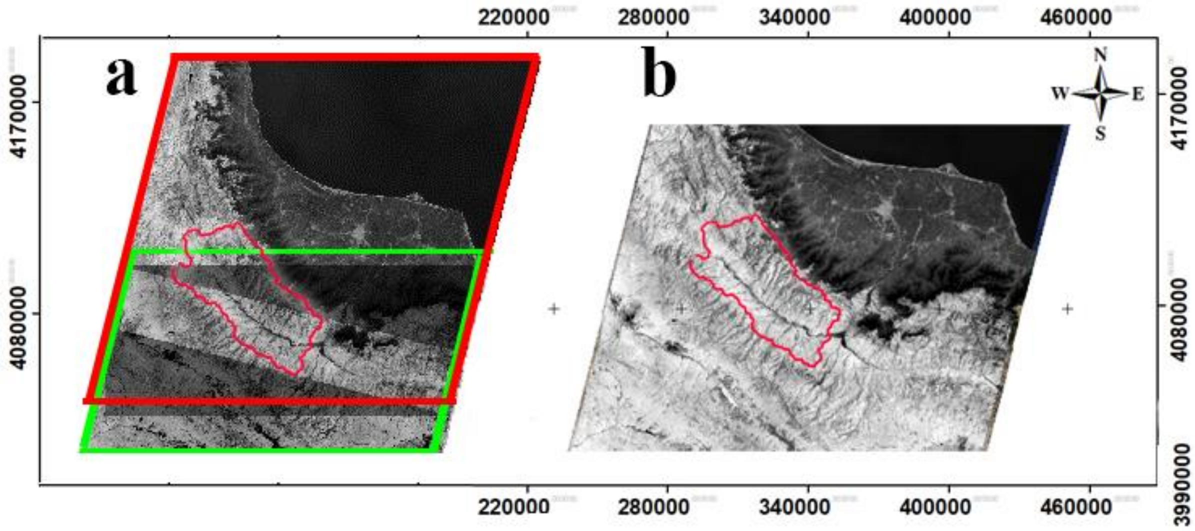

Figure 3: Thermal bands before (a) and after (b) mosaicking.

Figure 4: River flow and the place of the bridge between Koohkan and Vaneysar

Although National Aeronautics and Space Administration (NASA) provides level 1 geometrically corrected images (Storey and Choate, 2008; Gutman, *et al.*, 2013), some researchers have reported the necessity of checking the accuracy of the images to produce optimal results after classification (Tatem, *et al.*, 2006). To achieve this objective, a number of locations (or points) in the studied area were examined in terms of geometric accuracy. These locations were typically placed in intersections of roads and positions of certain buildings for which UTM was available. Analysis of these locations showed that the imageries of L1 for the studies area (i.e., Tarom) had sufficient accuracy. For instance, by depicting the bridge connecting Gheytoun and Guilvan in Google earth and transferring the produced shapefile on the Landsat image, the bridge was presented in its exact location. In Figure 4, the position of the bridge in the location and in Landsat imagery is shown. It should also be mentioned that in this picture, the depicted curve for river axis is hypothetical.

The next stage in the procedure of classification is determining the number of land-use classes through the study area; in this case study, five land-use classes were chosen for collecting the training samples. These samples for each category (waterbody, agriculture, mountain and rock, forest and bare land) prepared from the Tarom basin area via land surveying by GPS and also using Google Earth software to make polygons at different altitudes and slopes (Brandt, *et al.*, 2013).

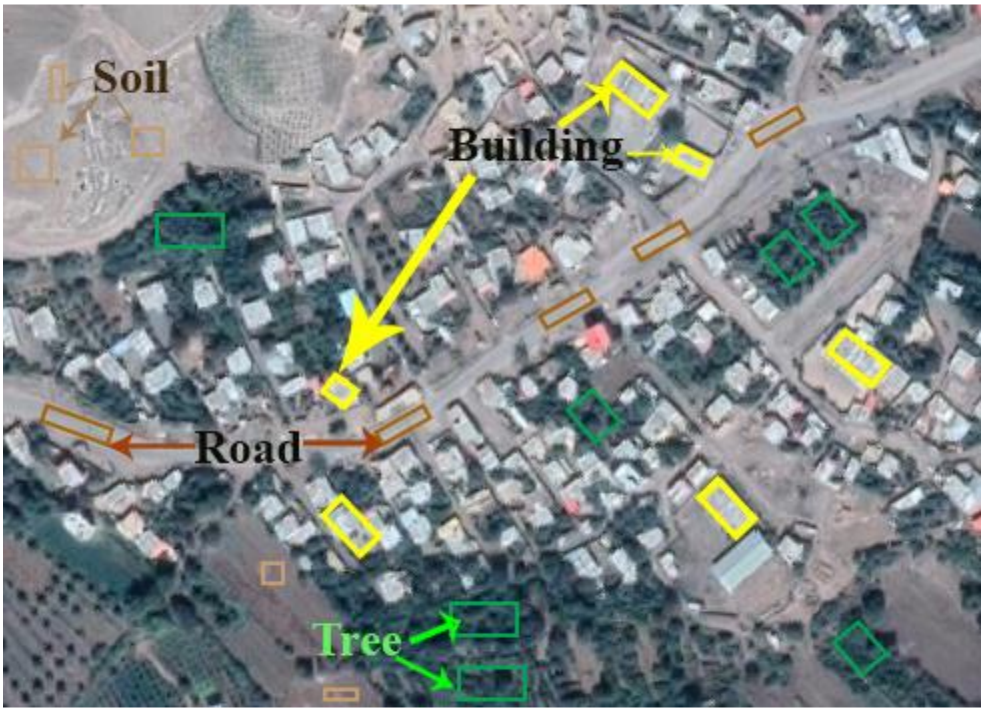

Figure 5: Google Earth capability for getting training data (courtesy of Google Earth)

About 70% of collected polygons, were applied in the classification procedure, and the remaining 30% utilized to assess the precision of the classification. Fig 6 clearly shows that the imageries taken from Google Earth in upper zoom can be an appropriate source of creating educational samples and are also useful for testing purposes. For instance, in these pictures, agricultural, garden, constructive, and road domains can be accurately segregated.

The general stages of image classification include: designing a proper classification system, image processing, selecting educational samples (training samples) from existing images and using local views or high-resolution pictures (such as Google Earth), processing after classification and evaluating the accuracy of the work. After collecting samples for each category and checking Landsat image geometric accuracy, at the next step of preprocessing of OLI data, DNs should be converted into at-satellite radiance using algorithms such as FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes). In this study, we used an advanced FLAASH algorithm module for Atmospheric correction of images in ENVI 5.3, according to Anderson, (2002). Then, three classifiers, including maximum likelihood classification, support vector machine classification (SVM), and artificial intelligence technique (artificial neural network or ANN) were used to classify and prepare land-use map for the year 2017. In the MLC method, ENVI computes the likelihood of each pixel and determines that it belongs to each category (Elhag and Boteva, 2016). The support vector machine is a learning technique that is supervised, non-parametric, and statistical (Vapnik and Chervonenkis, 1979; Cortes and Vapnik, 1995). Detailed definitions of these methods (parameters and architectures) are provided by different researchers (Petropoulos, *et al*., 2010; Kynova and Dobrovolny, 2015; Elhag and Boteva, 2016).

4. PRECISION EVALUATION

The results of the classification procedure in remote sensing technique cannot be trusted until the accuracy of the generated images or maps is verified. This is a critical step and to ensure the accuracy of the present study; we need to measure the accuracy of the generated images. In this study, we used more than half of the samples (70%) for categorization of the pixels, and the remaining 30% for assessing the precision of generated maps. To achieve this goal, two common parameters which are known as overall accuracy (OA) and kappa coefficient (KC) derived from error matrix are used (Brandt, *et al*., 2013; Schmitt-Harsh, 2013). In a confusion or error matrix, the value of each known pixel that belongs to reference data goes into the columns of the matrix and the pixel which was classified, lists in the rows of the matrix. It should be mentioned that the pixels that are precisely classified, list in the main diagonal of the error matrix (Banko, 1998). The overall accuracy is used to show the correctly classified pixels (in percent), and the kappa coefficient calculates the percent of chance-corrected pixels (Rosenfield and Fitzpatrick-Lins, 1986). In this study, OA and KC were used to determine the best classification method between MLC, SVM, and ANN, pixel-based algorithms. Also, the land-use map for 2017 was prepared and transferred into ArcGIS to calculate the area of each land-use category.

5. RESULTS

The multispectral and thermal dataset used in our experiments is the Landsat 8 remote sensing images of the Tarom area taken on August 8th, 2017. The first step was to make the image preprocessing and feature extraction. This part is done in the ENVI software environment. The second step is the realization of the algorithms and the image classification. Three classifiers including, MLC, SVM, and ANN were used to classifying and preparing land-use maps for the year 2017. The comparison results acquired by the ML, SVM, and ANN methods are shown in Table 1.

Table 1: OA and KC of three classifiers.

Statistic (%)	ML	SVM	ANN
Overall Accuracy	91.55	89.45	88.24
Kappa Coefficient	0.88	0.86	0.84

Based on the results of Table 1, it seems clear that the ML method has the best precision in generating land-use imageries. The comparison of results in Table 1 showed that the ML technique has better output than the other two methods in classification accuracy and classifies the remote sensing image more accurately. Classified Landsat-8 image for 2017, is presented in Figure 6.

The area for each class in the classification is provided in Table.2. It should also be mentioned that in Table. 2, bare land class (path and soil) referred to the places in which no cultivation or harvesting was seen during the satellite imagery. In addition, dirt and gravel roads were classified under this category.

Table 2: Area of different classes.

Class	Area (km^2)	Percent
Mountain and Rock	3527	68.37
Bare land (roads and settlement)	1212	23.49
Vegetation	225	4.36
Forest (garden)	141.5	2.74
Waterbody	53.5	1.04
Total	5159	100

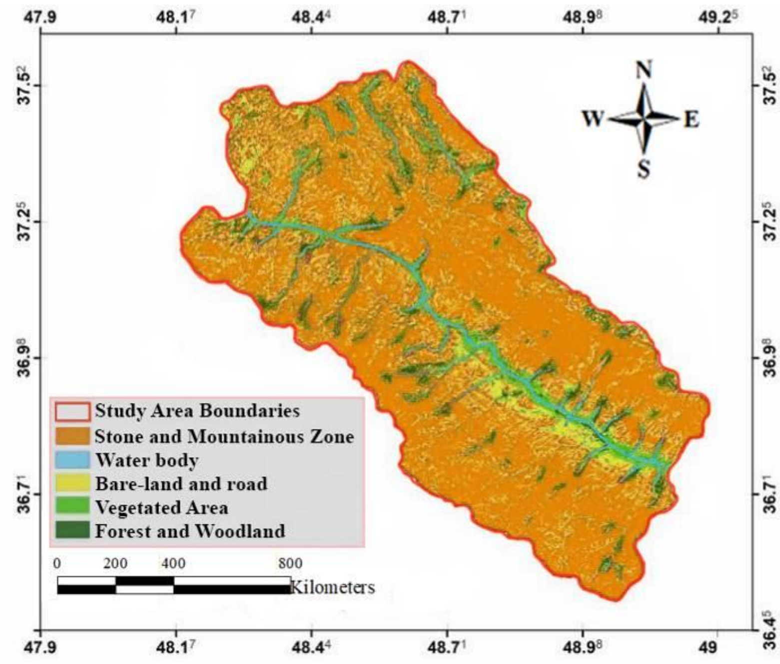

Figure 6: LULC images for 2017.

As mentioned before, the accuracy assessment for the 2017 classified picture (with three classifiers) was performed by using the 30% of gathered samples. Table 3 presents the User's and producers' accuracy for the MLC method.

Table 3: Precision evaluation for the generated images.

Class / Statistic	User's Accuracy	Producer's Accuracy
Waterbody	93.16	94.31
Forest	87.42	95.25
Bare Land	63.72	71.04
Vegetation	75.68	78.59
Mountain and rock	76.37	72.84
Overall Accuracy	91.55	
Kappa Coefficient	88	

Based on the estimates in Table 3, the model has a considerable capability in the segregation of the aqueous domain. In addition, the model can be beneficial for the segregation of garden class or trees in Landsat imageries and also for areas such as Tarom with a huge amount of slope, vicissitudes and a variety of tree species. Conclusions drawn from previous studies verify the precision of the methods as mentioned earlier (Akar, 2012; Duarte, *et al*., 2016). Though highly accurate MLC method with the kappa coefficient, more than 85% is proved to be a propped classification method. (Anderson, *et al*., 1976). Although two other methods-specially ANN method-has been introduced as the appropriate methods in numerous studies, they are reported to be time-consuming due to low calculation speed, the necessity of diverging architectures and change in map generation parameters.

6. CONCLUSION

Land cover is the physical material at the earth's surface and an essential variable which links the physical environment by human activities, and land-use is the description of how we utilize the land for the socio-economic activities purposes. Population and society growth increases the demand for food, water, and energy, which causes a prompt change in land cover and pattern of land-use. The mentioned process depends on social and economic development of the nation.

In order to have appropriate and unrestrictive management of natural resources (water and soil), it is a necessity to have complete information about the pattern of land-use and its alteration pattern over time. Thus, it can be concluded that remote sensing is a proper technique to investigate the land-use changes using satellite imagery. Spatiotemporal analyses of LULC help us to manage the environmental changes, which are an appropriate tool for decision-makers on water resources' to enhance their decisions.

In the presented study, LULC map for Tarom basin, Iran, acquired from OLI sensor data sets (Landsat-8) by applying three pixel-based classification method (MLC, SVM, and ANN) with the aid of remote sensing technology. The finding results that are presented in this study proved the usefulness, effectiveness and also convenience of the MLC technique for generating land-use maps by using the free archive of Landsat data and processing the digital images through the ENVI software. Accuracy assessment using OA and KC for MLC algorithm (the best classifier), was 91.55% and 0.88 respectively. But then, the OA for SVM Algorithm was 89.45%, and the calculated kappa coefficient was 0.86. Finally, for the third classifier (ANN), the OA and KC values were 88.24%, and 0.84, respectively.

Anderson, *et al*., 1976 have also recited the approval of the USGS kappa coefficient of 85% in their article as the minimum requirement for land-use classification with Landsat data. However, some researchers stated lower than standard kappa coefficient in their study, for example, Rozenstein and Karnieli (2010), reported 53% for MLC method, which is lower than the standard 85% which has been approved by USGS. Some researchers stated that SVM classification method performs better than ANN (Halder, *et al*., 2011; Yousefi, *et al*., 2015). Obtained data from the study area showed the dominant coverage of the area is belong to mountain and rock category in Tarom basin covering about 3527 Km^2. The latter considerable type of land cover in this basin was bare land, including bare lands, roads, and settlement areas (225 Km^2).

What matters most in this regard is the accuracy, speed, and quality of land-use maps. In the present study, it was shown that due to high speed and accuracy in generating land-use maps of Tarom, ML method, can act as the best classification method in this area. However, it is suggested to classify the data by using other methods and compare the results with image output provided by Landsat 8 satellite. In addition, it is also recommended to generate maps for different time periods (e.g., five years ago) and evaluate land-use change classes in order to have a better understanding of changes' patterns (Panda, et al., 2018). So at the same time, we are able to provide a number of strategies to preserve the fields which may result in prevention from detrimental or unstructured land-use in Tarom. Finally, as some researchers stated, due to altitudinal structure, and a variety in LULC classes in each study area, a unique guideline for choosing the best classification method cannot be applied to all areas (Xie, *et al*., 2010; Schulz, *et al*., 2010; Zhou, *et al*., 2018).

7. AVAILABILITY OF DATA AND MATERIAL

Data used or generated from this study is available upon request to the corresponding author.

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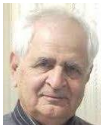

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