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Classification of Satellite Imagery Data to Estimate Cultivated Areas of Grape Farms

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ABSTRACT

Agricultural sector is of great importance in economy due to climate variations and imbalanced population growth. Having accurate information of cultivated area can be helpful in formulation and implementation of agricultural programs. Analysis of satellite data by Remote Sensing techniques is a useful method for investigation and monitoring of the cultivated areas. Using high resolution imagery data can be an economical technique to delineate the cultivated area and to reveal temporal changes. The objective of this research is to estimate the area of cultivated farms of grape using Landsat 8 and Sentinel 2 for July 2016 in Shahroud County. We have initially taken 50 grape gardens for training samples to conduct different classification methods for each of the Landsat and Sentinel images. The results of the methods on the two images have been compared based on Kappa coefficient, accuracy values, and cultivated areas. Based on the results of the analysis, it can be concluded that just in Mahalanobis Distance classification method we obtained relatively the same value of 3600 hectare in both the images for the cultivated area. The value is also close to the value 3550 hectares measured directly by Jihad Agricultural Organization of Shahroud for the year 2016. Thus, the Mahalanobis can be the best classification method for measurement of cultivated areas of grape farms.

Keywords: *Estimation Of Cultivated Area, Remote Sensing, Supervised Classification, Grape, Shahroud.*

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1. INTRODUCTION

Agriculture is one of the key factors to meet the needs of communities for food. Thus, it is necessary to have access to agriculture information about cultivated area, crop rate, and agriculture pests for a useful decision making, resource management, and macro-planning (Gardin-pedrosa and Alvarez-Lopez, 2012). Accordingly, it is inevitable to monitor plant health, understand stresses, determine photosynthesis capacity, and crop yield of a region for a sustainable agriculture (Campos et al., 2018; Ghahroudi Tali et al., 2012). A suitable, low cost, and fast method to have access to the information is to use satellite imagery (Barrett, 1992). As the agricultural crops are required to be distinguishable in visible and infrared wavelengths of electromagnetic spectrum relative to other surface covers (Shalaby and Tateishi, 2007; Soffianian et al., 2011), the sensors with more spectral bands in the range can be better to discriminate different agricultural crops. This is true for hyper-spectral images (Pan et al., 2018). However, in multi-spectral images, spectral curve of different agricultural crops are near to the fragmental lines increasing similarity among them and decreasing discrimination among them. This is due to low number of bands with high bandwidth in visible and infrared spectrums. To distinguish between the agricultural crops using the multi-spectral images, therefore, it is better to utilize multi-temporal images (Shao et al., 2018). As the spectral behavior of different agricultural crops are variable during growth period (agricultural calendar), it is not possible to observe all the crops in a given time in a same situation on the images (Caren et al., 2001). It is likely that in a given time some crops are in initial stages of growth, some other in maturation period, and other crops in elderly stages. Thus, some plants may be mingled either with each other or with soil classes (Campos et al., 2018).

Convenient access to proper data, highly accurate and rapidly available, is essential for any planning. In agricultural sector, access to fast and accurate spatial information is important due to climate variations in one hand and unbalanced population development on the other hand (Alavipanah and Nezammahalleh, 2013; Yousefi et al., 2011). Satellite data along with remote sensing technology are efficient tools to examine and determine the agricultural cultivated areas. The remotely sensed data of high spectral resolution, temporal resolution, and spatial nature are useful, economical, and valid method to detect cultivated areas and temporal changes (Shao et al., 2018; Tucker and Arikan, 2000).

The remote sensing technology not only can make a classification of agricultural products in a region, but it can also determine cultivated area of a region and estimate the performance. Given that up-to-date information is required for proper decision making and management, planning for delivery of agricultural products and foods for sale involves the up-to-date information about cultivated area and performance of the agricultural products (Sawasawa, 2003; Wardlow et al., 2007; Baez-Gonzalez et al., 2002; Quintano et al., 2011).

The Parallelepiped classification method is based on minimum and maximum pixel values of defined training points in each class. In Mahalanobis Distance it is assumed that the bands of the image have normal histogram using covariance matrix. In Minimum Distance, spectral average values in each band are determined and, then, the distance of each unclassified pixel and the average pixel values are compared to assign a given pixel to the class that has the least distance to the average value. The Spectral Angle Mapper (SAM) based on spectral bands applies a non-dimension angle to attribute the corresponding pixels to band spectrum. In Maximum Likelihood method, the classification is based on variance and covariance and a given pixel is attributed to the class that it is most likely to belong to (Li et al., 2014). There are many studies (Foody et al., 2006; Lu and Weng, 2007; Wijaya, 2005; Pan et al., 2018) compared different image classification methods in land cover features.

Many studies (Pan et al., 2018; Alavipanah and Nezammahalleh, 2013; Arekhi and Adibnejad, 2011; Huang et al., 2002; Bocco et al., 2007) used the supervised classification methods to achieve the cultivated area map to introduce the best method for this purpose. The performance of the classification methods are influenced by a variety of factors including characteristics of region, properties of training points, and ground control points.

The purpose of this research is to determine the cultivated area of some special crops as exact management unit using Landsat and Sentinel images (2015) in Shahrood County as a major agricultural center in Semnan. This can provide helpful information about net production, shortage, and surplus agricultural products for market management. No similar study was conducted in the county. Another purpose of this research is to find the best image classification method in estimation of cultivated areas using remote sensing techniques.

2. MATERIALS AND METHODS

In this research, we have used the images of Landsat 8 and Sentinel, 2015, to create thematic map of cultivated area by the image classification using 6 different classification methods. The images have been obtained from United States Geological Survey (USGS). We have also used the cultivation map from Iran Agricultural Organization (Jihad Agriculture) that is based on field survey. For accuracy assessment of the results, in a field survey we have employed GPS and taken 50 training points of the grape gardens in the study area.

To ensure the quality and accuracy of the imagery data, we have initially assessed the atmospheric, geometric, and radiometric errors of the data. True color composition has also been processed for primary understanding and selection of training points. Histogram matching has also been conducted before making the mosaic of the images. To evaluate the accuracy of the classification results, Kappa coefficient has been used.

3. RESULTS AND DISCUSSION

Supervised classification has been carried out for the two images of Sentinel and Landsat to compare them with each other. Some training areas by Region of Interest (ROI) have been considered for the classification. The classes of grape garden, barren land and mountain, vegetation cover except grape, and urban area have been detected by five classification methods including Parallelepiped, Minimum Distance, Mahalanobis Distance, Moximum likelihood, Spectral Angle Mapper.

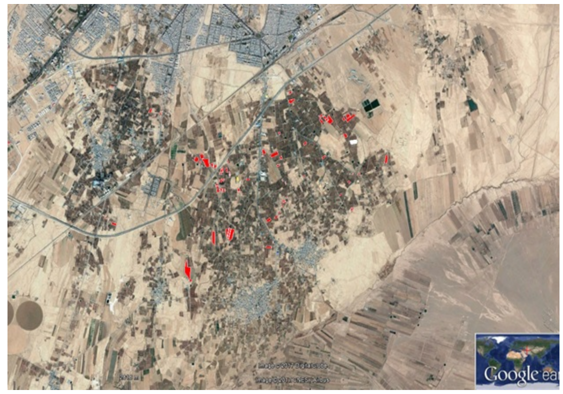

Figure 1: sample training points located by GPS in the study area

It is necessary to evaluate the accuracy of classification results. One of the methods for the evaluation is to select some known pixels as ground reality or reference data and compare them with the classification results. Two parameters of general accuracy and Kappa coefficient are usually applied to assess the classification results. The general accuracy is ratio of the accurately classified pixels to total known pixels. The Kappa coefficient is calculated relative to an absolutely random classification.

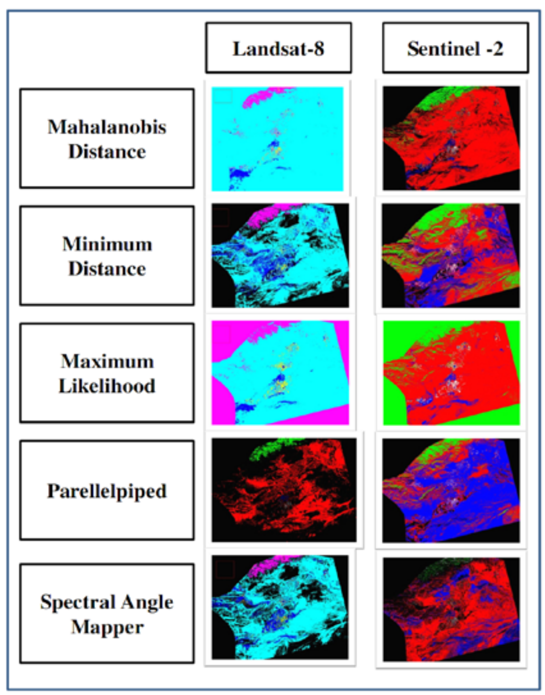

Figure 2: classified image of Sentinel 2 and Landsat by different methods

Table 1: evaluation of accuracy and Kappa coefficient in the classification methods

Classification methods	Cultivated area of grape (hectare)		Accuracy		Kappa coefficient	
	Landsat 8	Sentinel 2	Landsat 8	Sentinel 2	Landsat 8	Sentinel 2
Parallelepiped	278.46	3418.8	59.59	17.02	0.064	0.022
Minimum Distance	5279.32	3151.530	69.67	91.14	0.097	0.316
Mahalanobis Distance	3636.45	3589.09	99.80	91.60	0.956	0.308
Moximum likelihood	7767	6540.39	99.85	98.44	0.968	0.736
Spectral Angle Mapper	3099.06	3096.72	81.99	55.52	0.169	0.031

The results have indicated that the accuracy and Kappa coefficient of Landsat 8 are the highest for Maximum Likelihood method. The Mahalanobis method has presented a more real estimation of the cultivated area of grape orchards. The estimated area by the Mahalanobis method using Landsat 8 and Sentinel 2 is 3636.45 and 3589.09, respectively. This value is not much different from the value 3550 measured by the Agriculture Organization of Iran.

4. CONCLUSION

According to the statistics of Iran Cultural Organization of Shahroud, the cultivated area of the grape in the county in 2016 was 3550 hectare. Thus, the best method can be extracted based on the general accuracy and Kappa coefficient. The results of the accuracy assessment have indicated that the best method of supervised classification to obtain the cultivated areas of grape products in the study area using Landsat-8 and Sentinel-2 is Mahalanobis Distance with precision 98 and 97 % relative to the value reported by Iran Cultural Organization. In parallelepiped method just Sentinel method has a fairly good result.

The results have also indicated that the best time of imaging is July in the peak of greenness. The study has also approved that just the resolution of the image cannot be a factor for getting more suitable results. The findings of this research have demonstrated that remote sensing technology using free data to estimate the agricultural cultivated areas is a good economical choice.

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