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Full Length Research Paper

Proposing a methodology in preparation of olive orchards map as an important medicinal plant in Iran by remote sensing (RS) and geographical information system (GIS)

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Present study focuses on identification and mapping of olive in the part of Roodbar region, Guilan, Iran by IRS images and GIS. Two methods were evaluated to separate olive orchards spectrum reflex from the other surface covers. At the first method, upper and lower limit of digital number of olive orchards were determined by the addition and subtraction of standard deviation from the mean in each band and initial classified map of olive orchards was prepared in every band. The final map of olive orchards was prepared from crossing three initial maps of olive orchards. At the second method, olive orchards map was prepared by four models include: Box classifier, maximum likelihood, minimum distance and minimum Mahalanobis distance. Methods accuracy was evaluated from crossing the map of training points (pixel) with olive orchards map. The results indicated that in classification of less-condensed olive orchards, because of spectrum wave interference of olive green canopy and the soil zone between the canopy cover, the interference of digital number of low-condensed olive is observed with the other vegetation cover and bare lands. There was this issue even for wave interference of low-condensed olive with urban and residential regions. There is the interference of spectrum reflexes between the agriculture land and olive. This issue also exists for different methods of supervised classification.

Key words: Spectrum reflex, olive, training points, map.

INTRODUCTION

Olea earapae is a medicinal plant that grows as wild and cultivated in north and west of Iran. Oil, olive leaves and bark have a medicinal value. This plant can be planted in areas prone to developing cultivation. In addition to financial benefits for the residents of these areas, it prevent of deforestation and soil erosion. The use of medicinal plants without an estimation of cultivated areas tends to lack of precise programming. The most important principle to exploit of forests and pastures is continuous production (Eslami, 2008).

The information of digital imagery acquired by Remote Sensing technology can be used for mapping, monitoring and assessing the properties of the environmental and terrestrial features. Land use and land cover is found as significant information in an area that may assist managers and decision-makers to take drastic measures. One of the most important land uses is agriculture lands as well as orchards, which may play an important role in providing human food. Land-use changes in farming areas that derive from agricultural practices or overexploitation of water resources in many semiarid regions of the world have led to designing urgent strategies of water management towards sustainable development (Hugget, 1993; Brandt and Thornes, 1996).

As human demands increase, the sustainability of land use is in question. Better land management involves identifying land-use changes, understanding current land-use patterns or features, and assessing economic and ecological benefits and costs that arise from land-use practices, as well as finding the best alternatives for each area (Wu et al., 2001). Remotely sensed data frequently

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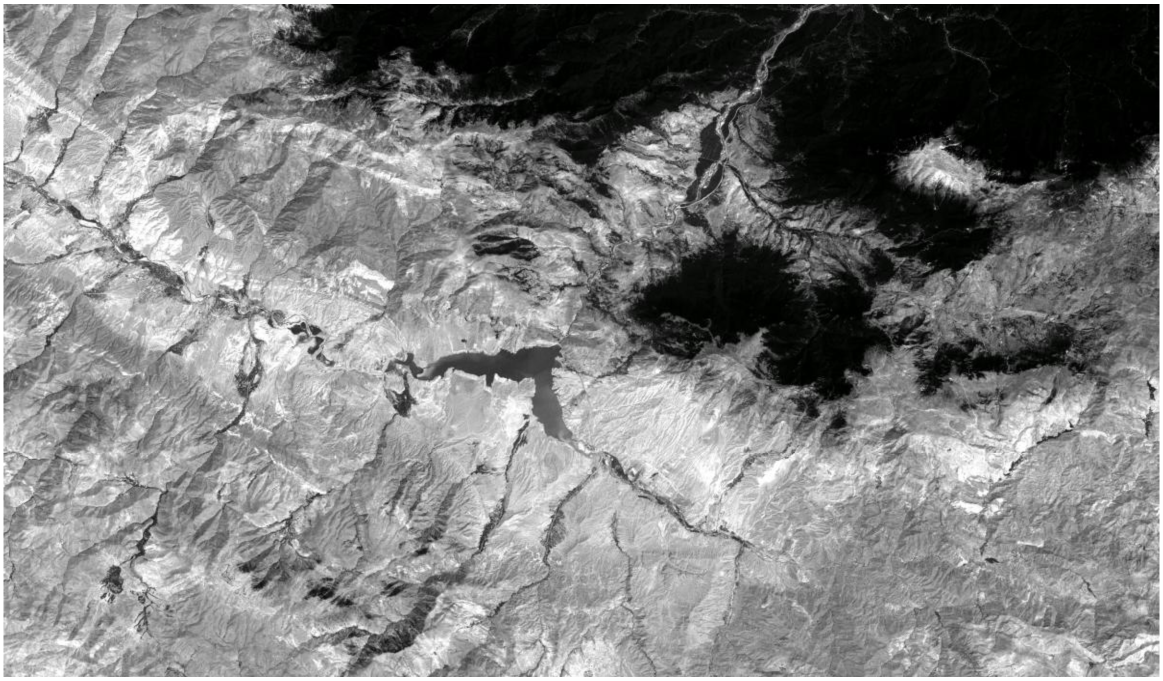

Figure 1. Satellite image of study region (band 2 of IRS satellite).

are used to map land surface cover for use in a variety of resource assessment, land management, and modeling applications. Mapping from coarse spatial resolution images and with multispectral instruments necessarily has focused on land cover and broad vegetation types (Loveland, 2000) rather than discrimination of vegetation at a species level.

Crop yield forecast in an area usually requires crop area estimation, which is mainly concerned by some relating organizations. Satellite data along with remote sensing technique may be employed as a useful and effective tool to estimate crop area. Recent developments of image processing technique as well as availability of high resolution satellite imageries avail to use this technique as a quick and low cost method in compare to conventional methods for crop area estimation while it is obvious that due to limited period of growing season in case of some crops it is very tedious and difficult task to estimate crop area using time consuming conventional methods.

Many studies have been conducted concerning the use of satellite data for different crop type area estimation throughout the world. Olive area estimation has been carried out in a few olive-growing countries as Turkey, Spain and Portugal. Ediz (2004) used Land sat 7 and IRS data to survey olive, pistachio and vineyard in Gazin-Tab area Turkey. He used image supervised classification technique to estimate olive plantation area. Teresa and Granado (2004) has compared land sat images with aerial photo to map olive gardens in Portugal. Ramos et al. (2007) quantified the eventual land movement and the subsequent displacement of olive trees produced by continuous tillage erosion. They analyzed these movements on a property of olive orchards located on variable sloping land. Berni et al. (2009) applied models based on canopy temperature estimated from high resolution airborne imagery to calculate tree canopy conductance (Gc) and the crop water stress index (CWSI) of heterogeneous olive orchards.

In this research, surveying of olive orchards was investigated by using IRS Satellite images in the region including some parts of Roudbar, Manjil, Loushan and Abbar, Guilan, Iran.

MATERIALS AND METHODS

The study area is located between eastern longitudes of 48°55′48″ and 49°52′54″; and northern latitudes of 36°31′19″ and 36°59′57″ that the region area is 459 km^2. Administrative boundary of the study area includes Roodbar Township along southern part of Guilan province, Iran. Figure 1 shows studying region on band 2 of IRS satellite. From the physiographic point of view, lands are gently sloping foothills, mountainous lands and upper terraces. Lithic units are sandstone, limestone, marl, conglomerate, andesite and diorite. During recent years, government policy with increasing demand has promoted the area of this crop and development of olive processing factories in this region. Different image processing techniques are usually available to highlight a certain land use. In present research, two techniques were employed to highlight olive orchards from other land covers which are going to be described in following: 1. By spectral reflectance stochastic (DN) of different land covers and slicing and 2. By different methods of supervised classification.

IRS images of July 2006 were used to map olive farming area

Table 1. Some properties of IRS bands.

Band No.	Standard Deviation	Median	Mean
1	13.3	28	19.58
2	51.33	99	67.3
3	47.99	98	67.7

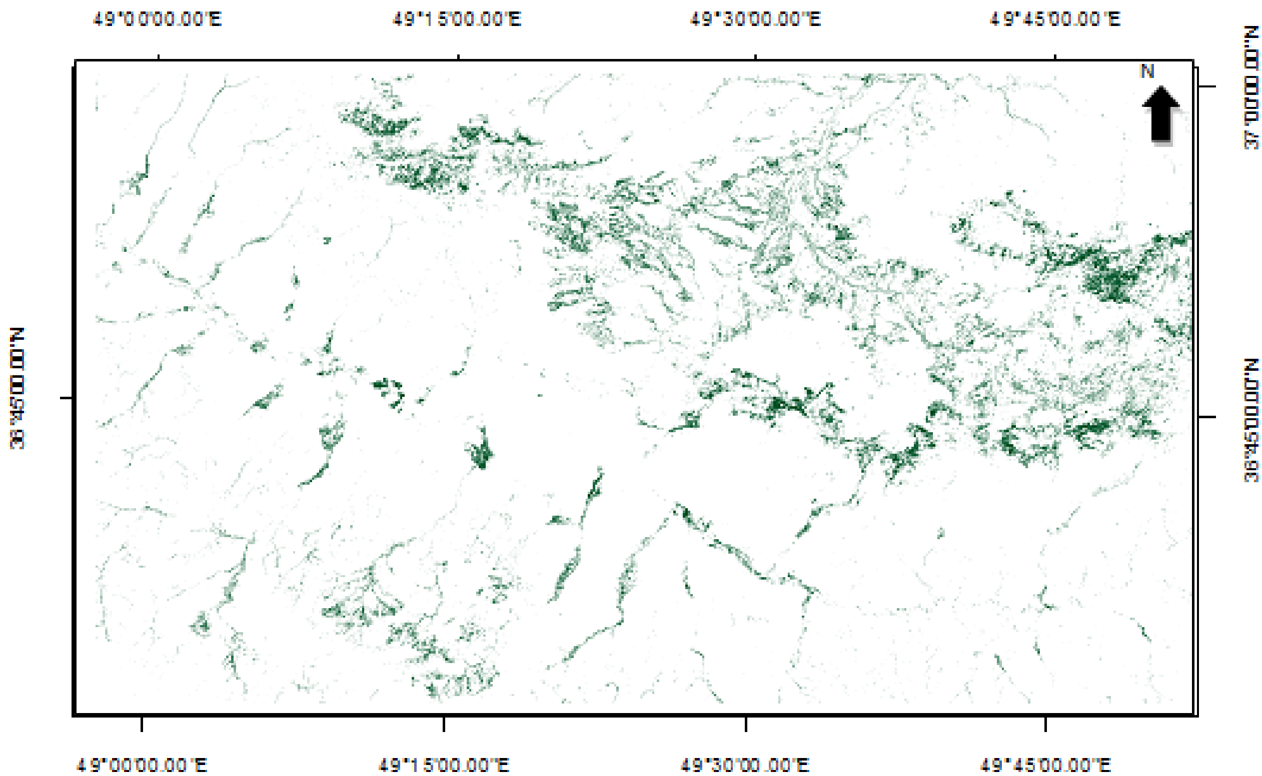

Figure 2. The final map of olive orchards prepared from crossing three initial maps of olive orchards in their spectrum bands.

and software ILWIS 3.3 Academic was used for processing data. Some properties of IRS bands are observed in Table 1. Topographic maps of 1:25000 prepared by National Cartographic Center and 23 ground control points were used for geo-referencing of images.

Global positioning system (GPS) was also employed for training area selection in the field. Field views (248 points) were done to determine accurate positions of land covers including: 1. Olive, 2. Hard wood forest, 3. Soft wood forest, 4. Cultivation lands (paddy), 5. Bare lands, 6. Non olive-plant covers, 7. Water area and 8. Urban regions.

Spectral reflectance stochastic

A point map of training and auxiliary point of different land covers was prepared to overlay on a sample set of color composite (Bands 1, 2 and 3). The mean and standard deviation of training and auxiliary pixels of olive orchards was calculated. Upper and lower limits of digital number of olive orchards class pixels determined with the addition and subtraction of standard deviation from the mean in each band and initial classified map of olive orchards prepared in each band with them (Equation 1).

$$\overline{X}(B_1, B_2, B_3) \pm 2S.d \tag{1}$$

Olive orchards map was prepared by slicing of these limits in every band, separately. The final map of olive orchards prepared from crossing three initial maps of olive orchards in there spectrum bands that Figure 2 indicates this map. The method accuracy was evaluated from crossing the map of training points (pixel) with olive orchards map.

Supervised classification

Taking into consideration training and auxiliary points of different land covers, the supervised classification of IRS images was done in four methods: 1. Box Classifier, 2. Maximum likelihood, 3. Minimum distance and 4. Minimum Mahalanobis distance. They were selected as the most common supervised per-pixel classification useful for obtaining thematic maps from multispectral satellite data (Richards and Jia, 2006). Supervised algorithm were tested by changing bias and threshold values in order to select the best boundaries in the spectral space beyond that a pixel has such

Table 2. Indicates mean, standard deviation and upper/lower limits of training pixels spectrum reflexes-Olive in order to image slicing in Bands 1, 2 and 3.

	$\overline{X}$ *			$S.d$ **			$\overline{X}-2S.d$			$\overline{X}+2S.d$		
Band number	1	2	3	1	2	3	1	2	3	1	2	3
	24.1	64.6	102.3	0.8	6.7	6.2	22.5	51.3	90.0	25.7	77.9	114.7

*Digital numbers mean of training points in olive orchards class. **Digital numbers standard deviation of training points in olive orchards class.

Table 3. Indicated the crossing result of training points map with Olive map. According to results, more than 60% of training points in classified Olive map recognized as olive class. Spectrum reflexes interference of agricultural and paddle lands with Olive had been found, so that, 17.7% of training pixels of agricultural lands in the classified map had olive class.

	N_t*	N_{t-o}**	N_{t-o}/N_t***
Olive	2016	1416	70.23
Hard wood forest	10884	97	0.89
Soft wood forest	208	-	-
Non olive-plant covers	293	270	92.15
Bare lands	38734	-	-
Cultivation Lands (paddy)	1213	215	17.72
Water area	8597	-	-
Urban	1134	-	-

*Total numbers of training points. **Numbers of olive class-pixels after crossing classified map of olive with training points map. ***Olive class-pixels/total pixels ratio (%).

a low probability of inclusion in a given class that it is excluded from that class.

In the supervised classification methods, we differentiated dense olive orchards of its low dense orchards. Finally, the olive orchards map has been crossed by training point map to calculate the accuracy of method. The classification accuracy was assessed on the entire study area by estimating the overall (A), producer's (PA) and user's (UA) accuracies and Cohen's Kappa coefficient (K) (Congalton and Green, 1999) derived from the error matrix that is the core of accuracy assessment of a classified map (Foody, 2002; Liu et al., 2007).

$$A=\frac{1}{N}\sum_{i=1}^{r}n_{ii} \tag{2}$$

$$PA=n_{ii}\,/\,n_{icol} \tag{3}$$

$$UA=n_{ii}\,/\,n_{irow} \tag{4}$$

$$K=N\sum_{i=1}^{r}n_{ii}-\sum_{i=1}^{r}n_{icol}n_{irow}\,/\,N^{2}-\sum_{i=1}^{r}n_{icol}n_{irow} \tag{5}$$

Where n_{ii} is the number of pixels correctly classified in a category; N is the total number of pixels in the confusion matrix; r is the number of rows; and n_{icol} and n_{irow} are the column (reference data) and row (predicted classes) total, respectively. The overall accuracy incorporates the major diagonal and gives the crude percentage of pixels correctly allocated. PA and UA detail the omission and commission errors, respectively. PA shows what percentage of a category on the ground is correctly classified by the analyst, and can define a measure of pixels omitted from its reference class (omission error). Likewise, commission error can be estimated from UA that, highlighting the interest in quantifying the correspondence between the two maps by users, implies a residual percentage of pixels of a category that do not “truly” belong to the reference class, but are committed to other ground-truth classes (commission error). K includes off-diagonal elements also taking into account the commission and omission errors. K, by including also information on these errors, represents a more realistic and reliable indication about the probability that a pixel classified on the map actually represents that category on the ground.

RESULTS

Table 3 indicates the user’s accuracy in various methods of surface cover classifications. Producer accuracy of different methods for preparing the classified map of surface covers is showing in Table 4. It must be consider that user’s accuracy is the main criterion to method accuracy in preparing the map of olive. As it can see, user’s accuracy in box classifier with 0.73 threshold of standard deviation is 41.77% and user’s accuracy reduced sharply in classification of olive, so that, in the threshold of 2.73 and 3.73 standard deviation, user’s accuracy to classify olive is 2.67 and 46%, respectively. Therefore, it seems that even in low threshold, this method is not enjoying of suitable accuracy to prepare olive orchards map. It must be considered that in maximum likelihood method, the change of threshold

Table 4. The Users Accuracy in different methods of supervised classification.

Classification method kind of lands cover	Box classifier				Maximum likelihood	Minimum distance to mean			Minimum Mahalanobis distance	
	Standard deviation				Thresholds 10, 50 and 100%	Search radius (m)			Search radius (m)	
	0.73	1.73	2.73	3.73		1	50 and 10	100	1	10, 50 and 100
Olive	41.7	12.0	2.6	0.04	52.5	66.6	54.9	57.1	66.4	65.5
Low dense olive	62.5	36.6	8.0	3.3	75.5	0	51.6	63.4	53.5	55.8
Hard wood forest	99.2	98.2	95.2	69.0	97.6	97.9	97.2	73.2	99.2	97.4
Soft wood forest	100	100	99.5	100	98.0	100	100	100	100	97.4
Non olive-plant covers	65.7	84.2	82.9	55.3	41.1	0	44.9	42.1	39.0	31.8
Bare lands	53.0	24.5	9.5	4.4	56.3	66.6	56.7	48.4	62.1	48.1
Cultivation Lands (paddy)	95.8	89.7	93.5	98.0	89.4	100	85.1	64.8	96.9	73.8
Water area	100	100	99.9	99.7	99.6	100	99.9	99.7	100	99.5
Urban	79.1	88.5	86.2	66.6	70.4	0	55.3	65.1	51.4	61.4

Table 5. The producer accuracy in different methods of supervised classification.

Classification method kind of lands cover	Box classifier				Maximum likelihood	Minimum distance to mean			Minimum Mahalanobis distance	
	Standard deviation				Thresholds 10, 50 and 100%	Search radius (m)			Search Radius (m)	
	0.73	1.73	2.73	3.73		1	50 and 10	100	1	10, 50 and 100
Olive	80.7	75.1	9.4	0.18	79.3	66.6	76.9	74.0	75.9	71.7
Low Dense Olive	65.4	51.7	34.2	42.8	54.9	0	60.0	61.1	62.2	38.2
Hard wood forest	100	100	99.9	100	99.9	100	99.2	98.1	100	99.9
Soft wood forest	100	89.1	78.7	38.8	67.3	100	68.6	8.9	98.3	78.4
Non olive-plant covers	22.6	14.7	11.4	1.7	15.1	0	19.1	17.7	22.6	16.0
Bare lands	99.0	99.2	98.3	96.2	98.9	100	98.3	98.7	87.0	97.4
Cultivation Lands (paddy)	91.0	63.0	42.2	14.6	64.1	66.6	69.0	13.3	87.0	75.9
Water area	100	100	99.9	99.7	99.8	100	100	99.8	100	99.9
Urban	2.9	2.2	1.9	1.6	3.2	0	2.2	97.2	2.3	2.3

had no effect on map accuracy and user's accuracy in classification of olive orchards was 52.5%. The most important point is that box classifier accuracy in all standard deviations in classification of low condensed olive had been more than the classification of condensed olive. With regard to the results of Table 5, it is found that user's accuracy in maximum likelihood method in classification of condensed olive in various thresholds of likelihood percent was 52.5%, but this accuracy with the mentioned method in classification of low condensed olive

Table 6. The classified area of different lands covers as compared with basin area in different methods of supervised classification.

Classification method kind of lands cover	Box classifier				Maximum likelihood	Minimum distance to mean			Minimum Mahalanobis distance	
	Standard deviation				Thresholds 10, 50 and 100%	Search radius (m)			Search radius (m)	
	0.73	1.73	2.73	3.73		1	50 and 10	100	1	10, 50 and 100
Olive	1440.8	5151.9	6990.7	6862.6	14200.5	14.9	5887.3	19723.5	1886.5	19068.7
Low dense olive	4638.7	13049.8	5497.8	1285.6	20762.7	4.8	6019.1	17535.5	2685.1	19949.2
Hard wood forest	13092.8	61861.9	73849.0	63834.5	79799.9	205.1	26352.9	47334.4	20468.3	78455.6
Soft wood forest	29.1	505.3	1452.5	4950.6	2133.4	1.1	1753.9	27916.7	43.2	1061.9
Non olive-plant covers	2694.0	17547.3	45333.7	126150.4	17661.6	9.2	5239.8	10610.3	1403.8	11689.1
Bare lands	66145.9	32328.9	10712.3	4015.6	125761.8	206.0	78781.2	11523.7	80549.0	174194.5
Cultivation Lands (paddy)	1178.3	9364.2	20576.0	39799.3	12338.5	12.8	7879.4	44607.8	1663.8	6870.6
Water area	553.5	2606.8	2933.6	3095.3	3153.1	10.7	2357.0	3272.0	765.5	3102.7
Urban	65549.0	254627.5	282128.5	208299.6	183187.4	0.0	78997.4	172134.1	41138.8	144606.5
Total Area (ha)	155322.1	397043.6	449474.1	458293.7	458999.5	464.6	213268.0	354658.0	150604.0	458999.5
Unknown area of Basin (ha)	303677.1	61955.9	9525.4	705.8	-	458534.9	245731.5	104341.5	308395.5	-
Classified area ratio to total area of basin (%)	33.8	86.5	97.9	99.8	100	0.1	46.5	77.3	32.8	100

orchards is more than 75%. Table 6 indicates the classified area of different lands covers as compared with basin area in different methods of supervised classification. It is correct that in box classifier, user's accuracy is reduced in classification of low condensed and condensed olive as increasing the threshold, but it must be considered that in 0.73 threshold, just 33.8% of area had been classified and 67.2% of area had been considered as unknown cells. As increasing the threshold, the percent of classified area will be increase, so the accuracy will be reduced. In maximum likelihood method where user's accuracy in classification of condensed olive in little, total area of the basin had been classified. Therefore, maximum likelihood method had been given more suitable response in classified area and user's accuracy.

In minimum distance method, the most users' accuracy in classification of olive obtained in 1 m search radius, although in 100 m search radius, user's accuracy had been had more than 10 m search radius. In one m search radius, only 0.1% of area had been classified. In this method with 1 m radius, no cells located in low condensed olive category. Also, as increasing the amount of search radius to 50 m, it is not found a difference in olive accuracy with 10 search radius.

In minimum Mahalanobis distance method, in 1 m radius, user's accuracy in classification of condensed olive orchards is 66.47% and in classification of low condensed olive is 53.5%. The increase of search radius in this method to 10, 50 and 100 m had been caused to little reduce of user's accuracy in classification of condensed olive orchards and to increase of classification accuracy of low condensed olive orchards.

Table 7 indicates the overall accuracy and Kappa coefficient in various methods of surface cover classifications. The largest overall accuracy and Kappa coefficient is related to minimum distance method. Overall accuracy and Kappa coefficient have decreased with increasing standard deviation or search radius in box classifier or minimum distance and minimum mahalanobis distance methods.

DISCUSSION

Separating olive orchards helping spectrum reflex statistics caused to separate these orchards from forest zones, well. Of course it must consider that, in each of spectrum bands, there is wave interference of some of surface covers, so considering 3 spectrum bands with each other, caused to reduce the interference of reflexes and to increase the possible to separate olive. The results indicated that there would be possible to separate olive spectrum reflexes from broad

Table 7. Overall accuracy and Kappa coefficient of different lands covers classification in different methods of supervised classification.

Classification method	Box classifier				Maximum likelihood	Minimum distance to mean			Minimum Mahalanobis distance	
	Standard deviation				Thresholds 10, 50 and 100%	Search radius (m)			Search radius (m)	
	0.73	1.73	2.73	3.73		1	10 and 50	100	1	10, 50 and 100
Overall accuracy	61.8	48.8	39.4	29.9	70.4	87.9	69.8	59.4	71.3	65.0
Kappa coefficient	59.4	39.2	32.4	24.6	58.6	82.8	58.3	46.4	54.8	53.0

leaf forest (hard wood forest), conifer forest (soft wood forest), urban and residential regions, bare lands, ranges and water zones, but because of intensive spectrum reflexes interference, it was not possible to separate the olive from non- olive crops including the other orchards, woods and parks green spaces. Shrimali et al. (2001) in the classification of land use/land cover derived an overall accuracy of 83%, that some classes such as agriculture (terraced), agriculture (fallow), and water body had a classification accuracy of more than 90%. The classification of forest into three classes (dense, moderate and open mixed forest) was 85.5% accurate. The reason for the percentage of error was signature overlapping of fallow areas with grass cover and overlapping of grass and moderate (dense) forests with open mixed forests. Accuracy could be further improved if the quantification of standing bio-mass in the forest area could be done in the training sets. In this study, there is overlapping of olive orchards with other vegetation, while there was no such problem for dense forest.

In supervised classification of surface area, the number of training points, dispersion of training points, classification method, defined threshold, the number and kind of surface covers classes are influencing on map accuracy from classification.

The aim of current study was to separate the olive orchards regions from the other surface area, so as the condensed of olive canopy cover impact on spectrum reflections, olive orchards have been considered in two condensed and low condensed categories. When there is a low condensed olive orchard, it is natural that in one pixel, spectrum reflections is influencing on olive green canopy cover and soil zone of the lands between olive trees.

In various regions, the type of surface phenomenon impact on map accuracy from classification, intensively. For example, separating of water zones in IRS 3-bands images from surface phenomenon maybe possible, simply which in turn have its own certain condition , so, when the issue of separation one vegetation from the other vegetation is consider the possible of separating is most difficult . In this research, olive consider as one class and the other vegetation including orchards, woodlands , garden and etc had been considered in another class by the title of non-olive vegetation. Also, the vegetation of broad-leaf and conifer are considered in a separate class.

To identify a suitable method to prepare surface area map, some indexes must be consider: 1. User's accuracy 2. Overall accuracy 3. Kappa coefficient and 4. The capacity of method in classification various vegetation and classified area.

Minimum distance method was not a suitable method to prepare olive map. In this method, when search radius rate was 1 m, only 0.1% of area classified as identified pixels or in other words, nearly all area of unknown domain classified. In this method also in higher search radius, more part of area classified as unknown area. As it could find, spectrum reflections interference of olive and non-olive vegetation cause to hesitate in using minimum distance method. When the spectrum classes are close to each other, this classification method is not so good (Alavi panah, 2004).

Out of minimum distance methods, classification method with 100 m search radius because of 77.3% cover area and 64.37% user's accuracy in classification of olive orchards was relatively better than the other rate of search radius in this method. It must be consider that the overall accuracy of this method was about 60%, but Kappa coefficient was less than 50 and 46.4%, so as the goal is to prepare olive orchards map, the main judge criteria is user's accuracy in classification of olive, since it consider the Kappa coefficient, correct classified pixels and error pixels of all surface vegetation classes. Cuneo et al (2009) provided a map of African olive distribution was produced from the image analysis and checked for accuracy at 337 random locations using ground observation and comparison with existing vegetation maps. Results indicated that a total area of 1907 ha of dense African olive infestation was identified, with an omission error of 7.5% and a commission error of 5.4%.

Minimum distance method was not a suitable method to prepare olive map. In this method, when search radius rate was 1 m, only 0.1% of area classified as identified pixels or in other words, nearly all area of unknown domain classified. In this method also in higher search radius, more part of area classified as unknown area. As it could find, spectrum reflections interference of olive and Sepulcre-Canto (2009) monitored a total of 1076 olive orchards in area in southern Spain, gathering the field location, field area, tree density, and whether the field was drip irrigated or rainfed by. An approach based on a cumulative index using temperature and the normalized difference vegetation index (NDVI) information for the 6-year ASTER time-series was capable of detecting differences between irrigated and rainfed open-canopy orchards, obtaining 80% success on field-to-field assessments. The method considered that irrigated orchards with equal vegetation cover would yield lower temperature and NDVI than rainfed orchards; an overall accuracy of 75% and a kappa (kappa) of 0.34 was obtained with a supervised classification method using visible, near infrared and temperature information for the 6-year ASTER imagery series.

Maximum likelihood method in all likelihood percent thresholds could classify 100% of domain area but in box classifier, it was only in 2.73 standard deviation threshold that nearly whole area was classified, so they were not correct method in olive orchards classification. Unal et al. (2004) used maximum likelihood method to classify cultivated land and separation of pistachio garden and orchard from the other vegetation in Gaziantep province of Turkish. Also, Muschen et al. (2001) tried to separate agricultural area from non-agricultural area using controlled classification of integrated images of TM5 with ORS IC PAN land sat and ERS 2 radar by this method (maximum likelihood). Maybe, minimum mahalanobis distance is the best method in user's accuracy classified area of the domain. In 10 and 50 m thresholds, this method had 65.57% and 55.87% classified user's accuracy in the classification of condensed and low condensed olive, respectively, which in the whole, its user's accuracy in olive orchards classification was 60.21% which was the most user's accuracy in the classification of olive.

Overall accuracy indicates the efficiency of a method in classification of various surface covers, but it is possible in an overall accuracy that user's accuracy be less in classification of olive. For example, in maximum likelihood method, overall accuracy and user's accuracy in classification of olive was 60.4 and 64.6%, respectively, but in the minimum Mahalanobis distance method with 10 m or more radius, overall accuracy was less than the maximum likelihood method (65.0%), but it enjoyed the higher user's accuracy in classification of olive (60.2%). Therefore, as the goal is to classify olive, user's accuracy is enjoying from the most importance in classification of this olive orchards. Ahadnejad (2003) in a research concluded that PCA analysis is the most effective method to increase discrimination factor among different classes. Color composites of PCA1 PCA2, PCA3, consisting the majority of information were used for training area selection. He employed maximum likelihood classifier to highlight olive farming area that olive area estimated around 3843 ha. Mohammadi and Nikkami (2008) compared the accuracy of different methods including satellite imagery and data layers integration and concluded that differentiating photomorphic units in satellite imagery makes more uniform units for using as working units in erosion feature studies.

Since spectrum waves interference of various surface cover cause to raise error in classification and true pixels of a certain class locating in a difference class of surface cover, so Kappa coefficient is enjoying certain importance because with regarding the whole of pixels correct classified pixels, user's accuracy and producer accuracy is the more reliable coefficient comparing to overall accuracy. In classification of condensed olive orchards, as there is high error in classification of olive, non- olive vegetation and agricultural lands, so the increase of kappa coefficient indicating less error and more capacity of this method in classification of surface covers and olive.

In classification of less-condensed olive orchards, because of spectrum wave interference of olive green canopy cover and the soil zone between the canopy cover, the interference of digital number of low-condensed olive observed not only with the other vegetation cover but also with bare lands. There was this issue even for wave interference of low-condensed olive with urban and residential regions as some part of olive located in urban and residential regions and one pixel digital number can be an average of reradiating wave of olive canopy cover and urban and residential region. So, some true pixels of low-condensed olive had been classified as residential region or vice versa.

Conclusion

To compare various classification methods to spectrum reflections statistic classification indicate that the classification based on spectrum reflections statistic while having accuracy same as the best image supervised classification, enjoying more simplicity. In this method, because of image classification, only focusing on olive spectrum reflexes statistic, the likelihood olive regions had been separated and preparing the maps is done with regard to goal, that is, olive and the other surface covers are not consider.

As a whole, it seems that, if preparing the map of olive orchards is doing with the help of spectrum reflexes statistic in the regions with olive and non-olive vegetation, the separated area must indicated under the title of mixed olive land and non-olive vegetations. Also, it must be consider that the commune spectrum reflexes found between the agriculture land and olive. This issue is true to supervised classification with box classifier, maximum likelihood, minimum distance and minimum Mahalanobiss distance.

With regard to this issue that olive always has green canopy cover in Mediterranean climate, it is suggested that the possible to prepare olive map study using satellite picture in winter season.

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