Providing a Supervised Map of Olive Orchards by IRS Satellite Images

Ali Mohammadi Torkashvand [1] and Shahryar Sobhe Zahedi [2]

[1] Islamic Azad University-Rasht Branch
[2] Research Center of Agriculture and Natural Resources, Guilan, Iran
Torkashvand@iaurasht.ac.ir, m.torkashvand54@yahoo.com

Abstract: Due to some changes which are created above time in olive cultivated surface preparing updated map of olive is one of the most important requirements in the management and region agricultural planning. In this research, surveying of olive orchards investigated using IRS Satellite images in the region including some sector of Roudbar, Manjil, Loshan and Abbar, Guilan, Iran. Two methods evaluated to images controlled classification in order to separate olive orchards spectrum reflex from the other surface covers which include: 1.classifcation using spectrum reflex statistics and slicing and 2. classification with Minimum Distance method. The results indicate that in classification of images with spectrum reflex statistics, more than 60% of training points had again olive class in the olive orchards classified map.

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1. Introduction

Much efforts had been carried out to simplify automatic preparation process of land covering map, which and refer to use Normalized dressing vegetation index (NDVI). In this index the curves of vegetation radiation are unique. To from this index, in addition to identify vegetation can refer to identify the region under volcano burst. NDSI index had been obtained using bands 2 and5 data of TM. This index is effective to distinct snow from upper soil, vegetation, features and cloud. NDBI index which is the fraction differential of two hands 4 and 5 to sum of this two bands, is very effective to prepare residential regions map (Zha and Gao, 2003; Chen et al., 2006).

In order to investigate the changes vegetation on soil erosion rate, Essa (2004) used remote sensing and GIS. In this line, the estimation of soil erosion had been carried out revised universal soil loss equation (RUSLE) in GIS medium. He obtained landuse map from MSS land sat (1972) and TM land sat (1992) digital images and calculated the vegetation changes during past 20 years. The results indicate lost of the soil in the region in 1972 to 1992 as a result of land use changes.

Increased destruction during two past decades had been because of reducing vegetation. Rembold et al. (2000) investigated land cover changes in a 22 years period at Lakes region in south of Ethiopia by aerial photographs (1972) and classifying TM land sat images (1994). The analyses indicate that cultivated surface had been increased and more erosion had been occurred in new cultivated lands.

Unal et al. (2004) rendered to classify cultivated land and separation of pistachio garden and orchard from the other vegetation in Gaziantep province of Turkish. Ramos et al. (2007) tried to measure and identify of soil movement in various gradient using GPS, GIS and DEM. Also, Moschen et al. (2001) tried to separate agricultural area from non-agricultural area using controlled classification of integrated images of TM5 with IRS IC PAN land sat and ERS 2 radar by maximum likelihood method. In addition to this separation, they tried to separated wheat, maize farm and rangelands. Using AIF (adaptive image fusion) index, Fletcher (2005) used high resolution QuickBird satellite images to recognize citrus with black mold (capnodium citri) in Texas region of America and indentified it as a suitable method. Das et al. (2009) tried to prepare map for regions with reducing citrus production capacity in Meghalaya region of India using IRS satellite images. The map of regions where citrus production capacity had been reduced was prepared using soil erosion information, vegetation condition and humidity tension.

Classification of enhanced images from SBI, NDWI and NDVI performed with maximum likelihood method to recognize the regions where citrus culture had been reduced. The results of their study was the identification of 29 villages with humidity tension from heavy soils in steep stop which because of lacking nutrients balance, be followed by reducing citrus production.

Due to some changes which are created above time in olive cultivated surface preparing updated map of olive is one of the most important requirements in the management and region agricultural planning. With regard to this that land surveying required high cost and time and also preparing the map through aerial photographs is required to prepare aerial photograph which still along with high cost, use of satellite data along with remote sensing technique may be employed as a useful and effective tool to estimate crop area.

2. 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 4590 km^2. Administrative boundary of the study area includes Roodbar Township along southern portion of Guilan province, Iran. 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[1]) of different land covers and slicing and 2. by Minimum Distance method.

IRS images of July 2006 were used to map olive farming area and software ILWIS 3.3 Academic was used for processing data. 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. 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 DN-olive orchards were distinguished by the adding standard deviation to mean or diminishing of that ($\overline{X}(B_1, B_2, B_3) \pm 2S.d$).

After rounding the upper/lower limits of Olive spectrum reflexes, 22-26, 51-78 and 90-115 of spectrum reflexes limits had been considered for bands 1, 2 and 3 with olive class. In each band, Olive limits introduced to software and slicing method used to prepare Olive map. Final map of Olive obtained from crossing of these three maps. The olive orchards map has been crossed by training point map to calculate the accuracy of method.

In another way, taking into consideration training and auxiliary points of different land covers, the supervised classification of IRS images was done by Minimum Distance method. 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 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. Figure 1 shows the provided map of Olive orchards by minimum distance method with search radius 10 m. 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, producer's and user's accuracies and Cohen's Kappa coefficient (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).

The overall accuracy incorporates the major diagonal and gives the crude percentage of pixels correctly allocated. Producer's and user's accuracies detail the omission and commission errors, respectively. Kappa coefficient 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.

3. Results

Table 1 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. As we can see, in band 1, there is a shared DN between Olive spectrum reflexes and the other surface covers including barren land, hard wood and soft wood forests, non-olive vegetation and even urban regions. In band 2 of IRS satellite image, the greatest spectrum reflexes interference with olive class in non-olive vegetation and then soft wood forests and agricultural and paddle land in found. In this band, in $\overline{X}(B_1, B_2, B_3) \pm 2S.d$, spectrum reflexes interference of hard wood forest, bare lands and urban regions had been lasted, but still DN interference of water zones with Olive is seen. Also, in band 3, there is interference between broad leaf wood, non-olive vegetation, agricultural lands, residential and industrial regions with Olive, but soft wood DN interference and water zones with Olive had been lusted.

[1] Digital Number

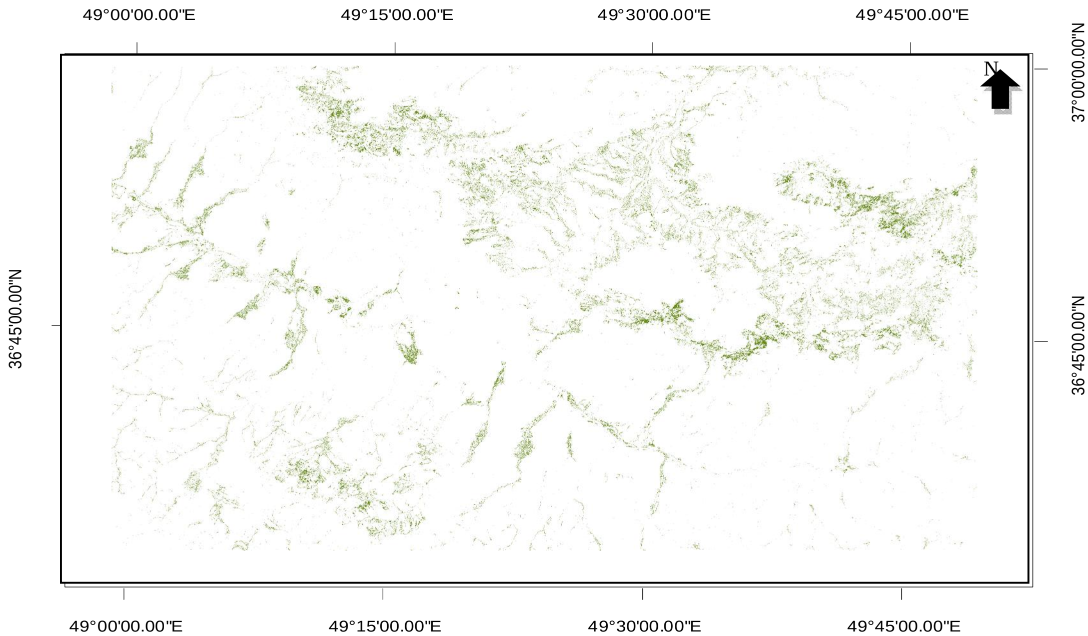

Figure 1. The provided map of Olive orchards by minimum distance method with search radius 10 m

Table 2 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. Only 0.89% of training points of broad leaf forest class in classified map of Olive by slicing method had olive class which is negligible. Also, no one training points soft wood forest were not placed in classified map of olive class. Also in surface cover classes of barren lands, urban and water, none of the training pixels classified in 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.

Confused matrix of minimum distance with search radius 1m (Tabel 3) indicate that this method have user's accuracy 67% in preparing Olive map. Table 4 indicated the confused matrix of minimum distance with search radius of 10m. User's accuracy in the classification of condensed Olive is 55.0%, in classification of low is 51.6% and in classification of total Olive orchards is 60.3%. 27.7% of training points of condensed Olive after classification had been classified in non-olive vegetation class and 11.4% in agricultural land class. Also, 17.3% of training point of low-dense Olive had been introduced as barren land after the classification .with regard to table 4 relating to confused matrix of minimum distance with search radius of 50m, increasing the radius from 10 to 50 m cause not change the accuracy of surface cover classes.

Confused matrix of minimum distance with search radius of 100 m (Table 5) indicates that user's accuracy in classification of dense Olive is 57.1%. 23.2 and 11.6% of training point of dense Olive class had been placed in non-olive vegetation class and agriculture and paddle land after the classification, respectively. Also, in low-dense Olive, 23.6% of training point had been placed in non-olive vegetation, agriculture and paddle land class, after the classification. In sum 64.3% of training point of Olive class had been placed in this class, after the classification.

Table 6 indicates the overall accuracy and Kappa coefficient in various search radiuses. The largest overall accuracy and Kappa coefficient is related to search radius 1 m, but this point is important that in 1 m search radius, only 0.1% of area had been classified (Table 7).

Table 1. The Mean, Standard Deviation and Upper and Lower Limits of spectral reflectances in training and auxiliary points of olive orchards class in the bands of IRS satellite images for image slicing

Band Number	$\bar{X}$ *			$S.d$ **			$\bar{X}-2S.d$			$\bar{X}+2S.d$		
	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 2. Crossing classified map of olive orchards by training points map

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

* 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 (%)

Table 3. Confused matrix of minimum distance method with search radius 1m

Surface cover class	O	O-l,d	F	F-s	P	R	C	W	U	Total number	Users Accuracy (%)
O	2	1	-	-	-	-	-	-	-	3	67.0
O-l,d	-	-	-	-	-	-	-	-	-	-	0
F	-	-	93	-	-	-	2	-	-	95	97.9
F-s	-	-	-	1	-	-	-	-	-	1	100
P	1	-	-	-	-	-	-	-	-	1	0
R	-	-	-	-	-	46	-	-	23	69	66.7
C	-	-	-	-	-	-	4	-	-	4	100
W	-	-	-	-	-	-	-	51	-	51	100
U	-	-	-	-	-	-	-	-	-	-	0
Total number	3	1	93	1	-	46	6	51	23	224	
Producer Accuracy (%)	66.7	0	100	100	-	100	66.7	100	0		

O Olive, O-l,d Low dense forest F Hard wood forest, F-s Soft wood forest, P Cultivation lands (paddy), R Bare lands, C Non olive-plant covers, W Water area and U Urban regions

Table 4. Confused matrix of minimum distance method with search radius 10 and 50 m

Surface cover class	O	O-l,d	F	F-s	P	R	C	W	U	Total number	Users Accuracy (%)
O	780	82	-	-	393	2	162	-	-	1419	55.0
O-l,d	18	146	-	-	44	49	19	-	7	283	51.6
F	29	3	8889	-	13	-	205	-	-	9139	97.3
F-s	-	-	-	208	-	-	-	-	-	208	100
P	113	11	-	-	110	1	9	-	1	245	44.9
R	-	-	-	88	-	18792	-	-	14221	33101	56.8
C	74	-	66	-	14	-	879	-	-	1033	85.1

W	-	-	-	7	-	-	-	6758	-	6765	99.9
U	-	1	-	-	-	263	-	-	327	591	55.3
Total number	1014	243	8955	303	574	19107	1274	6758	14556	52784	
Producer Accuracy (%)	76.9	60.9	99.3	68.6	19.2	98.3	69.0	100	2.2		

Table 5. Confused matrix of minimum distance method with search radius 100 m

Surface cover class	O	O-l,d	F	F-s	P	R	C	W	U	Total number	Users Accuracy (%)
O	1220	141	17	6	496	3	249	-	3	2135	57.1
O-l,d	18	305	22	-	66	2	48	-	20	481	63.4
F	38	5	17036	180	23	-	5984	-	-	23266	73.2
F-s	-	-	-	208	-	-	-	-	-	208	100
P	121	23	10	-	131	1	21	-	4	311	42.1
R	4	13	-	1853	4	30092	-	17	30080	62063	48.5
C	242	2	267	3	15	-	973	-	-	1502	64.8
W	-	-	-	26	-	-	-	8565	-	8591	99.7
U	4	10	-	39	5	385	-	-	826	1269	65.1
Total number	1647	499	17352	2315	740	30483	7275	8582	30933	99826	
Producer Accuracy (%)	74.1	61.1	98.1	9.0	17.7	98.7	13.4	99.8	97.2		

Table 6. Overall Accuracy and Kappa Coefficient of minimum distance method in the classification of different lands covers

search radius (m)	1	10, 50	100
Overall Accuracy	87.9	69.8	59.4
Kappa Coefficient	82.8	58.3	46.4

Table 7. The classified area of different lands covers as compared with basin area in different methods of supervised classification.

Kind of Lands Cover	Search Radius (m)		
	1	50 and 10	100
Olive	14.9	5887.3	19723.5
Low Dense Olive	4.8	6019.1	17535.5
Hard wood forest	205.1	26352.9	47334.4
Soft wood forest	1.1	1753.9	27916.7
Non olive-plant covers	9.2	5239.8	10610.3
Bare lands	206.0	78781.2	11523.7
Cultivation Lands (paddy)	12.8	7879.4	44607.8
Water area	10.7	2357.0	3272.0
Urban	0.0	78997.4	172134.1
Total Area (ha)	464.6	213268.0	354658.0
Unknown area of Basin (ha)	458534.9	245731.5	104341.5
Classified Area Ratio to Total Area of Basin (%)	0.1	46.5	77.3

4. Discussion

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 each consider in a separate class.

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, 2003). 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 (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%. 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.

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. Therefore, as the goal is to classify olive, user's accuracy is enjoying from the most importance in classification of this olive orchards. Ahadnejad Reveshty (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.

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.

5. 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.

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Corresponding Author:
Dr Ali Mohammadi Torkashvand
Department of Soil Science,
Agriculture Faculty,
Islamic Azad University-Rasht Branch
Torkashvand@iaurasht.ac.ir,
m.torkashvand54@yahoo.com

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