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Evaluation of LISS-III Sensor Data of IRS-P6 Satellite for Detection Saline Soils (Case Study: Najmabad Region)

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Abstract

Soil Salinity has been a large problem in arid and semi arid regions. Preparation of such maps is useful for Natural resource managers. Old methods of preparing such maps require a lot of time and cost. Multi-spectral remotely sensed dates due to the broad vision and repeating of these imageries is suitable for provide saline soil maps. This investigation is conducted to provide saline soil maps with sensor LISS-III of IRS-P6 satellite data, in Najmabad of Savojbolagh. Satellite images belonging to 25 June 2006. For enhancement of images, salt Indices, Digital Elevation Model (DEM), False Color Composite imageries (FCC) and Principal Component Analysis (PCA), were used. Supervised classification method includes Box classifier, Minimum Distance, Minimum Mahalanobis Distance and Maximum Likelihood classifier, DEM, PCA1, PCA4 and Saline Indices (SI) were used. After classification, the class map salinity S0, S1, S2, S3 S4, were prepared. The results shows highest overall accuracy and kappa coefficient for the maximum Likelihood classifier estimate, respectively 99% and 97% and the lowest overall accuracy and kappa coefficient for PCA1 estimate, respectively 1% and 0% were obtained. Using Digital Elevation Model (DEM) also due to the difference in height position to the separation of saline lands is usefully. Most spectral interference related to non-saline soils and low saline soil. From among indices INT2 and PVI greatest ability to segregate is salty soils (especially classes S0 and S1).

***Keywords**:* LISS-III Sensor; Saline soil maps; Classification; Salt indices; DEM; PCA

1. Introduction

Soil salinity is a phenomenon that most of arid and semi arid areas occur and is an important factor in soil degradation. Since Iran is among countries in arid regions, around 15% of desert areas are surface of its makes up. Ghasemi et al. 1995 have expressed saline lands around the world 1 billion hectares.

This value in Iran and Egypt has been expressed about 30% that including primary and secondary salinity is. Therefore, investigation of soil salinity is great importance. If bare soil salinity is directly with the help of satellite data is determined and If the soil surface is covered by vegetation cover, type to condition of their growth and development that is affected by salinity could be with the help of satellite data, they can be identified. Generally identified with high salinity and moderate to low salinity areas (in the early stages of salinity) are to be more successful. For example, when McGowen (1996) the TM data used to estimate than-expected gain from saline areas. On the other estimates are lower than expected levels of salt with remote sensing due to the slightly saline soils mixed with non-saline soils has been. Field studies and reflections spectral measurements show that in most cases reflect in visible and infrared of saline soils is more than non-saline soils. The main factors that influence reflections are quantity, mineralogy, moist of soil, color and surface roughness. (Mougenot et al., 1993)

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Surface phenomena in areas affected by salt and this factor may cause changes in soil and can be reflected when using remote sensing data to detect these soils can be used. Moreau (1996) in Bolivia Using Map TM images soils affected by salinity and alkalin can be obtained. Siegal et al (1980) for the diagnosis of Sulphate Soils with a thermal band can be suitable. Farifteh & Farshad (2002) knew Landsat and ASTER suitable for studying the soil properties and salinity and soil moisture. Alavi Panah et al (1998) in their research thermal band TM6 plays a key role in the diagnosis of gypsy soils pointed out in Yazd, Ardakan. Wang et al (2002) suggest that a better evaluation of plant response to salinity is one of the possible ways to measure the use of plant salt tolerance is an indiuces. Soil salinity affected of topography and geomorphology. For example, more saline soils in regions such as the playa and are rarely seen in these soils are high points. Therefore, the use of digital elevation models (DEM) for land application of soils has a large separation This study identified salinity-affected soils using LISS-III image sensor area is dry Najmabadi Savojbolagh.

2. Material and Methods

The study area in north-west of Tehran and is located south-east of the city Hashtgerd. Study area with metric coordinate system (UTM) is 4405628 wests, 470398 to east and 3960539 norths to 3960578 south. Physiographic region includes plains, hills, flat land and an average height of 1153 meters (Figure 1).

This climate zone classification system Ambereghe and DeMartin is cold dry and dry respectively. (source: Najmabad climatic station). Sub orders Classification of soils in is Typic Torriorthents and Haplosalids Typic and Xeric Torriothents.

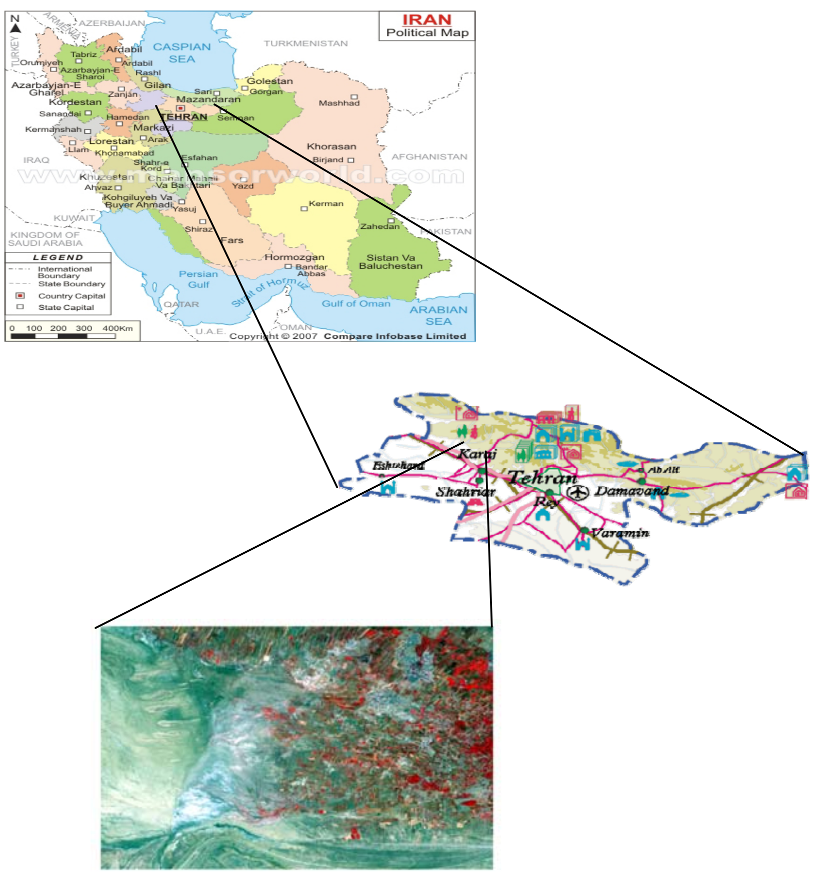


Fig. 1. The location of study area in Iran

In this study, the first keneral LISS_III satellite sensor data IRS_P6Resource related to the study area was selected. View of this sensor property is given in Table 1.

Table 1. Property of LISS-III sensor of IRS_P6 Resource

LISS_III		
23.5 meter	BAND GREEN	Spatial resolution
23.5 meter	BAND RED	
23.5 meter	BAND NIR	
23.5 meter	BAND SWIR	
140 kilometer	All bands	SWATH
7 bit	All bands	Radiometric resolution
520-590 nm	BAND GREEN	Microwave
620-680 nm	BAND RED	
680-770 nm	BAND NIR	
1550-1700 nm	BAND SWIR	
1*6000	BAND GREEN	CCD Arrays
1*6000	BAND RED	
1*6000	BAND NIR	
1*6000	BAND SWIR	
2006/june/16		date
916		row
1244		column
systematic		Level correction
GEOTIFF		format

The pre-processing was carried out on images. For this purpose, images of geometric errors exist, Radiometric and atmospheric were investigated.

Studies show geometric corrections are needed. Geometric data to assess the status of drainage layer, 1:25000 digital maps were used. Mark on the drainage layer and satellite images indicates geometric mismatch satellite data with maps was necessary to correct them. On the other hand the lack of topography, imageries doesn't need to correct of ortho correction. To georeference imageries, 14 Ground Control Points (GCP) were used. These points to the similarity of points on digital maps and satellite imageries have been selected. RMSE as the rate from less than 5 pixels on the image and 12 meters on the ground, that this rate is acceptable.

Supervised classification on the satellite imageries with different classification methods and different approaches was done and the accuracy of each method and approaches were done. Finally salinity maps are prepared and then maps must be accurate with the ground truth map to investigate the accuracy of maps produced to ensure. Using the slope map, geomorphologic and geological units were selected uniformly and each of these units working with random sampling-systematic diggings soil profiles was determined. The property of digging profile had been shown in Table 2 and Figure 2 show the location of soil profiles.

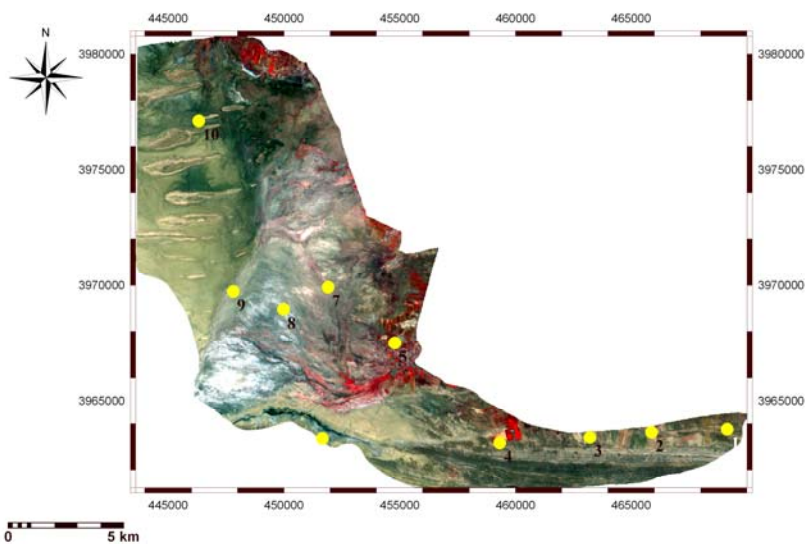


Fig. 2. Sampling point and soil profiles at study region

Table 2. The properties of soils

x	y	number	HORIZON	DEEP	tick	EC	SAR	PH	C(%)	OC(%)	TVV	c	si	s	TEXTURE	Caso	landuse
469120	3963773	1	A	0-5	5.	5.45	0.14	7.4	0.48	0.82	28.4	14.0	22.8	63.2	Sandy loam	0.00	range poor
			C1	5-45	40	0.7	0.17	7.3	0.09	0.16	34.0	14.0	18.8	67.2	Sandy loam	0.00	
			C2	100-45	55	2.34	0.11	7.2	0.09	0.16	29.9	12.0	18.8	69.2	Sandy loam	0.00	
465859	3963646	2	A	0-3	3	6.54	0.12	7.2	0.29	0.50	37.9	22.0	32.8	45.2	Clay	3.33	bare land
			C1	3_25	22	2.31	0.11	7.3	0.19	0.33	29.2	20.0	34.8	45.2	Clay	3.26	
			C2	25-115	90	2.33	0.11	7.3	0.09	0.16	30.7	16.0	22.8	61.2	Clay	3.23	
463198	3963431	3	A	0-5	5	4.62	0.10	7.6	0.58	1.00	34.4	22.8	23.6	53.6	Sandy clay loam	0.00	range poor
			C1	5-55	50	0.49	0.12	7.5	0.20	0.50	38.9	20.8	11.6	67.6	Sandy clay loam	0.00	
			C2	55-95	40	2.6	0.47	7.6	0.19	0.33	32.9	20.8	17.6	61.6	Sandy clay loam	0.00	
459307	3963182	4	A	7-0	7	1.17	0.09	7.2	0.48	0.82	31.0	12.0	18.7	69.2	Sandy loan	0.00	dry farming
			C1	7_27	20	0.94	0.03	7.3	0.38	0.67	31.0	14.0	16.8	69.2	Sandy loan	0.00	
			C2	27-87	60	2.31	0.11	7.5	0.48	0.82	30.7	14.0	14.8	71.2	Sandy loam	0.00	
451651	3963374	5	A	5-0	5	2.67	0.11	7.0	0.29	0.50	31.1	24.0	21.2	54.8	Sandy loam	3.71	garden
			C1	5_26	21	2.33	0.13	7.0	0.19	0.33	33.2	22.0	21.2	56.8	Sandy loam	3.30	
			C2	26-126	100	4.23	0.16	7.1	0.09	0.16	34.0	20.0	21.2	58.8	Sandy loam	0.00	
454771	3967502	6	A	0-2	2	17.5	17.47	7.4	0.38	0.67	39.0	14.0	16.8	69.2	Sandy loam	4.43	bare land
			C1	2-32	30	15.0	12.70	7.6	0.48	0.82	39.0	14.0	14.8	72.2	Sandy loam	4.43	
			C2	32-122	90	18.7	19.80	7.2	0.48	0.67	33.2	14.8	7.6	77.6	Sandy loam	4.90	
451894	3969911	7	A	0-7	7	15.7	13.20	7.6	0.38	0.50	21.6	56.0	27.2	16.8	Clay	0.00	bare land
			C1	7-54	47	74.0	16.60	7.7	0.29	0.50	22.5	46.0	39.2	14.8	Clay	0.00	
			C2	54-110	56	39.3	11.10	7.6	0.29	0.33	23.2	48.0	37.2	14.8	Clay	30.09	
449970	3968959	8	A	0-5	5	30.9	25.00	7.7	0.19	0.83	18.6	50.0	37.2	12.8	Clay	0.00	high salty
			C1	5-45	40	82.0	27.90	7.5	0.48	0.67	18.0	44.0	37.2	18.8	Clay	0.00	
			C2	45-105	60	100.4	46.70	7.6	0.38	0.67	18.0	46.0	37.2	16.8	Clay	0.00	
447804	3969725	9	A	0-4	4	7.5	1.00	7.4	0.38	0.67	21.6	54.0	33.2	12.8	Clay	0.00	range poor
			C1	4_29	25	12.0	1.00	7.4	0.38	0.67	22.5	70.0	25.2	4.8	Clay	0.00	
			C2	29-44	15	44.5	10.00	7.3	0.38	0.67	23.3	50.0	25.2	24.8	Clay	4.91	
			C3	44-120	76	85.0	27.90	7.3	0.29	0.50	23.8	54.0	15.2	30.0	Clay	4.95	
446309	3977121	10	A	0-5	5	8.1	15.40	7.4	0.29	0.50	21.0	52.0	25.5	22.8	Clay	3.80	range medium
			C	5-105	100	69.8	21.40	7.5	0.19	0.33	21.6	50.0	23.2	26.8	clay	3.30	

The study area landuse classes from satellite imageries extracted with the help of accessories data and field studies and classes of salinity were obtained. The results of laboratory studies point's salinity, classes 0, 4, 8, 16, 32, 64 ds / m was defined and each points in its own salinity classes were gotten and The ground truth map were created. At this stage, imageries with different classification algorithms were done. At this stage to classification, of algorithms using methods is box classifier, minimum distance, minimum Mahalanobis distance, and maximum likelihood and other classification method is combining satellite imagery with a map list as salinity indices; Principal Component Analysis (PCA1 & PCA4) and Digital Elevation Model (DEM). Table 3 shows salinity indices used in this study and the used methods.

Table 3. Salinity indices and their calculations

Salinity	Formula	Reference
BI[1]	$\sqrt{R^2+NIR^2}$	Gao (1996)
INT2[2]	$\frac{G+R+NIR}{2}$	Haboudane et al. (2004)
INT1[3]	$\frac{Green+\mathrm{Re}\,d}{2}$	Haboudane et al. (2004)
SI1[4]	$\sqrt{G*R}$	Markham & Barker, 1985)
SI2	$\sqrt{G^2+R^2+NIR^2}$	Markham & Barker, 1985)
SI3	$\sqrt{G^2+R^2}$	Markham & Barker, 1985)
PVI[5]	sin(b)NIR-cos(b)RED	Wiegand & Richardson 1997
VNIR1[6]	$\frac{NIR-G}{NIR+G}$	Leprieur et al. (1994)
TVI[7]	$\frac{NIR-R}{NIR+R}+0.5$	Broge and Leblanc (2000)

1- Brightness index
2- Intensity within the visible spectral range
3- Intensity within the VIS_NIR spectral range
4- Saline Index one
5- Perpendicular Vegetation Index
6- Vegetation Normalized infrared Ratio
7- Triangular Vegetation Index

The satellite imageries supervised classification was performed and each class algorithm to salinity map produced and crossed with the ground truth map and error matrix was prepared. Then algorithm the highest accuracy was used for mapping salinity. Table 4 classification algorithms have been shown.

Table 4. Algorithms for classification

Collection of bands	Algorithm
box classification method	1
minimum distance method	2
maximum liklihood method	3
minimum mahalanobis distance method	4
DEM+ total bands	5
PCA1+ total bands	6
PCA4+ total bands	7
Indices + total bands salt	8

Figure 3 spectral reflectance of sampling points have been shown.

According to the figure 3, saline soils are reflected waves highest in visible bands and lowest in the near-infrared bands. vegetation cover, depending on percentage of plant coating, are reflected the lowest in visible bands and highest in near-infrared bands (due to unfavorable conditions for plant growth, vegetation zone average less than 30% and poor vegetation cover in some areas even less than 10% is therefore reflected the soil is and have more effect only where irrigation and gardens as there is dense vegetation cover is denser). Bareland in the area, particularly the red waves, visible spectrum are the highest reflection. Because the land remain fallow vegetation residue on the surface have more reflects the near infrared.

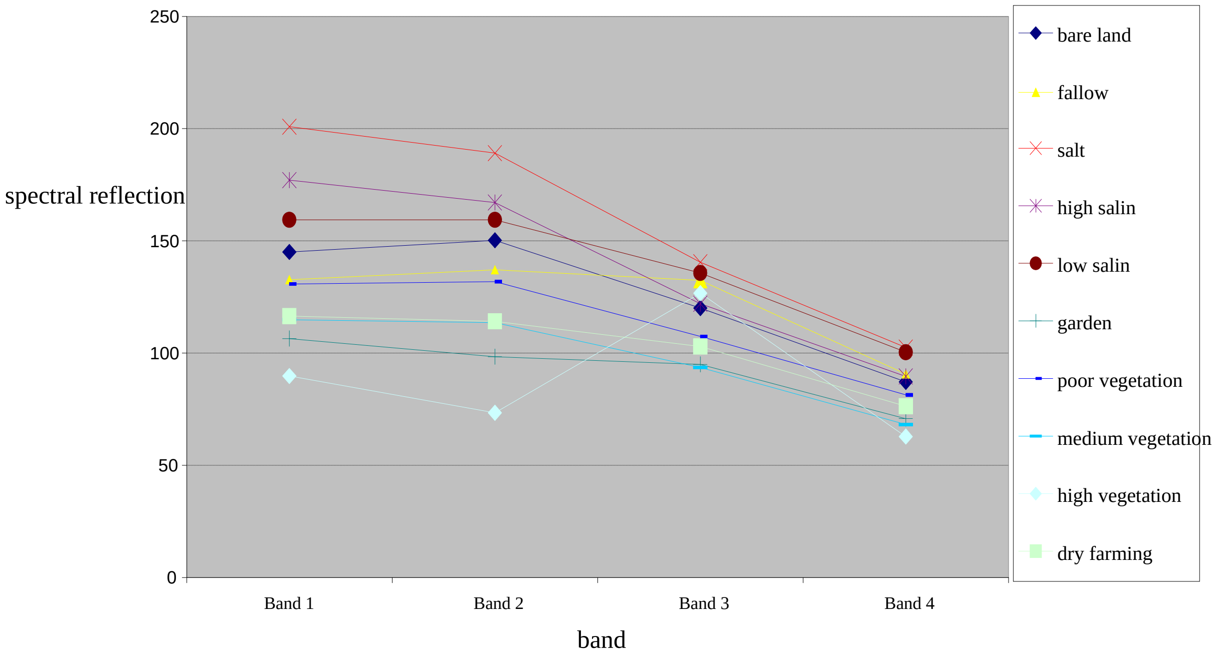


Fig. 3. Spectral reflection of sampling points

3. Results and Discussion

Figure 4, two-dimensional (scatter gram) nir band to red band and training samples is shown. With two-dimensional diagram that showing pixels selected action training samples and Training samples were gotten from all of imageries. Then with survey of classes and accessories data, similar classes were merged, So that, from 28 primary classes after merging similar classes, their numbers were reduced to nine classes. With considering two-dimensional diagram of training samples, medium Vegetation in the triangle vertex and triangle rule centered near latitude high vegetation samples and bare soil on the soil line are located. In the end, the soil line placed saline soils.

Then total of classification on imageries were done. The usually algorithms to classification is box classifier, minimum distance, minimum mahalanobis distance and maximum likelihood classification. Figures 5 to 8 the maps what has built with these classification methods have been shown.

In parts of the white box classifier areas that are not classified. At minimum distance method the areas of salinity (S2) is bigger than the Ground Trust. At minim Mahalanobis distance method, non-saline areas (S0) are bigger than Ground Trust but at maximum likelihood classification method is more similar to Ground Trust.

Other classification method is, combining satellite imagery with a map list as salinity indices; Principal Component Analysis (PCA1 & PCA4) and Digital Elevation Model (DEM). Principal component analysis of image enhancement techniques is useful to extract important information from them.

The first component of this conversion is the highest correlation with total percentage of bands. This method is a linear transformation in which the spatial coordinate axes so few bands are suffering from the first rotation axis in the direction of maximum variance takes values band. In the next axis perpendicular to the first axis is placed along the remaining variance. Thus, the band participated in the transformation n, n new band (PCA1 to PCA4) is created that no correlation is high and the matrix contains n rows and m columns will be formed. Figure 9 bands of data storage components in the PCA shows. Information highest bands (99%) in PCA1 there knowledge about the other components of this amount is reduced to about 0.04% in PCA4 seems. In the first PCA component bands of all information is shared. Figures 10 to 13 show the maps of the classification algorithms.

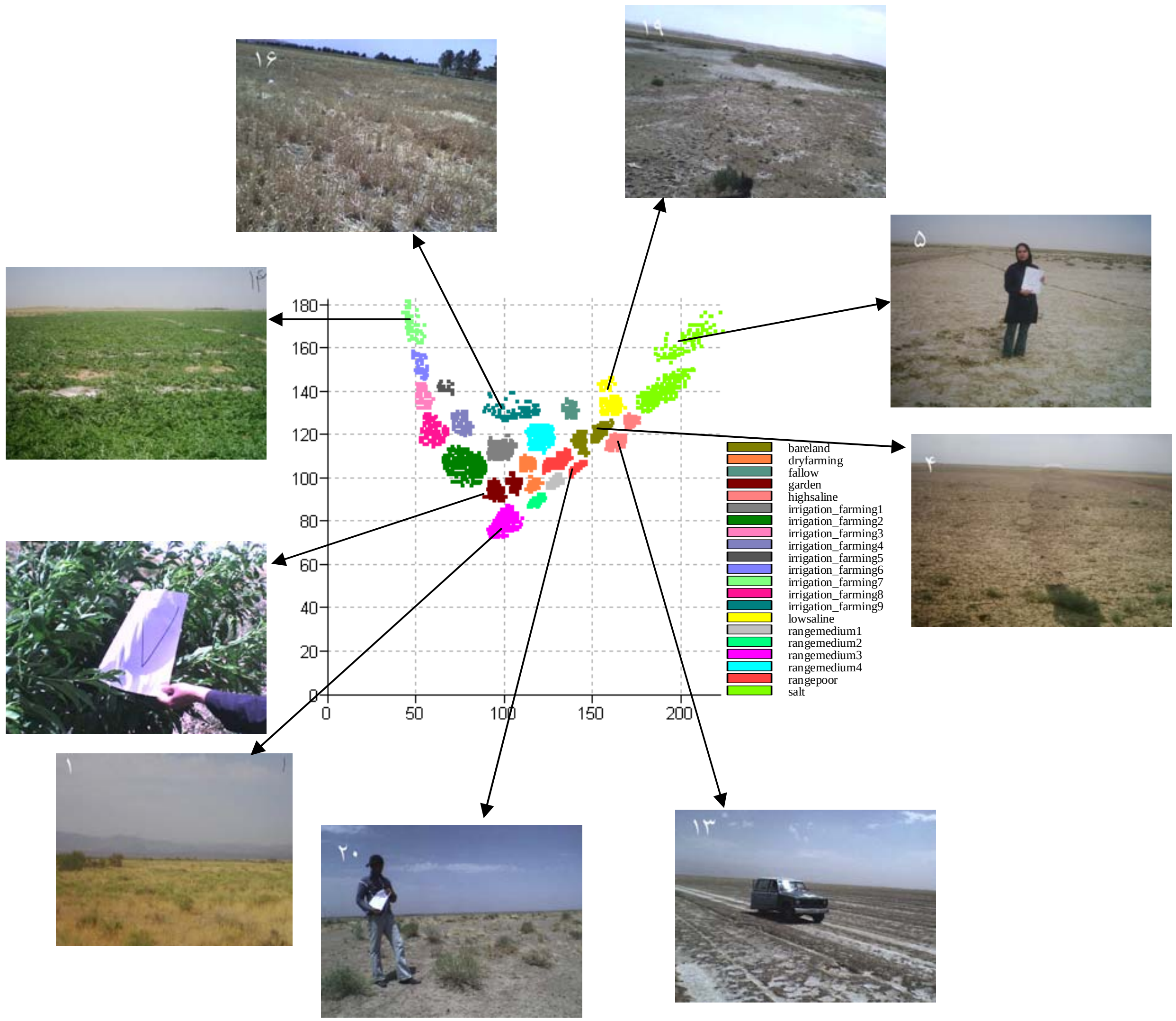


Fig. 4. Feature space plot (scatter gram) of B3 to B2 and training samples

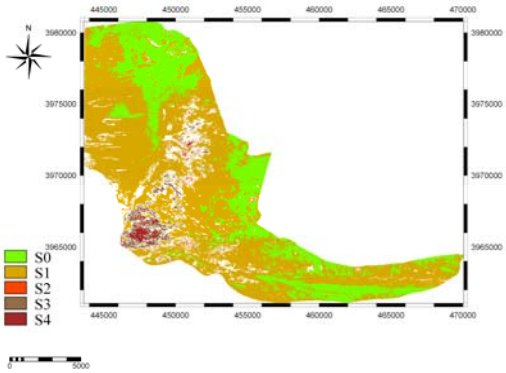


Fig. 5. Soil map with box classifier method

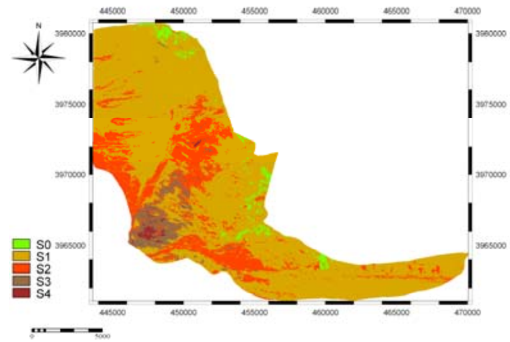


Fig. 6. Soil map with minimum distance method

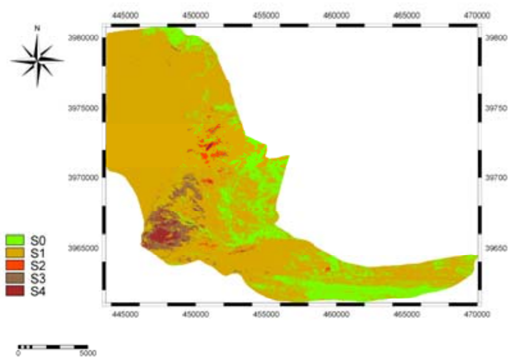


Fig. 7. Soil map with minimum malananobis distance method

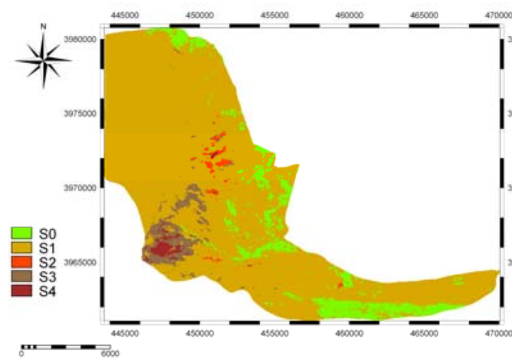


Fig. 8. Soil map with maximum likelihood method

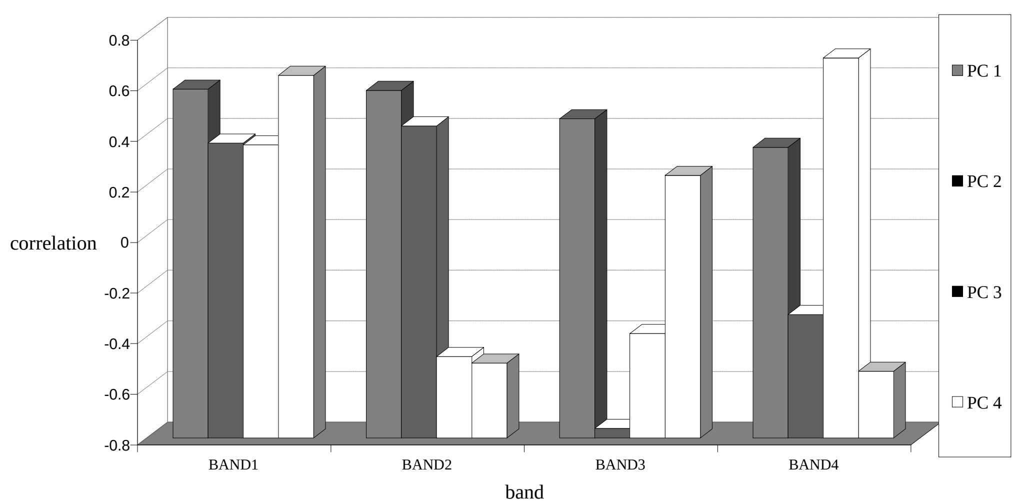


Fig. 9. Correlation of PCA with bands

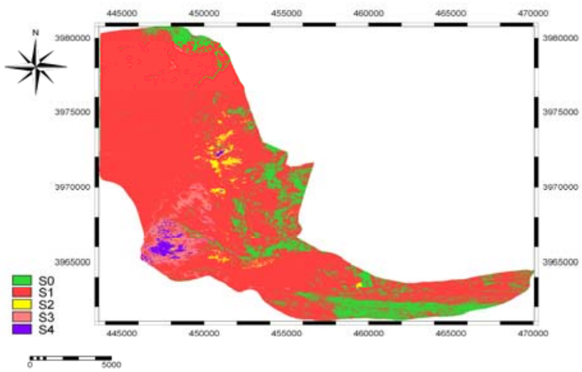


Fig. 10. Soil map with combination of total bands and salinity indices

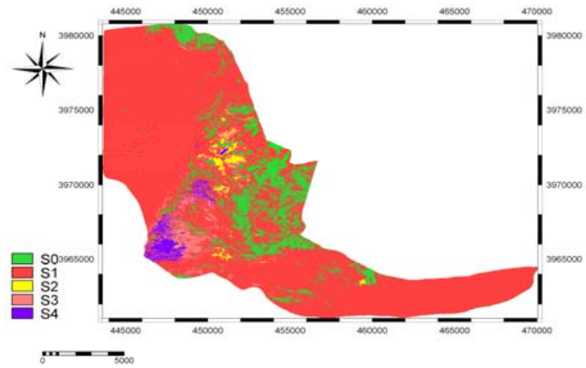
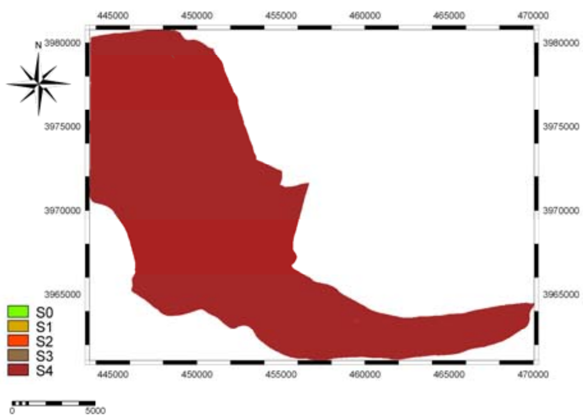


Fig. 11. Soil map with combination of total bands and DEM



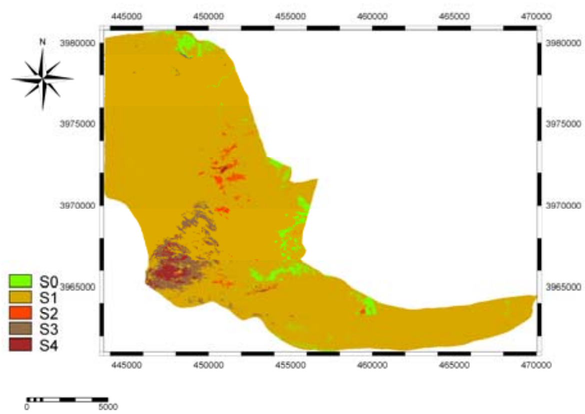


Fig. 12. Soil map with combination of total bands and PCA1

Fig. 13. Soil map with

Figure 14 shows graphs the overall accuracy and kappa coefficient for each classification algorithms. The diagram above the highest overall accuracy and kappa coefficient is related to the method of maximum likelihood classification. And the lowest overall accuracy and kappa coefficient is related to the use of PCA1.

PCA1 of LISS_III imagery has more information of all the bands to a stored.

Saline soils reflect the most in visible bands and least reflected in the infrared bands. Because most information stored in visible bands is PCA4 so use PCA1 not effective in separating saline soils. Table 4 shows matrix error in maximum likelihood classification.

Table 4. Matrix error of maximum likelihood classification

saline class	S0	S1	S2	S3	S4	producer accuracy	SUM
S0	33331	915	0	0	0	0.97	34246
S1	524	302354	24	192	0	1	303094
S2	0	112	3131	9	3	0.96	3255
S3	0	315	11	13722	40	0.97	14088
S4	0	38	10	128	3453	0.95	3629
user accuracy	0.98	1	0.99	0.98	0.99		
SUM	34246	303094	3255	14088	3629		358312

According to Table 4, soils with low salinity (S1) are maximum range of interaction with soils without salinity (S0). Also because of spectral composition in high and medium saline soils, these soils could not be well separated from each other. Fig. 15 saline soil map provided by maximum likelihood classification have shown.

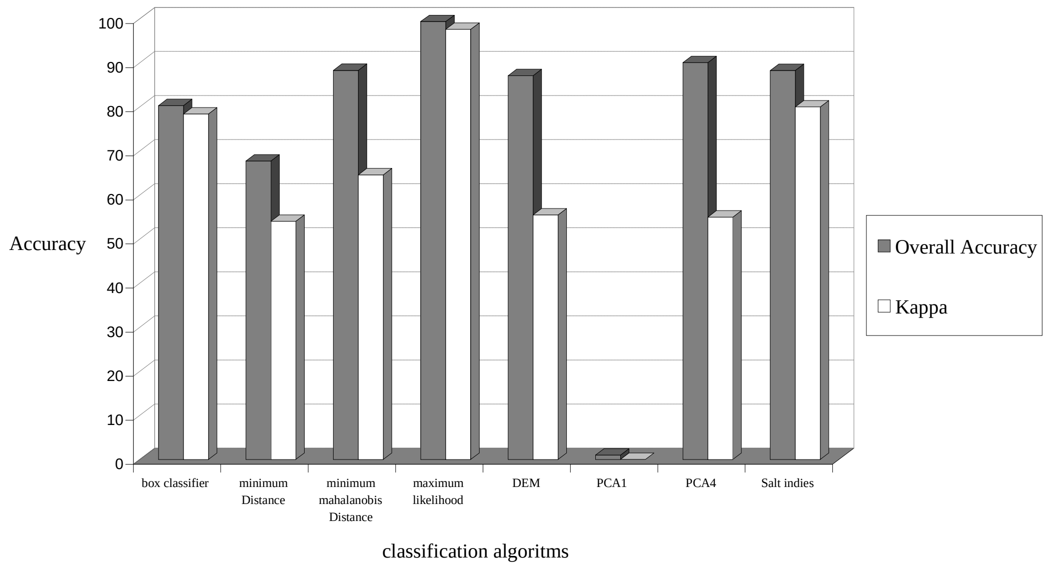


Fig. 14. Overall accuracy and Kappa coefficient in classification algoritms

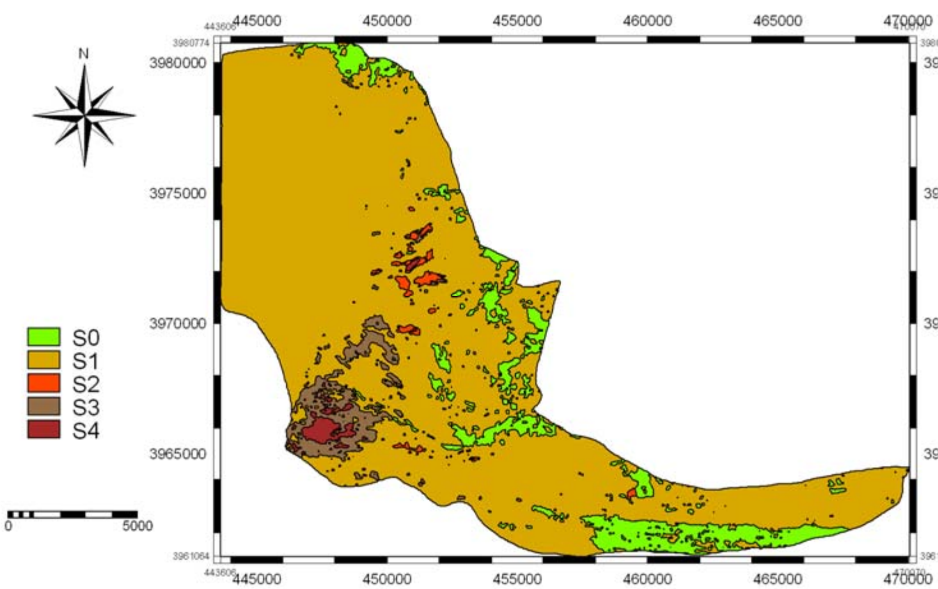


Fig. 15. Saline soil map with maximum likelihood classification

Indices of satellite imageries are the detection methods. With the help of indices, depending on the purpose index, can detect the earth surface phenomena, and phenomena are better diagnosis that looking for. One of the algorithms used in this study is the use of salinity indices. Although other indices of salinity used with accuracy and kappa coefficient of 90% with acceptable accuracy are in distinguishing saline lands, but because it INT2 and PVI index than other indices, with the overall accuracy and kappa coefficient is greater. Other indices are not interpretation. Figure 16 shows overall accuracy and Kappa coefficient of salinity indices. Figure 17 (a and b) shows PVI and INT2 indices that could have been more enhancement of salinity.

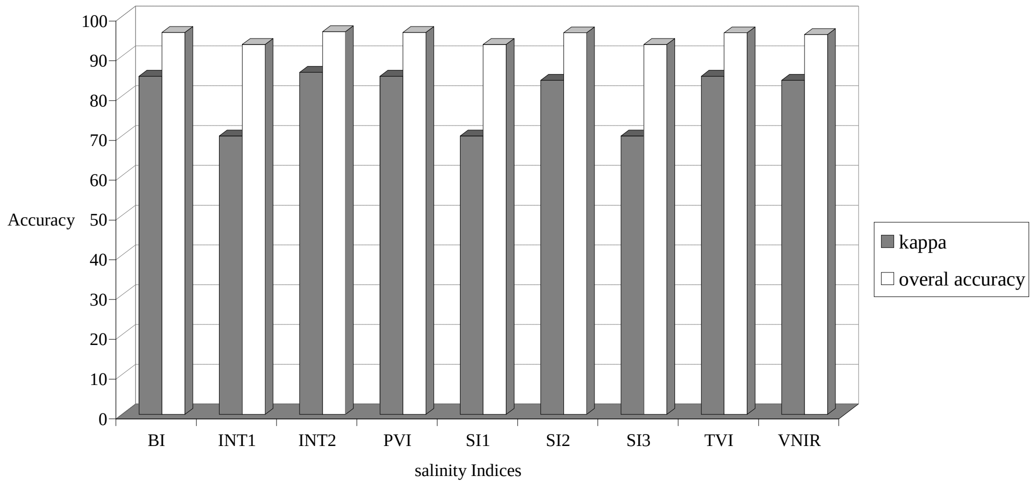


Fig. 16. Overall accuracy and Kappa coefficient of salinity Indices

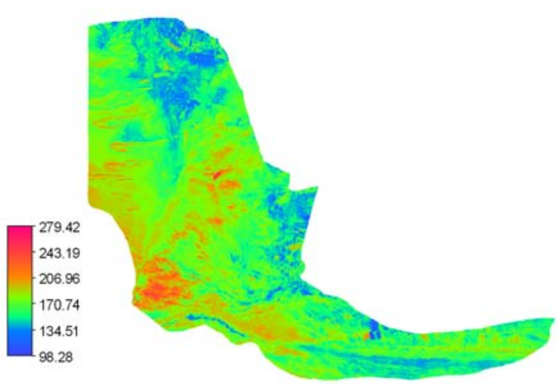


Fig. 17a. Salinity indices of PVI

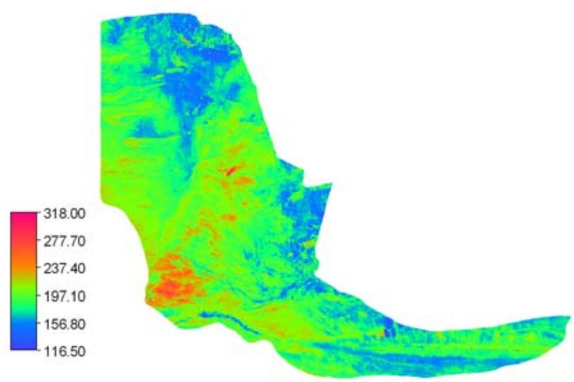


Fig. 17b. Salinity indices of INT2

These indices have highest value in salt and high salinity and the lowest levels are related to vegetation covers. INT2 to PVI closer than saline soils from non-saline soils has been separated. In INT2 value for salt and high salinity is 318 and for vegetation cover is 116.5, while PVI had value for salt and high salinity 279.4 and for vegetation cover 96.2.

Table 5 shows the area of saline classes. With note to this table, S1 class has the most areas. The most area is about salinity whit class 4-8 ds/m. Figure 18 shows comparison of producer accuracy and user accuracy.

Table 5. The area of saline classes.

Soil class	Physiographic unit	Area(ha)	texture	Salinity(ds/m)
S0	2, 3, 4 and 7	1945.787	Sandy loam	4>
S1	7	17456.62	Sandy loam	4-8
S2	6 and 7	182.5325	clay	8-16
S3	5 and 7	807.5454	clay	16-32
S4	7	200.9237	clay	<32

2: Hill 3: terraces 4: pediment 5: fluvial plain 6: lowland
7: flood plain

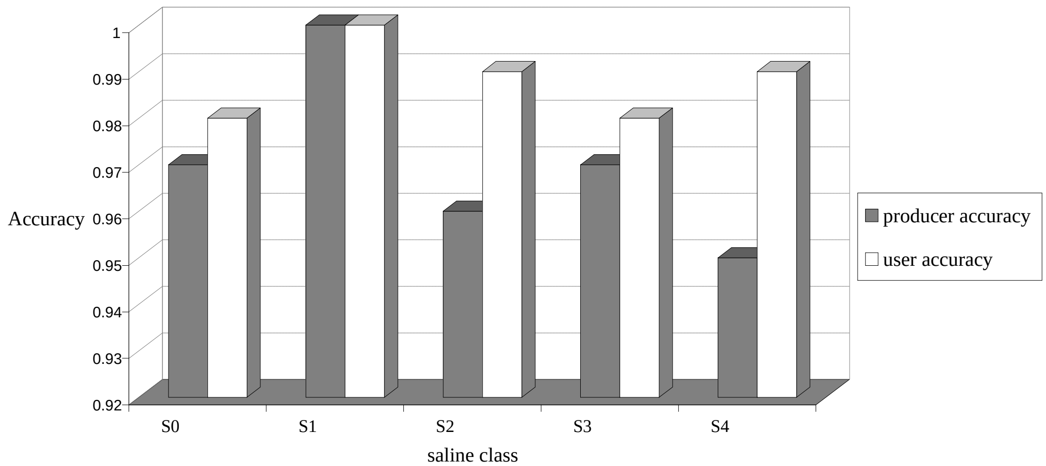


Fig. 18. Comparison of producer accuracy and user accuracy accuracy

4. Conclusion

The views of Anderson (1976), acceptable accuracy in classification using satellite imagery data classes should be more than 85%. Nasiri (1996) expresses acceptable accuracy should be higher than 85%. The results show that the highest accuracy to an acceptable maximum likelihood classification method is so maximum likelihood algorithm could separate salinity soils from non-salinity soils. This result is consistent to Alavipanah (2001), Alavipanah et al (2005), Khodadadi (2006), Matinfar et al (2006) and Janfaza (2007). Considering the proximity of the overall accuracy and kappa coefficient, which can receive the maximum likelihood classification method, has acceptable accuracy in salinity map is produced. The fact that the kappa coefficient classification accuracy than the case when an image is randomly classification. Kappa coefficient gives about 97% salinity mapping method, the maximum likelihood classification in 99% overall accuracy is very well. This result Janfaza (2007) and Movahedian (2005) is consistent. Using DEM and salinity indices are also able to separate saline soils. It shows the importance of DEM to mapping saline soils. The reason could be the cause of non-saline and saline lands in terms of height situations are different. This situation has caused the difference in approach to DEM resolution of these areas. This result Movahedian (2005), Matinfar et al (2006), Masoud (2006) and Liu (2005) is consistent.

The first component (PCA1) of all bands in a ratio of information are stored so saline soils have the most reflection in visible bands and less in nir bands, we have to use those component of PCA that have reserved information content of visible bands.

Low salinity (S1) is formed highest area of lands. The highest accuracy in classification of low salinity class map can be obtained from sensor data, the criterion of reality salinity in the study area considered. Despite the low number of bands of this sensor and the low band width, the sensor spectral separation is as successful; indicating the efficiency of this sensor to providing salinity maps. That defines the best approach to classification (maximum likelihood classification method), User accuracy and producer accuracy in all salinity classes is more than 90% so, LISS-III sensor has full accuracy to classification of these classes.

References

Alavipanah, S.K. Poyafar., A.M., Khalilpor, S.A., Mashadi., N., 2001. Study of vegetation cover and saline soil maps with remote sensing and geography information system (case study: Salt river of Karaj). Journal of Research In Geography. 6:1:69-86.

Alavipanah, S.K., Morgano, D., 1998. Analysis of Thermal band TM at study of desert soils.). Journal of Desert. Vol 3. NO 1 & 2., pp 51-64.

Alavipanah, S.K., Khodaei, K., Jafarbiglo, M., 2005. Capability of Remotely sensed in the study of water Quality of the both sides of Urumieh lake Causeway. Journal of Research In Geography,. No. 53, pp 57-69.

Farifteh, J., A. Farshad, R.,J. George, 2006. Assessing salt-affected soils using remote sensing, Solute modeling and geophysics, Geothermal, 130: 191-206.
Janfaza, E., 2006. Study of salinity and quality with digital data of satellite in Damghan playa. M.Sc. thesis,University of Tehran, 196pp.(In Persian).
Khodadadi, M., 2006. provide saline and alkaline soil maps with remote sensing and geography information system (case study: Chamestan region). M.Sc. thesis, University of Tehran, 217pp. (In Persian).
Liu, X. J. Peterson, Z. Zhang, & S.Chandra, 2005. Improving soil salinity prediction with high resolution DEM derived from LIDAR data, the 9th international symposium on physical measurements and signature in Remote Sensing. China, pp. 201-215.
Movahedian, M., 2005. The Preparation of soil Infected soil Data Maps With use of ETM Data in part of Qazvin Plain. M.Sc. thesis, University of Tehran.211pp. (In Persian).
Matinfar, H., 2006. Investigation of ASTER & LISS-III & ETM & TM & MSS sensor for soil Identification base on land studies with GIS in Kashan Area. Ph.D. Dissertation. University of Tehran, 311 pp.
Movahedian, M., 2005. The Preparation of soil Infected soil Data Maps With use of ETM Data in part of Qazvin Plain. M.Sc. thesis, University of Tehran, 186 pp.

McGowen, I., & S. Mallyon, 1996. Detection of Dry land salinity using single and multi-temporal Landsat imagery. Proceedings of the 8th Australasian Remote Sensing Conference, Canberra, pp. 26-34.
Moreau, S.S., 1996 Application of remote sensing and GIS to the mapping of saline\sodic soils and evaluation of codification risks in the Province of Villarreal, central Altiplano, Bolivia. The 4th International Symposium on High Mountain Remote Sensing Cartography. Siegel, B., & Gillespie. 1980 Remote Sensing in Geology. New York Wiley, 222 pp.
Mougenot, B., Pouget, M, & Epema, G., 1993. Remote sensing of salt affect soil. Remote sensing Reviews. 7: 241-259.
Masoud, A, & K.Kike, 2006, Arid land Stalinization detected by remotely – sensed land cover changes, A case study in the Siva region, N W Egypt. Journal of Arid Environments , 66: 151-167
Nassiri, A., 1998. Spatial and Spectral classification for provide land use map. Agriculture Ministry, Programming and Deputy and General Administration of Statistics and Information. No 77/26: 45.
Wang. D., C . Wilson. & Shannon. 2002, Interpretation of salinity and irrigation effects on soybean canopy reflectance in visible and near-infrared spectrum domain, International Journal of remote sensing. vol.23, No. 5: 485-492.