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Assessing Soil surface Salinity with Basic pixel Data Sensor TM

Mohammad Zeinali*, Ali Asghar Jaafarzadeh**, Farzin Shahbazi, Shahin Oustan*** and Khalil Valizadeh Kamran*******

**Ph.D. Student, Department of Soil Science, University of Tabriz, Tabriz, Iran*
***Professor, Department of Soil Science, University of Tabriz, Tabriz, Iran*
****Associate Professor, Department of Soil Science, University of Tabriz, Tabriz, Iran*
***** Associate Professor, Department of Geographic, University of Tabriz, Tabriz, Iran*

(Corresponding author: Mohammad Zeinali)
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ABSTRACT: Soil salinity and salinization of lands, as one of the main problems of agriculture, has paramount importance and can be avoided with proper understanding of its progress. This is the first step in identifying areas of salt and salt mapping in these soils. With the development of remote sensing technology and efficient use of satellite imaging, this study compared the salinity maps produced by a variety of classification image algorithms (Maximum likelihood, Minimum distance and Parallelepiped) by Land sat 5 TM satellite data in the East of Khoy. In this study, 269soil samples were analyzed and the results obtained were implemented on TM image. For initial identification, topography maps, ENVI 4.8 software and satellite image processing were used but to increase the accuracy, geometric correction was performed with specific locations using GPS. The results indicate the existence of a correlation between bands 1, 4 and 5TMimage with soil salinity data and classification algorithms, using the Pixel-based method. The highest accuracy of the map is the maximum likelihood algorithm. This map is also consistent with field observations of different classes of soil salinity measurement and shows high accuracy of the algorithm among soil salinity maps.

Key words: Pixel-based, Classification Algorithm, Salinity, TM Sensor, Khoy.

INTRODUCTION

The distribution of soil salinity covers a wide range of countries and also threatens adjacent lands. This is the first step in identifying areas of salt and salt mapping of these soils. On average, 20% of the world's irrigated lands are affected by salts, but this figure increases to more than 30% in countries such as Egypt, Iran and Argentina (Ghassemi *et al* 1995). In the future, more Dry lands will be put into agricultural production because of increasing population pressure. This will mainly be achieved with irrigation and will thus expand the salinization hazard. There are many ways to do that, each is remarkable according to the existing facilities. Kalra and Joshi (1996) determined the ability of images from Lands at satellite data, spot and IRS in recognition of soil salinity. They showed that the resolution of the sensor and the data collection season directly determines the class of soil salinity. Northrop (1982) concluded that Land sat Satellite could be used to detect salinity features when it is incorporated with extensive ground data. He also stated that the techniques used had limitations on accuracy due to the spatial and spectral resolutions of the Multi-Spectral Scanner (MSS) sensor. Csillag and Beil (1993) used a modified stepwise principal components slope with mean analysis to access the effectiveness of individual bands in discriminating salinity status from the high resolution spectra provided by the narrow absorption band (10nm) within the range of 495-239 nm. Csillag and Beil (1993) worked with a large data set from California and Hungary. They achieved 80-90% overall recognition accuracy. Abdul Hamid (1992) studied the north area of the Nile Delta (Egypt) to identify are as devoid of vegetation with data sensor MSS, TM and showed thatreflectivebands1 to 5 and 7 bands of TM have a high positive correlation with soil electrical conductivity. However, the band 6 (thermal) is only effective in soils with electrical conductivity of more than 50dS/m. Josh and Sahai (1993) used sensor data from MSS, TML and sat to map salt lands affected by salinity production based on soil parameters such as vegetation and hydrology, salinity conduction which can be divided into three classes namely severe, moderate and weak. They also reported reliable accuracy in salinity mapping production and showed the spread of saline lands using satellite data so that MSS and TM sensors were equal to 90and 74%, respectively. According to many researches in the field of soil science, satellite images are used for different purposes (Goldshleger *et al* 2004; Saxsena *et al* 2003; Farifteh and Farshad 2002; Metternicht and Zinc 2003) to check the status and changes in soil salinity using images of multispectral sensors and microwave, geophysics and aerial photography.

The results showed that remote sensing data used in detecting and mapping land affected by salinity are very important, especially when these data are combined with data from ground-based perceptions and entered into the GIS environment, where it will be of greater value. Kinal *et al* (2006) determined the efficiency of the ETM+ sensor for product of salinity map in the soil from a forest in Australia for two seasons. They investigated and concluded that the correlation coefficient between salinity and bands of ETM+ sensor in the spring season is 0.66 while that of the autumn season is 0.64. Al-Hassoun (2012) carried out a study in the northern part of Saudi Arabia, in agricultural areas around the town of Skaka with an area of 612 km2; product and water quality samples were prepared. With the use of remote sensing and with the help of images from TMsensorin1987and 1993, image preprocessing with ERDAS software was supervised with maximum likelihood algorithm, which help in the preparation of salinity map for the study area. The results indicate that the TM sensor can be used to distinguish and investigate soil salinity; with the use of computer enhancement techniques, accuracy assessment can be significantly improved. Using remote sensing techniques, time, cost and less effort is required. In addition, most of the cultivated Lands in the study area are affected by verified levels of salinity, such that for grand investigation, the use of remote sensing data can greatly improve the play maps of soil salinity. Thus, this study also aimed at assessing salinity conduction in surface soil in eastern lands of Khoy with a variety of image classification algorithms (maximum likelihood, minimum distance and parallel epiped) using the Land sat TM sensor data.

MATERIALS AND METHODS

A. Study area

The study area is located in the eastern part of Khoy, Northwest Azerbaijan Province of Iran, with East latitude of 44°59 ´59" to 45°03 ´15" and North latitude of 38° 32´02" to38°47´ 08" with an area of 29,931 ha. Its height from the sea level is variable from 916 min the northeastto1431 min the West area (Fig. 1).

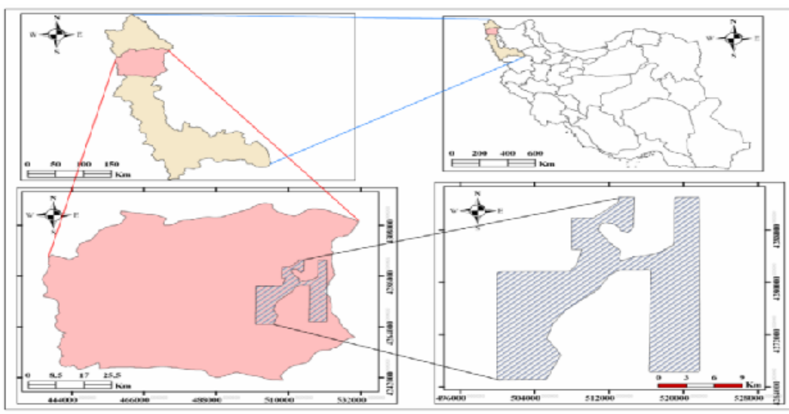

Fig. 1. The geographical location of the area study.

B. Sampling and chemical analysis

The samples were taken in late September; sampling time with imaging time was synchronized. In this study, 269 samples were taken from the intersection of network regularly stopped at 1 × 1 km and a depth of 0-5cm of bare soil surface. In preparation for physical and chemical analysis, soils were transported to the laboratory.

C. Satellite data

A variety of remote sensing data has been used for identifying and monitoring salt-affected areas, including aerial photographs, video images, infrared thermography, visible and infrared multispectral and microwave images, and even remotely sensed data collected by airborne geophysics and electromagnetic induction. Extensive research on the application of satellite imagery covering the visible to infrared regions of the spectrum for identification and mapping of saline areas has been conducted in countries like Australia, Bolivia, China, Egypt, India, Iran, and USA Metternicht and Zinck (2003). Works by Csillag *et al* (1993), Epema (1990), Evans and Caccetta (2000), Everitt *et al* (1988), Kalra and Joshi (1996), Metternicht (1996), Metternicht and Zinck (1996), Mougenot *et al* (1993), Mulders (1987), Rao *et al* (1995), Srivastava, Tripathi and Gokhale (1997), and Verma, Saxena, Barthwal and Deskmukh (1994) provide illustrative application examples. In general, good results are reported when discriminating only two surface types, namely, saline and non saline (Evans and Caccetta 2000). Attempts have also been made to verify the efficiency of this kind of remote sensing data in mapping salinity types and degrees (Kalra and Joshi, Metternicht and Zinck 1996). The satellite data used in this study consists of TM multi-spectral digital data from 19 September 2003. Topographic maps of 1:50,000 for the initial identification of the study area and ENVI4.8 software for processing of satellite images were used.

D. Pixel-based classification

Pixel-based classification methods are the main process of image processing. The main purpose of the classic classification methods is automatic classification of all the pixels of the image within classes with specific applications (Tso and Mather 2009). Pixel-based image analysis is same the classification scheme the classic image that classification is remote sensing images based on the spectral information and classification method that is pixel to pixel (Xiaoxia *et al* 2005). In the Pixel-based classification methods, maximum likelihood method is by far the most exact and most frequently mentioned. Maximum likelihood method, variance and covariance can be used to evaluate classes (Lilles and Kiefer 1995).

E. Processing satellite data

Processing satellite data on the TM image, including geometric correction, which help to control ground points were applied on the images (Richards *et al* 1995). Given that the study area was located in two frames of TM images. Therefore, to increase the accuracy in this image, geometric corrections with distinct points were performed using GPS. Other image processing functions include a separate study area on the satellite image and image enhancements were performed (Tso and Mather 2009).

F. Determine the correlation between bands

One of the methods selected for suitable bands classification is comparing their correlation coefficient. This index showed that soil salinity parameter is determined by the bands of image to have higher correlation that can be used for image classification. Higher correlation coefficient showed that the data in the desired image bands are very similar to each other. Therefore, the bands can be selected or classification based on low correlation coefficient. The relationship between the different bands of satellite images are very effective aid in detecting bands available in false color composite, as well as their separation into different salinity levels. Many false images can be created with a TM sensor because it has 7-bands.

G. Selection training and testing samples

The overall objective of the selected training samples is to find a collection of statistics that reflects the spectral range of ground covered in the image. The minimum number of pixels required for each class is N +1, where *N* is the number of bands used in classified operations. To classify the soil surface salinity, a total of 269 samples were collected from the study area. Selected train samples must have good distribution in the image. So in this research, salinity classes were prepared from 1 to 9 and the total Number of samples for each class were determined. From the number of samples for each class, 80% were regarded as train samples and 20% were considered as test samples (Table 1).

Table 1: Training and testing samples resolution for each class.

Class Number	Testing samples	Training samples	Total samples	Salt Class dS/m
1	10	42	52	0-1
2	9	32	41	1-2
3	3	11	14	2-3
4	2	9	11	3-4
5	4	13	17	4-5
6	8	30	38	5-6
7	9	37	46	6-7
8	3	10	13	7-8
9	7	30	37	8<
Total	55	214	269	-----

H. Embedded training samples on the satellite image

Since the samples in GIS (Arc GIS 9.3) were stored in the form of vector layers with a shape fileformat,80% of the samples (training samples) in nine (9) salinity classes, from Arc Map 9.3 environment were used to classify basic pixels and were driven into the ENVI4.8 software environment and examples of each class of salt were placed carefully with single pixel size in each image on the corresponding pixel and stored with ROI format, because they had the coordinates.

I. Resolution of spectral training sample in selected bands

The phenomenon of spectral resolution in quantitative terms is closer to the maximum which shows that the used bands were more appropriate and that classification would be more accurate. With the changes and movement of spectral bands used in the above method and test report related to spectral resolution, the best state can be created and then classified. The study area of the images were classified in ENVI software, after classifying selected bands of the TM sensor image and selected training samples. After classification of classes for selected images, the classification accuracy in evaluating the accuracy of test samples was analyzed.

J. Classification accuracy assessment

To ensure the accuracy of the carefully produced map using satellite imagery, an accurate map that shows the level of confidence in the extracted map is assessed.

For this purpose, indicators such as error matrix, Producer's Accuracy, User's Accuracy, overall accuracy and kappa Coefficient were used. Error matrix is a contingency table used to compare information ground sources with information to be found from classified hat expressed its value as a percentage and information about the classes participating in classified, it offered in the quantitative for min the tables. Diagonal elements of the matrix error, number of pixels correctly classified and non-diagonal Elements, showed the pixels error. In the error matrix, the columns indicate the reference data and rows indicate the classification produced from remote sensing data (Congalton and Green 2009). However, the Producer's Accuracy obtained from dividing the number of pixels that were correctly classified in each class(diagonal) by the number of pixels as the ground realities(training sample) for that class(total column) were used. Also, the User's Accuracy was obtained by dividing the number of pixels correctly classified(on the diagonal), by the number of total pixels in the class(total row)and Commission Error is equivalent to those pixels group that do not be long to the class desired; but have been considered as a particular class section. Omission error is related to the percentage of pixels that are actually related to the class desired, but classified according to other class sections and overall accuracy is average of the classification accuracy and is calculated based on the data matrix. To calculate the overall accuracy of the resulting number closer to100, higher classification accuracy and compliance in formation will be better. Overall accuracy is the ratio of pixels that have been classified correctly by total number of pixels compared. Overall accuracy is expressed as a percentage and shows the degree of agreement and consistent image obtained from classification with the ground reality. Finally, Kappa coefficient measures classification accuracy ratio to random classification. In calculating the Kappa index in addition to correctly classified pixels, pixels that were incorrectly classified were involved, which is a good test for comparing the results of different classifications. The amount of the Kappa coefficient between zero and one varies; the classification accuracy rate is closer to reality when it is closer to 1.Inthe error matrix table, total area were divided into agricultural land and non-agricultural or without salt and salty lands. The classification stage and preparation of salting map made the separation of different classes according to the spectral reflections, to increase the accuracy of classification. Classification of different classes of soil salinity in different research using satellite data has proven the accuracy of classification (Goossens and Ranst1998).

RESULTS AND DISCUSSION

After measuring the salinity values of soil samples and performing the necessary processing on the image of the study, the correlation coefficients were calculated between the different bands in the image to identify the best combination of bands to create an image. For this purpose, the bands with the lowest correlation value of spectral with each other were selected (Table 2). In this image, bands 1, 4and 5 as well as known bands were used to create false color combinations to detect different levels of soil salinity and to pay attention to different reflections based on Pixel-based classification method and to be careful to match field observations and preparation of surface soil salinity mapping were measured.

Table 2: Correlation bands sensor TM.

Band	Band1	Band2	Band3	Band4	Band5	Band6	Band7
Band1	1						
Band2	0.94	1					
Band3	0.97	0.97	1				
Band4	0.84	0.93	0.92	1			
Band5	0.99	0.96	0.98	0.88	1		
Band6	0.97	0.98	0.99	0.93	0.99	1	
Band7	0.96	0.99	0.98	0.94	0.98	0.99	1

After determining the correlation coefficient between bands, training samples to determine the Classes of spectral resolution we replaced on the image. Spectral resolution of training samples in Table 3 is set for the TM image. The results show that the salinity classes 1to 9 in TM image have a higher resolution and the cause of it can be attributed to reflect on most of the high salinity of the land. In Pixel-based classification, Class 9 of the surface soil salinity in the study area was classified using the image of TM and in the end the three maps were studied for surface soil salinity method.

One of the main objectives of this study was to determine the amount of soil salinity level in the study area. The training samples were taken so that the appropriate distribution to the class of spectral patterns is well reflected. To ensure the resolution classes using training samples defined for each class, all classes were extracted for specified spectral resolution. After determining the correlation coefficient between bands, training samples that were used to determine the spectral resolution placement classes were evaluated on the image.

TM spectral resolution training samples in Table 3 is set for the image; the results in the picture show TM salinity classes1 to 9 with higher resolution, which can cause it to reflect more than the land that has high salinity. Pixel-based classification in Class 9 of the surface soil in the study area was classified using the image of TM; the three maps for the soil surface were studied using these methods. One of the main goals of this study was to determine the range of the different levels of soil salinity values in the range studied. The training samples were taken so that the appropriate distributions for the class of spectral patterns are well reflected. To ensure resolution classes, using from the training samples defined for each class, all classes were extracted by spectral resolution.

Table 3: Spectral resolution of training samples in 1,4 and 5 bonds TM sensor.

Salt Class	Class1	Class2	Class3	Class4	Class5	Class6	Class7	Class8
Class1								
Class2	0.17							
Class3	0.33	0.2						
Class4	0.42	0.4	0.41					
Class5	0.54	0.24	0.2	0.74				
Class6	0.51	0.209	0.24	0.62	0.23			
Class7	0.96	0.52	0.58	0.82	0.43	0.28		
Class8	1.41	1.34	1.39	1.32	1.53	1.42	1.09	
Class9	1.71	1.52	1.54	1.58	1.51	1.48	1.1	1.32

The purpose of quantitative assessment is measurement of errors in the map (Congalton and Green 2009). In fact, the accuracy of the classification is determining the correspondence between selected elements of the reference and data classified. To assess the accuracy of the classification that was carried out on the same test samples, reference samples for pixel-based classification method was used and the accuracy of the classified images by selecting test samples was based on the ground data extracted from the error matrix (Tables 4 to 6). Producer's and User's Accuracy, Commission and Omission Error (Tables 7 to 9) and also overall accuracy and Kappa Coefficient classification methods are shown on the bands of satellite images of selected samples (Table10).

Table 4: Error matrix classification using maximum likelihood of TM image.

Salt Class	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	Total
0-1	8	2	2	1	1	2	1	-	17
1-2	-	-	-	-	-	-	-	-	-
2-3	-	4	-	-	-	1	-	-	5
3-4	1	1	-	1	1	1	-	-	5
4-5	-	-	-	-	1	-	-	-	1
5-6	-	1	-	-	1	-	-	-	2
6-7	1	-	-	-	-	2	4	1	8
7-8	-	1	-	-	-	-	-	-	2
8<	-	-	1	-	-	2	4	2	15
total	10	9	3	2	4	8	9	3	55

Table 5: Error matrix classification using minimum distance of TM image.

Salt Class	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8<	Total
0-1	9	4	2	1	1	2	1	-	-	20
1-2	-	-	-	-	-	-	-	-	-	-
2-3	-	1	-	-	-	-	-	-	-	1
3-4	-	2	-	1	-	1	-	-	-	4
4-5	-	1	-	-	-	-	-	-	-	1
5-6	-	-	-	-	1	-	-	-	-	1
6-7	1	1	-	-	2	3	4	1	-	12
7-8	-	-	-	-	-	1	2	-	1	4
8<	-	-	1	-	-	1	2	2	6	12
Total	10	9	3	2	4	8	9	3	7	55

Table 6: Error matrix classification using Parallel Piped of TM image.

Salt Class	0-1	1-2	2-3	3-4	4-5	5-6	6-7	7-8	8<	total
0-1	10	9	3	2	4	8	6	3	6	51
1-2	-	-	-	-	-	-	1	-	1	2
2-3	-	-	-	-	-	-	-	-	-	-
3-4	-	-	-	-	-	-	-	-	-	-
4-5	-	-	-	-	-	-	-	-	-	-
5-6	-	-	-	-	-	-	-	-	-	-
6-7	-	-	-	-	-	-	-	-	-	-
7-8	-	-	-	-	-	-	-	-	-	-
8<	-	-	-	-	-	-	-	-	-	-
Non Classification	-	-	-	-	-	-	2	-	-	2
total	10	9	3	2	4	8	9	3	7	55

Table 7: Producer's and User's Accuracy, Commission and Omission Error Maximum Likelihood classifier of TM Image.

Salt Class	Producer's Accuracy (%)	User's Accuracy (%)	Commission Error (%)	Omission Error (%)
0-1	80	47.06	52.94	20
1-2	-	-	-	100
2-3	-	-	100	100
3-4	50	20	80	50
4-5	25	100	-	75
5-6	-	-	100	100
6-7	44	50	50	55.56
7-8	-	-	100	100
8<	85.71	40	60	14.29

Table 8: Producer's and User's Accuracy, Commission and Omission Error Minimum distance classifier of TM Image.

Salt Class	Producer's Accuracy (%)	User's Accuracy (%)	Commission Error (%)	Omission Error (%)
0-1	90	45	55	10
1-2	-	-	-	100
2-3	-	-	100	100
3-4	50	25	75	50
4-5	-	-	100	100
5-6	-	-	100	100
6-7	44.44	33.33	66.67	55.56
7-8	-	-	100	100
8<	85.71	50	50	14.29

According to the results from the accuracy of the classification methods, Observation in all three classification methods with the exception of parallelepiped classification method, show that the image of TM sensor has a high overall accuracy such that the overall accuracy value in the Maximum Likelihood classification method is 36.36%. The use of TM remote sensing data could only justify the 36.36% of the soil surface salinity classes.

Therefore, using other sensors data with higher resolution and lower sampling intervals can accurately estimate the salinity more in future studies. Also, the use of satellite data up to date or in other words simultaneous recording of satellite data and field operations reflects the actual pectral properties of the phenomenon in time data recording and presents more accurate results.

Table 9: Producer's and User's Accuracy, Commission and Omission Error Parallelepiped classifier of TM Image.

Salt Class	Producer's Accuracy (%)	User's Accuracy (%)	Commission Error (%)	Omission Error (%)
0-1	100	19.61	80.39	-
1-2	-	-	-	100
2-3	-	-	-	100
3-4	-	-	-	100
4-5	-	-	-	100
5-6	-	-	-	100
6-7	-	-	-	100
7-8	-	-	-	100
8<	-	-	-	100

Table 10: Total Accuracy and Kappa Coefficient Classification Methods.

Image	RGB	Classification Methods	Overall accuracy (%)	Kappa Coefficient
TM	145	Maximum Likelihood	36.36	0.26
		Minimum distance	36.36	0.25
		Parallelepiped	18.18	0.008

Taking a look at the Kappa coefficient, we find that the correlation between the overall accuracy of the coefficient is positive, because with increases in the overall accuracy, Kappa coefficient is also in an increasing pace. Parallelepiped classification method has a lower kappa coefficient, which shows the weakness of this method in classifying satellite images. Kappa coefficient indicates that the amount of pixels is classified properly and as such, much more amount has been classified correctly. Omission error on the one hand indicates the heterogeneity and complexity of spectral reflectance in the region and on the other hand is related to the mixing pixels located on the border between the two Class. In the maximum likelihood method, most of the omission error is related to the mixing of classes with low salinity. The commissioner or indicates the number of pixels located in wrong classes. In the method of maximum likelihood classification, most amounts of these errors are related to are as with low salinity. It seems to be that low salt content, salts are difficult to discriminate from other soil surface components (Mougenot 1993). Thus, ground validation is indispensable to correlate surface features, salt content, and reflectance.

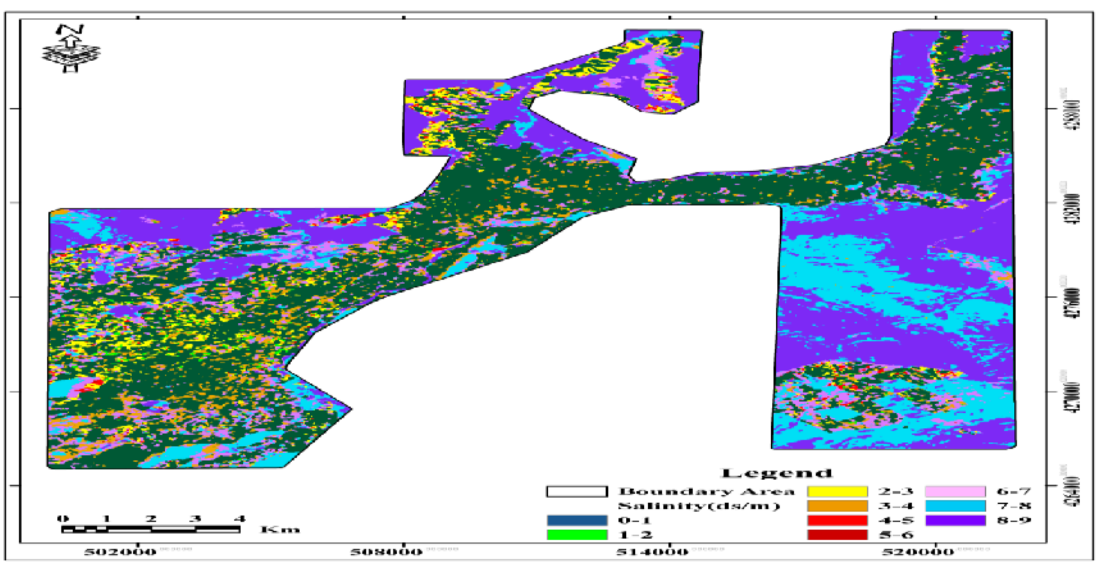

Fig. 2. The Salinity distribution of surface soil by parallelepiped classification method.

Selection of the best band combination is usually the first step to compress remote sensing data, while securing class reparability. As can be seen in the produced map sample, Parts of the south-east of the study area has as ever problem of salinity and is well separated from other areas. Kappa coefficient to maximum likelihood classification method was 26%, which represents a more accurate method than other methods. Maps prepared by all three methods of classification are shown in Fig. 2 to 4 and according to the Kappa coefficient calculated for maximum likelihood classification method, the map (Fig. 4) showed the most accurate map of the soil salinity region.

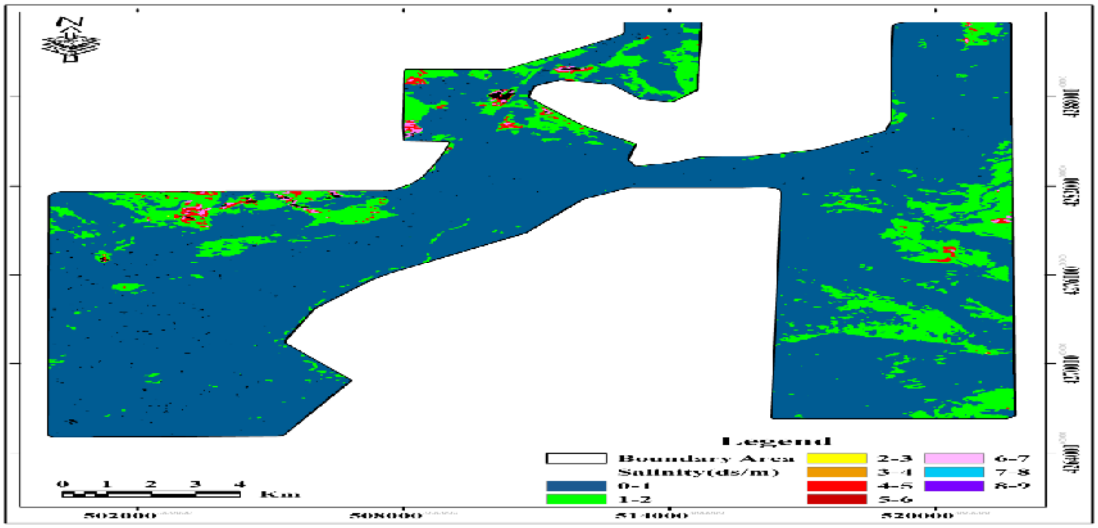

Fig. 3. Salinity Distribution of surface soil by minimum distance classification method.

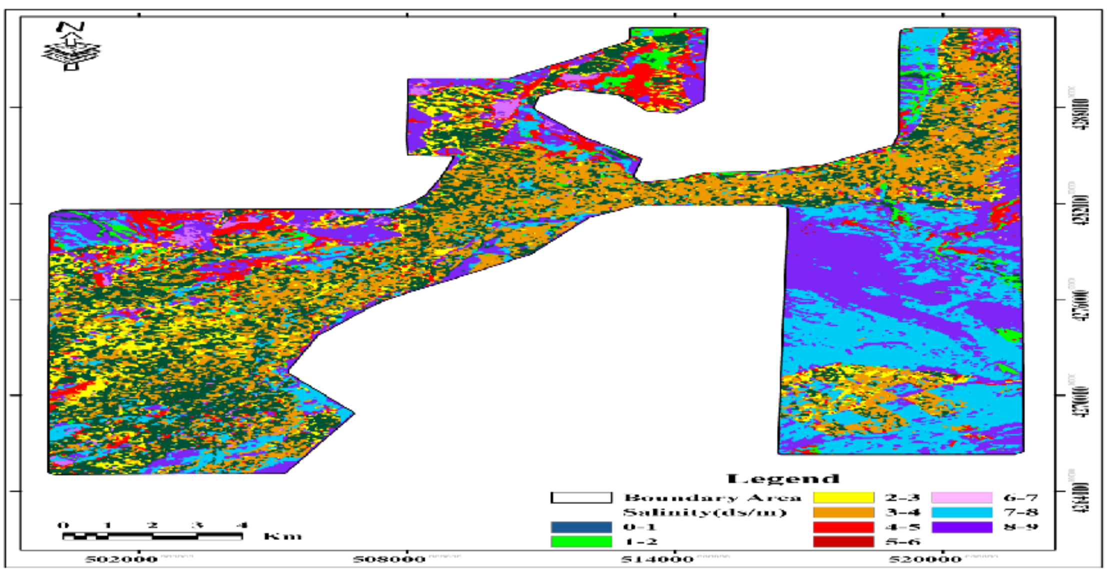

Fig. 4. Salinity Distribution of surface soil by maximum likelihood classification method.

Comparing the results with surveys of satellite images revealed that areas with maximum salinity has very sparse vegetation and are generally halophytic vegetation and in are as that have least salinity, vegetation and agricultural crops are dense. Abdul Hamid (1992) studied soils in the north of the Nile Delta areas without vegetation and showed that the bands 1 to 5 and 7TM Sensor has high positive correlation with the soil salinity values and this has also been studied by Al-Hassoun (2012) and Rekha *et al* (2011) who have proven the same results. The results of other researchers in studies of soil salinity using Lands at satellite images are very general and almost all TM bands for these studies have been reported.

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