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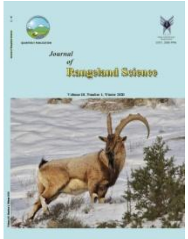

Research and Full Length Article:

Soil Salinity Mapping Based on ETM+ Data in Arid Rangeland, Iran (Case study: Damghan region, Iran)

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Abstract. Soil salinity has concerned people in arid and semi-arid rangelands. One of the most essential cases in relation to information for natural resource managers is preparation of soil salinity maps. Developing such maps, using traditional methods spends a lot of time and costs. Satellite data have broadened and integrated our vision for this purpose. This study was conducted in order to develop a model for providing a salinity map using ETM+ satellite data collected in 2012 and salinity values in Damghan rangelands, Iran. The geometric and atmospheric correction of satellite images was carried out. Necessary processing such as fusion of multispectral bands with panchromatic bands, tasseled cap transformation, the analysis of Principal Components Analysis (PCA), and rationing for composite bands creation were also performed. A total number of 114 surface soil sample points with the depth of 0-15 cm were taken through a random sampling method and their Electrical Conductivity (EC) was measured. Different bands extracted spectral values for each sample and the relation between spectral values (i.e. main bands, Tasseled Cap bands, and soil and vegetation index) with EC values of the samples was investigated. Using PCA analysis, the variables were categorized into four principle components to develop soil EC map according to the highest correlation. Results revealed that there was the highest correlation between PCA1 and variables of blue, green, red bands (R=0.7), Tasseled cap 1, 2, 4 (R=0.68) and indicators SI1, SI2, SI3 (R=0.7), GVI, BI (R=0.68), INT1, INT2, MND, WDVI (R=0.7). In PCA2, the variables of NIR, OSAVI, NDVI, SAVI, VNIR1 and TVI had a significant correlation with PCA2. Finally, using stepwise regression, three models were developed to determine soil salinity maps according to the utilized independent variables. Results showed that Landsat ETM+ images are good tools to estimate salinity maps of arid rangelands.

Key words: Soil Indices, PCA, Remote Sensing, ETM+

Introduction

Soil salinization is one of the most prevalent land deterioration processes in areas where the amount of precipitation is less than evaporation and transpiration (Abarsaji *et al.,* 2011). Such areas are called “arid” or “semi-arid” in terms of climate classification (Abdelfattah, 2009). On an average scale, around 20% of all worlds’ rangelands are affected by salinity and this amount increases in countries such as Iran and Egypt (Metternicht and Zinck, 2003). With respect to the growing population in Iran, the study of saline soils in arid rangelands seems vital (Amini, 1999). Using time data of soil in each region available, wide range of activities can be performed for the study of salinity process and reduction of the desertification (Bahtti et al., 1991). An effective tool in such studies is using remote sensing and utilizing satellite images (Akhzari *et al.*, 2013). Using remote sensing and satellite images can reduce the amount of time and costs, and increase the accuracy and speed (Alavipanah, 2003). Numerous researchers have used satellite images in rangeland soil studies for different purposes (Goldshleger *et al.*, 2004).

Saxsena *et al.* (2003) showed that using satellite data and GIS for developing thematic map could save 40-60% in mapping time compared to current methods. Therefore, integration of these two not only increases the accuracy of results and the quality of maps, but also saves time and costs and makes the maps updatable. In a study conducted by Dwivedi, R. S. (2006) on India’s Uttar Pradesh state, the soil characteristics of 1975 and 1992 were investigated by MSS images in alluvial plains affected by salinity using the data derived from principal components analysis (PCA) as well as spectral rationing. Result showed that the third component provided comprehensive data regarding the soil affected by salinity and all MSS and spectral rationing. So,Chitsaz 1999, used Regression analysis for modeling the DN–salinity relationship for generating interpolated salinity maps .

Khajeddin (1998) used MSS multi-temporal data to investigate the floral communities and different soil factors in JazMurian, Iran. He did not manage to find a significant relationship between MSS data and soil factors such as the percentage of sand, silt, clay, the percentage of rock and pebble, calcium and potassium; however, he found a significant relationship between EC and sodium concentration in July data.

Saxsena *et al*. (2003) showed the maximum convergence through separation of saline soil from gypsum soil with digital numbers in Kashan rangelands and using Pearson correlation and regression analysis in multivariate method between bands TM(Thematic Mapper) 6, TM5, TM1 by changing the superficial EC and bands TM7, TM6, TM5, TM3 by changing the superficial gypsum. Chitsaz and Khwajeddin (2000) developed salinity map and the soil alkalinity through TM data in Northeast of Isfahan province, Iran. The best bands that estimated the region’s soil samples’ superficial EC changes and in fact offered a suitable regression model were bands TM6, TM5, TM4. Abdi Naam (2004) used the data of this band for developing soil salinity using the convergence between satellite data and soil salinity values in Qazvin plain, Iran.

Rivero *et al.* (2007) used spectral data ASTER and ETM+ in developing the soil’s phosphor changeability and comparing the efficiency of Geostatistics as well as statistics using spectral data and gained high values of Mean Error (ME) and Root Mean Square Error (RMSE) with high SD (Standard deviation) and high difference of minimum and maximum of data. Fernandez-Boses *et al.* (2006) used the digital data of ETM and Aerial Photography in order to map the soil salinity around Texcoco, Mexico. They created a new branch called Cosri through adjusting the spectral branch of NDVI. The existence of high correlation between soil characteristics (SAR (Sodium Absorption Ratio), EC) and spectral values of this band, a mixture was offered in the form of a regression model for developing the soil salinity map. Noroozi and Homaii (2013) investigated the correlation between EC and 27 variables retrieved from satellite images using the EC data of soil in Garmsar Plain, Iran. They concluded that using spatial data offers more accurate data for mapping the salinity than classic data. The aim of present study is to determine the existence and amount of soil salinity in rangeland and offering the proper model for developing a salinity map and establishing a connection between ETM spectral sensor data in parts of Damghan region, Iran.

Materials and Methods

Study area

The study area covers a part of Damghan watershed that is surrounded by the Southern Alborz mountain range from north and is adjacent to Haj Ali Qoli Desert rangeland to the south. Due to changes in the salinity of the region, being northern-southern, the region is a suitable location for remote sensing studies. Damghan watershed is located in southeast of Damghan town, east of Semnan province, Iran and its eastern-western stretch covers 2,474,700 ha. In the internal watershed, there are two playas of Damghan and Shaq Bīār-e Arjomand (eastern Damghan). The area of Damghan playa is 239,100 ha and contains Haj Ali Qoli Desert (Chah-e-Jam) with an area of 46,600 ha. The altitude of playa is 1050 m above the sea level. The study area was located in 35◦53′ to 36◦17′ northern latitude to 54◦35′ to 55′ eastern longitude. The maximum and minimum altitude of the area is 1261 and 1047m, respectively. In total, 114 soils samples were taken using a random sampling method from the depth of 0-15 cm of superficial soil in November 2012. Some soil physical and chemical characteristics including the pH, EC, SAR, gypsum percent as well as the coordinates were measured (Fig. 1).

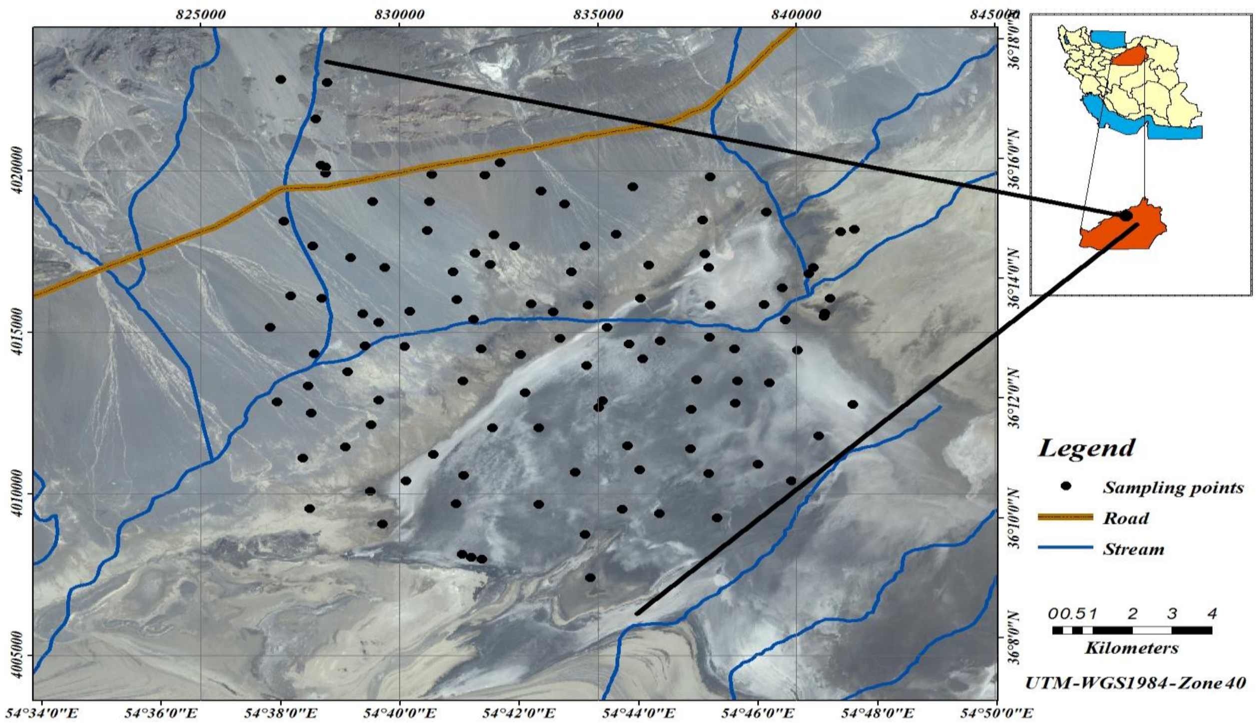

Fig. 1. The study area's location including the location of soil samples

Utilized satellite data

ETM+ multispectral digital numbers of Landsat 7 including 6 spectral bands with the spatial resolution of 30m and panchromatic band with the spatial resolution of 15 m were utilized from path 162 and row 35 related to November 2012.We did not use thermal band of ETM+ because of its low spatial resolution. In order to use true digital number of images for gaining true results, the images were corrected from atmospheric, radiometric Fast Line-of-sight Atmospheric Analysis of Hypercubes (FLAASH[)], and geometric Ground Control Points (GCP) distortions with RMSE=0.48 pixel methods with the scale 1:25000 and then were used.

Following the investigation of radiometric error and correction of geometric error, 26 criteria of salinity and vegetation were developed. Table 1 represents the variables utilized in this study.

Table 1. Utilized indices in this study

Variable	Equation	Variable	Equation
BI	$\sqrt{R^2+NIR^2}$	VNIR1	$\frac{NIR-G}{NIR+G}$
INT2	$\frac{G+R+NIR}{2}$	MND	$\frac{NIR-(1.2\times R)}{NIR+R}$
INT1	$\frac{Green+\mathrm{Re}d}{2}$	IPVI	$\frac{NIR}{NIR+RED}$
IR1	$\frac{NIR-SWIR}{NIR+SWIR}$	DVI	NIR-RED
MIRV2	$\frac{SWIR-NIR}{SWIR+NIR}$	PVI	$PVI=\sin(\alpha)NIR-\cos(\alpha)RED$
MSI	$\frac{SWIR}{NIR}$	WDVI	$BI=BrightnessIndex$ NIR-(GREEN×RED)
NDVI	$\frac{NIR-R}{NIR+R}$	SAVI	$\frac{NIR-RED}{NIR+RED+L}(1+L)$
SR	$\frac{NIR}{R}$	GVI	$0.2839*Green-0.6943*\mathrm{Re}d+0.6614*NIR$
PD322	$\frac{R-G}{R+G}$	TVI	$\frac{NIR-R}{NIR+R}+0.5$
RA	$\frac{NIR}{R+SWIR}$	PCA	PCA1, PCA2, PCA3
SI1	$\sqrt{G*R}$	Tasseled cap	Brightness, Greenness, Wetness. Fourth, fifth, sixth
SI2	$\sqrt{G^2+R^2+NIR^2}$	OSAVI	$\frac{IR-\mathrm{Re}d}{NIR+\mathrm{Re}d+0.16}$
SI3	$\sqrt{G^2+R^2}$		

B: soil line angle
α=angle between soil line and NIR axes
X: the factor that minimizes the soil reflection error; normally equal to 0.08
L: correction factor that equals 0 for good pastures and 1 for very poor pastures
INT2: Intensity within the visible spectral range
BI=Brightness Index
MND: Modified Normalized Differences
INT1: Intensity within the VIS_NIR spectral range
DVI: Different Vegetation Index
PVI: Perpendicular Vegetation Index
s: soil line slope
a: length from the source
I: 1-2×s×NDVI×WDVI
NDVI: Normalized Difference Vegetation Index
SR: Simple Ratio
PD: Perpendicular Difference
RA: Ratio Adjusted
VNIR: Vegetation Normalized Infrared Ratio
MND: Modified Normalized difference
IPVI: Infrared Percentage Vegetation Index

WDVI: Weight Differenced Vegetation Index
SAVI: Soil Adjustment Vegetation Index
GVI: Greenness Vegetation Index
SI: Saline Index
OSAV: Optimized Soil-Adjusted Vegetation
TVI: Transformed vegetation index
MND: Modified normalized differences
VNIR: Vegetation Normalized Infrared Ratio
IR: Infra-Red
MIRV: Modified Infrared Ratio Vegetation
MSI: Moisture Stress Index
PCA: Principal Component Analysis

Extracting digital numbers of samples location

A total number of 33 criteria were developed using the main bands of ETM images in ILWIS (Integrated Land and Water Information System (ILWIS)) 3.0 software environment. In the following, a point vector was developed according to the geographical latitude and longitudes of sampled points that were also registered by GPS. The vector was formed into a layer along with the sampling number for each point on criteria and different ETM image bands; then, the digital number where each point fell into was extracted along with 8 pixels around it and the average was registered in the Arc GIS9.3 software environment in the intended images. The procedure was performed for all the sampled points in the desert and for all intended bands in the study area.

Statistical Analysis

The statistics parameters of soil's EC as mean and SD was calculated. In order to determine whether the data was normal, kolmogorov-smirnov test was applied. Correlation coefficient between the EC and the image's different variables was calculated. Using PCA analysis, the important variables were categorized into four principle components and using stepwise regression model was developed to determine soil salinity maps according to the utilized independent variables. All statistical calculation was performed by SPSS v.17 software.

Results

Correlation between EC and utilized criteria

Table 2 shows the results of mean, SD, and the utilized criteria correlation with soil EC. The amount of superficial soil EC was calculated as 108.6±7.42 Deci Siemens (Ds/m). As it is clearly stated in Table 2, the criteria TASSELED BAND7, BAND6, VNIPI1, SAV1, RA, PCA3, PD322, MSI, NDVI, OSAVI, NIR, MIRVI, IRI, IPVI, DVI, CAP 3 and 5 had no significant correlation with soil EC (Table 2).

Principal Components Analysis (PCA)

Since many intended variables had a significant relationship with soil EC (Table 2), in order to reduce the number of variables and group them into relevant and similar criteria, factor analysis based on PCA was used. In PCA analysis, four components were performed for determining the relation patterns among the variables:

1- Matrix of correlation coefficient between the variables was calculated and therefore, the variables that seem to have a weak dependence than other variables were determined.
2- The second phase was developing the factors. This phase includes determining the number factor/components and the method of calculating them. The extent of model fitness for the data is also calculated in this phase.
3- Rotation and performing specific changes on the factors are performed in this phase so that the relationship among the data can be interpreted better.
4- The score of each factor was calculated for each observation. These scores can be the basis of various analyses.

At the end, Eigenvalue variables above 0.7 were chosen and categorized accordingly in four categories (Table 3).

Table 2. The results of the average, SD, and the utilized criteria correlation with EC

Variable	Mean	SD	Correlation coefficient
EC	108.62	40.8	1.00
SI3	116.82	17.35	0.700**
GVI	17.06	2.63	0.699**
DVI	-7.89	5.58	-0.531**
BI	125.97	16.69	0.671**
INT1	81.86	12.17	0.700**
INT2	124.36	16.97	0.684**
IPV1	0.5	0.02	0.050
IR1	-0.21	0.04	-0.050
MIRV1	0.21	0.04	0.050
NIR	0.92	0.08	-0.340
OSAVI	-0.03	0.06	-0.424*
NDVI	-0.04	0.06	-0.424*
MSI	1.6	0.09	0.020
MND	92.58	13.7	0.695**
PD322	0.13	0.04	0.230
PCA1	291	25.02	0.654**
PCA2	-28.43	22.24	-0.688**
PCA3	-6.02	12.54	-0.090
PVI	-100.9	12.5	-0.642**
RA	0.4	0.02	0.230
SAVI	-5.33	7.48	-0.408*
SI1	81.09	12.08	0.700**
WDVI	-6636.46	1968.11	-0.713**
VNIR1	0.09	0.05	-0.230
TVI	0.46	0.06	-0.424*
SI2	144.55	19.62	0.683**
Band1	122.28	20.31	0.696**
Band2	70.76	10.79	0.699**
Band3	92.83	13.75	0.695**
Band4	84.96	10.25	0.623**
Band5	135.98	17.19	0.598**
Band6	153.04	6.34	-0.502*
Band7	88.04	13.1	0.581**
tasseled cap 1 (Brightness)	222.72	25.81	0.681**
tasseled cap 2(Greenness)	-92.68	10.19	-0.681**
tasseled cap 3(Wetness)	-124.75	10.98	-0.190
tasseled cap 4	-27.58	13.44	0.667**
tasseled cap 5	-47.28	8.79	-0.571**
tasseled cap 6	31.97	3.25	0.625**

*, **= significant at 5% and 1% probability level

Table.3. Categorization of mentioned criteria along with the amount of specific values using PCA

Index	Factors			
	PC1	PC2	PC3	PC4
WDVI	-0.943			
TC6	0.592			
TC5	-0.656			
TC4	0.971			
TC2	-0.760			
TC1	0.980			
SI3	0.956			
SI2	0.982			
SI1	0.955			
PVI	-0.995			
PCA2	-0.968			
PCA1	0.969			
MND	0.957			
INT2	0.981			
INT1	0.956			
GVI	0.937			
BI	0.986			
B7	0.931			
B5	0.959			
B4	0.994			
B3	0.956			
B2	0.944			
B1	0.865			
VNIR1		0.803		
TVI		0.823		
SAVI		0.778		
OSAVI		0.823		
NIR		0.851		
NDVI		0.823		
DVI		0.861		
RA			-0.854	
MSI			0.832	
MIRV1			0.956	
IR1			-0.956	
TC3				-0.599
PD322				0.774
PCA3				0.658
B6				0.634

Stepwise regression

According to the specific criteria value, the benchmark of each group's characteristics as the independent variable and the EC value as the dependent variable were investigated by stepwise regression. In this phase, the model with best fitness was chosen. Based on model for the first group, the convergence was 0.69, its SD was 51.88 and the model's variance inflation degree was less than 10 (Table 4 and Fig. 2). For the first group variables, after entrance of all variables, the highest convergence was that of soil EC with MND criterion. Table 4 represents the offered model for the first group variables. This means that after entrance of MND, the model can predict salinity up to 69%. Fig. 4 shows the zoning of soil EC value through the derivative model of first group's variables.

Table 4. The relationship between soil EC and the first group's variables

model	R	R Square	Adjusted R Square	Std. Error of estimate	VIF[1]
EC=3.55MND-235.92	0.695[a]	**0.483**	0.461	51.88	1.00

MND= Modified Normalized Differences

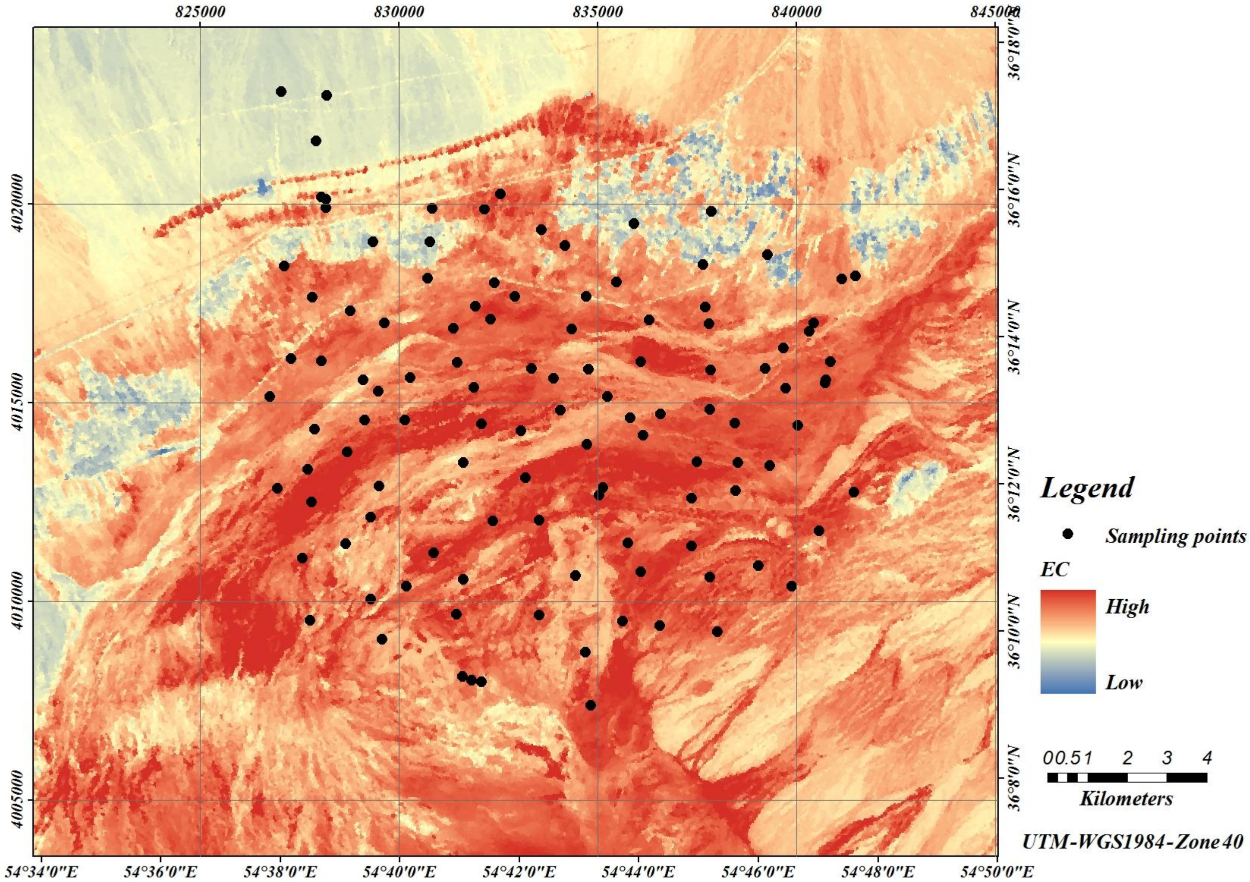

Fig. 2. The zoning of soil EC value through the derivative model of first group's variables

1 Variance Inflation Factor

For the second group variable, the highest convergence was gained between soil EC and DVI criterion. According to the models for the second group benchmarks, the amount of convergence was 0.5, the SD was 62.44 and the model's variance inflation degree was less than 1.0. Table 5 represents the second group variables. This means that the model isn't suitable to predict the salinity. Fig. 3 illustrates the zoning of soil EC value through the derivative model of second group variables

Table 5. The relationship between soil EC and the second group's variables

Model	R	R Square	Adjusted R Square	Std. Error of estimate	VIF
EC=23.22-7.459DVI	0.502	**0.252**	0.219	62.441	1.00

DVI= Different Vegetation Index

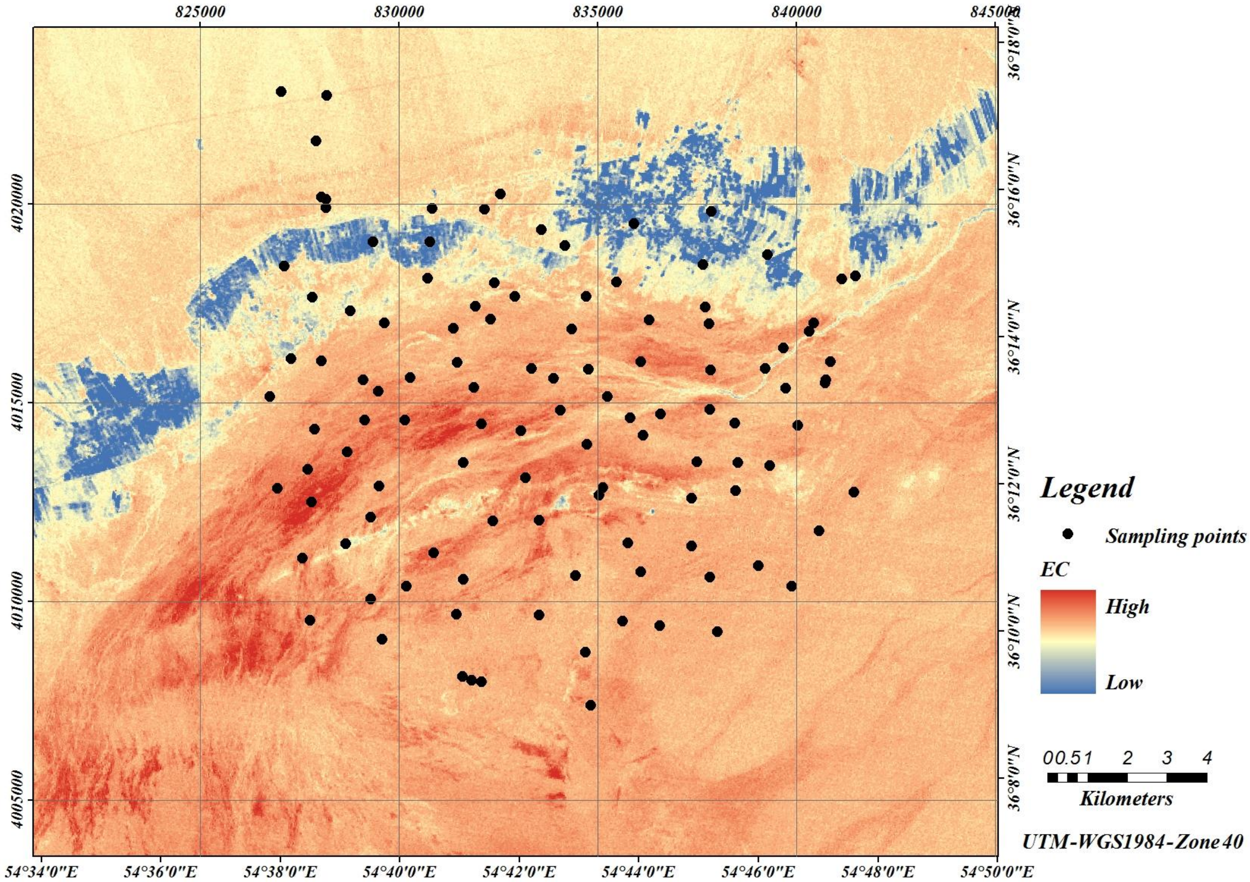

Fig. 3. The zoning of soil EC value through the derivative model of second group's variables

For the third group variable, no model was fitted to be able to predict the soil EC. For the fourth group variable, the highest convergence was gained between soil EC and B6 as well as PD322 criteria. According to the models for the fourth group benchmarks, the amount of convergence was 0.60, the SD was 58.89 and the model's variance inflation degree was less than 10. Table 6 represents the fourth group variables. This means that the model has no adequate efficiency to predict the salinity. The zoning of soil EC value through the derivative model of fourth group variables is shown in Fig. 4.

Table 4: The relationship between soil EC and the fourth group's variables

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	VIF
EC=960.1PD322-.66B6+988.95	0.603^b	**0.363**	0.305	58.892	1.043

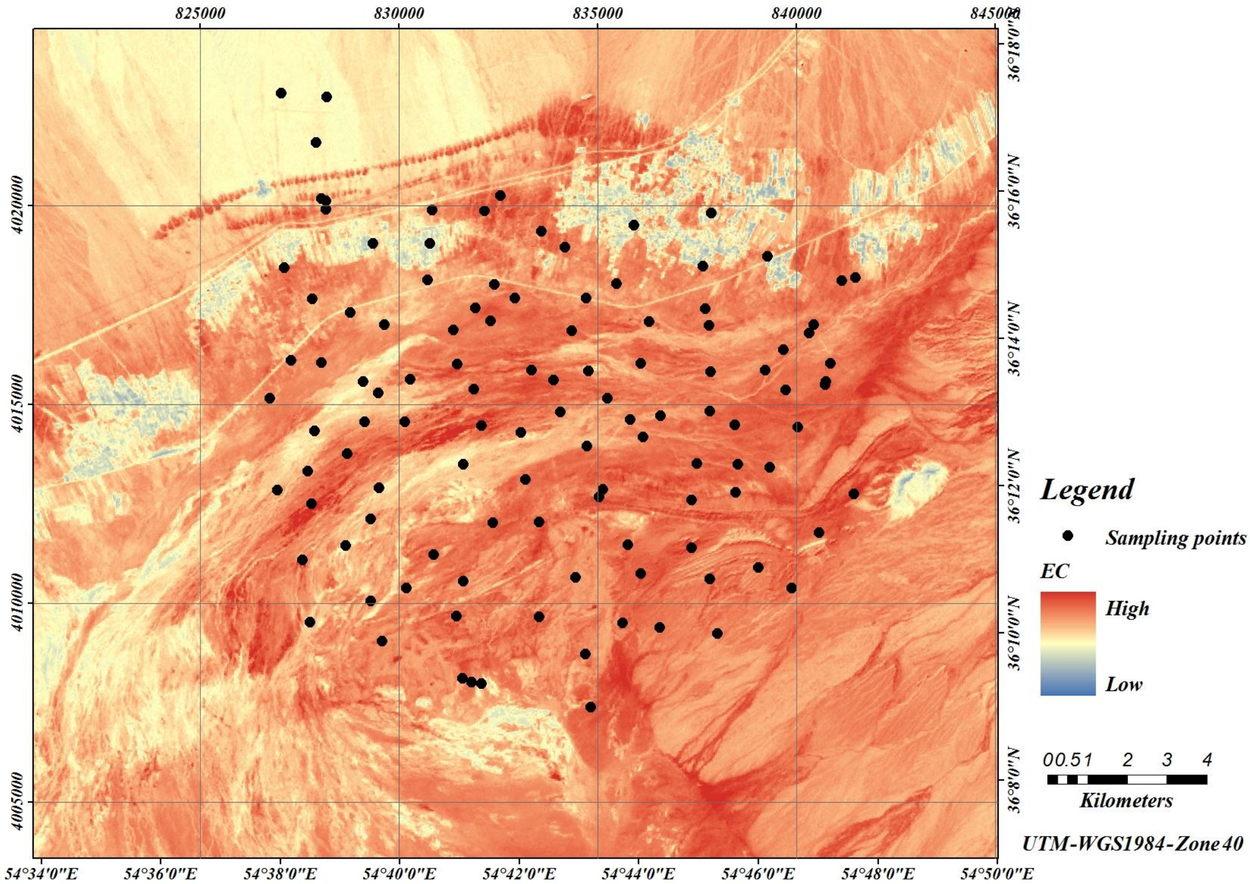

Fig. 4. The zoning of soil EC value through the derivative model of fourth group's variables

Conclusion and Discussion

Based on results of first group variable statistical analysis, the highest correlation has been gained between EC and MND with R about 0.7. This correlation coefficient for second group was more than 0.5 for soil EC and DVI. For the third group variable, no model was fitted and for the fourth group variable, the highest convergence was gained between soil EC and B6 as well as PD322 criteria (table 4). At the end, the location of soil EC values through the derivative model of first, second and fourth groups variables was shown in Figs. 2, 3, and 4. In the area, MND (Modified Normalized Difference) variable was introduced as the best variable to forecast soil EC values with acceptable accuracy based on Landsat indices values.

The soil EC's convergence with the utilized criteria in this study matches the brightness bands utilized by Jafari Gorzin (2002) and the b1, B2, B3, Tasseled cap 1, 2 and 4 bands utilized by Noroozi and Homaii (2013). The comparison of the study findings with other studies reveals that depending on the physiography, vegetation, climate, land use, the amount of salinity changes, and geological factors of a specific sensor, different bands can be useful for predicting the superficial salinity of an area. In this study, the main bands blue, green, red, tasseled cap 1, 2 and 4 and the criteria SI1, SI2, SI3, GVI, BI, INT1, INT2, MND, WDVI and the second component variables of NIR, OSAVI, NDVI, SAVI, VNIR1 and TVI showed the convergence in 1% level because low R^2 cannot estimate the superficial EC changes of soil samples in the region. Khajeddin (1998) do not believe that correlation coefficient and regression models are suitable for developing salinity map and soil alkalinity map while other researchers including Chitsaz and Khajeddin (2000), DarvishSefat (2002), Abdi Naam (2004), Fernandez-Boses *et al.* (2006) and Noroozi and Homaii (2013) developed the salinity and alkalinity maps by the correlation coefficient of Images' spectral values and EC and proper regression models. With regard to the above comments and comparison of different ideas with the ideas of other researchers in soil salinity, the study is on satellite, local, spatial and temporal data. Different researches believe in different bands for measuring the soil salinity. A band may seem unimportant in one region but reported as important or useful in another region. Therefore, it can be concluded that in different regions with different salinities, different climates, geographical and geological conditions, different bands can describe the salinity changes and EC of the soil in the region. Therefore, the results show that in the study area in Damghan region, bands B6 and criteria DVI, MND, PD322 can be utilized for predicting EC of the soil in the region with the correlation of 69, 50 and 60% and the inferences made by the superficial EC model seem more valid. It can also be noted that using in-time satellite data, or in other words the synchronization of registering the satellite data with the field operations can reflect the spectral characteristics of that phenomenon while registering the data will offer more accurate results. In order for the developed maps to be more practical, the output maps should be comparable to the normal maps.

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پهنه‌بندی هدایت الکتریکی خاک سطحی بر مبنای داده‌های سنجنده +ETM در مراتع خشک ایران (مطالعه موردی: منطقه دامغان)

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چکیده. شوری خاک از دیرباز گریبانگیر مردم مراتع خشک و نیمه خشک بوده است. یکی از ضروری‌ترین اطلاعات مورد نیاز مدیران منابع طبیعی، نقشه‌های شوری خاک و املاح می‌باشد. تهیه چنین نقشه‌هایی با استفاده از روش‌های سنتی مستلزم صرف زمان و هزینه زیادی خواهد بود. داده‌های ماهواره‌ای به دلیل دید وسیع و یکپارچه برای این امور مناسب می‌باشد. این پژوهش به منظور ارائه مدلی برای تهیه نقشه شوری با استفاده از داده‌های ماهواره‌ای +ETM و مقادیر شوری در منطقه دامغان مربوط به سال ۱۳۹۱ انجام شد. به این منظور تصحیحات هندسی و اتمسفری بر روی تصاویر ماهواره‌ای انجام شد. پردازش‌های لازم مانند ادغام باندهای چند طیفی با باند پانکروماتیک، تبدیل تسلدکپ، آنالیز مؤلفه‌های اصلی و نسبت‌گیری بر روی باندها به منظور ایجاد باندهای مصنوعی انجام گرفت. در مجموع ۱۱۴ نمونه خاک سطحی از عمق ۱۵-۰ سانتیمتر به روش آماربرداری تصادفی برداشت شد و هدایت الکتریکی آنها در عصاره اشباع اندازه‌گیری گردید. ارزش-های طیفی هر یک از نمونه‌ها در باندهای مختلف استخراج و ارتباط بین ارزش‌های طیفی (باندهای اصلی، باندهای حاصل از تسلدکپ و شاخص‌های خاک و پوشش گیاهی) با مقادیر هدایت الکتریکی مربوط به نمونه‌ها بررسی شد و به به کمک روش آنالیز مولفه اصلی به چهار مولفه تقسیم شدند و بر اساس بالاترین همبستگی صفات مهم در هر مولفه به منظور تهیه نقشه هدایت الکتریکی خاک تعیین شدند. نتایج نشان داد که مولفه اول بیشترین همبستگی با باندهای اصلی آبی، سبز، قرمز(R=۰/۷) و ۴، ۲، ۱ Tasseled cap (R=۰/۶۸) و شاخص‌های SI1, SI2, SI3, GVI, BI, INT1, INT2, MND, WDVI (R=۰/۷) داشت و به همین ترتیب مولفه دوم بیشترین همبستگی با شاخص‌های NIR، OSAVI، NDVI، SAVI، VNIR1 و TVI داشت. در نهایت با روش رگرسیون گام به گام ۳ مدل برای تعیین نقشه شوری خاک بر مبنای متغیرهای مورد استفاده تعیین شد. نتایج حاکی از توانایی بالای تصاویر +ETM ماهواره لندست در تهیه نقشه‌های تخمین شوری خاک می‌باشند.

کلمات کلیدی: شاخص‌های خاک، PCA، سنجش از دور، +ETM