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Rock Units Erosion Susceptibility Detection and Classification Using Nonlinear Correlation Analysis and Landsat ETM+ Data

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Abstract

The use of accurate lithological maps is inevitable in the preparation of rock unit's erosion susceptibility maps. In this study, rock unit outcrops in the Soh Basin (50 km Northern Isfahan) were extracted using nonlinear correlation analysis of satellite data. Moreover, rock unit's erosion susceptibility such as marl, shale, and quaternary deposits and resistant rock units such as sandstone and limestone were extracted based on soil erosion intensity factors. The lithology of the basin was studied using the virtual variables method. Initially, rock units, as a virtual independent variable, and the PC1 (the first principal component) of ETM+ multispectral bands were analyzed by a multiple linear regression model. Afterward, rock units were analyzed in logistic regression analysis as virtual dependent variables. The results revealed that logistic regression analysis is a suitable model for rock unit's extraction.

***Keywords**:* Satellite Data, Landsat ETM +, Lithological Mapping, Soil Erosion Susceptibility, Logistic Regression

1. Introduction

Rocks consist of the main foundation of the watershed and the produced soil is the most important factor that affecting the erosion and geomorphological facies creation (Ahmadi, 2011). Accurate lithological maps are essential in preparing erosion susceptibility maps. Geological maps are the main basis for extracting lithological maps in the country. These maps have been prepared with a scale of 1:100,000 for a limited part of the country. In other words, in these maps and geological maps with a scale of 1: 250,000, in many cases, the formations have been selected as the basis for the stratigraphic boundaries separation, and rock units have not been separated within a formation.

Remote sensing can be used as a suitable tool to verify lithological maps. Remote sensing has been widely used by geoscientists in the last decade. The spectral reflection of rock unit outcrops and their

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automatic detection are generally studied by statistical methods and sometimes based on spectral signature analysis of minerals and rocks and the chemical composition of their components (Shirazi et al, 2017).

Younis et al. (1997) investigated the relationship between the spectral signature of rocks, weathering processes, and its effects on the spectral signature of different bands of the electromagnetic spectrum. The satellite data capability for rock unit outcrops detection using spectral behavior and their natural conditions has been proven by the scientists. Krishnamurthy (1997) presented the index of data used to separate lithological units by comparing the spectral bands of IRS I and IRS Liss II sensors with the TM sensor. Using PCA and HSI Transform (Hue, Saturation, Intensity), Kene-a (1997) prepared a lithological map by Landsat (TM) data and found the data appropriate usage.

Rimal et al. (2002), while pointing to the difficulty of work and the limitations of traditional methods of preparing geological maps through ground operations in Nepal, recommend preparing a geological map using a false colours composition 1, 3, and 4 (RGB), principal component analysis and using different filters along with aerial photographs. Nilanchal and Rampal (1992) determined the spectral signature separation limit of different rocks by digital processing method and examined their spectral signature. The outcrop characteristics can be identified by a specific sensor used as a unique indicator for the automatic detection in the signature analysis phenomenon study, which is one of the most important points in using satellite data.

Parcharidis et al. (1998) studied the characteristics of karst areas using Landsat TM satellite data. They examined features such as morphology, drainage network, vegetation, and topsoil cover in these areas. By studying the spectral reflectance behavior of different rocks in the laboratory, Van der Meer (2001) tried to match their spectral behavior with the spectral reflectance curve received from the TM sensor and to extract the statistical relationships between the experimental curve and the TM spectral reflectance curve. Finally, He proposed different coefficients to correct the actual spectral reflectance curve received by the satellite and compared the obtained results.

Hassani (2017) detected different lithologies using false color composite images and improving the image resolution. Regarding the homogeneity of rocks in the basin, he investigated the origin of Quaternary deposits and the share of each lithological unit in the production of these deposits. Jafari and Fatemi (1387) used ETM + and Aster data to detect Quaternary deposits and found it appropriate to use the hybrid method and Aster data. Most of the research on the preparation of lithological maps is based on satellite image processing and visual interpretation of results. In order to assess the risk of erosion and identify areas susceptible to water erosion in the Casilian watershed in northern Iran, Esmaeili et al. (2020) Ismaili et al. (2020) used the ICONA model, using remote sensing technologies and GIS. Based on the erosion risk map, results show that the moderate class had the highest percentage of erosion risk at the watershed. 10.92% of the catchment area contains a very high erosion risk class, with most of it in rangeland and Rock outcrops second.

In their study, Lu et al. (2021) used Sentinel-1 data to identify specific lithology. From the comes about, the scientists recommend that the dual-pol Sentinel-1 information are able to accurately recognize particular rocks and has the potential to capture the variety of distinctive rocks. Ghrefat et al. (2021) evaluated the ability of Landsat 8 Operational Land Imager (OLI) data to identify lithological units in southwestern Saudi Arabia. Field sampling was performed using manual GPS. These data were analyzed and interpreted with satellite images. Their results showed that Landsat-8 image data has great capability to identify lithological units and could be applicable in several areas in arid and semiarid environments.

The main hypothesis of the research (H0 hypothesis) is that by digital processing of Landsat satellite (ETM+) information, lithological units of the region can be prepared. Therefore, the main purpose of this study was to provide an automated model for identifying rock units in terms of hardness and erosion sensitivity using an automated logistic regression algorithm (without the need for visual interpretation and extensive fieldwork). As innovation and creativity in this study, nonlinear correlation analysis of Landsat ETM+ data was used to identify erosion-sensitive lithological units in the Soh Basin (Isfahan Province).

2. Material and Method

2.1. Study Area

The Soh basin is located 50 km Isfahan northern with a longitude of 51 degrees 15 minutes to 51 degrees and 45 minutes and latitude of 33 degrees 15 minutes to 33 degrees and 45 minutes (Figure 1). The average altitude of the watershed is 2708 meters above sea level, the average annual rainfall is 180 mm, and the annual temperature is 12 °C. The northern region is covered with the Karkas protected area high mountains, and the southern region consists of pediment landform and plain. Soils from upstream to downstream are highly diverse but mostly without profile development and are poor in fertility. The watershed vegetation is poor and often less than 15% except around springs, (Mokhtari et al. 2000).

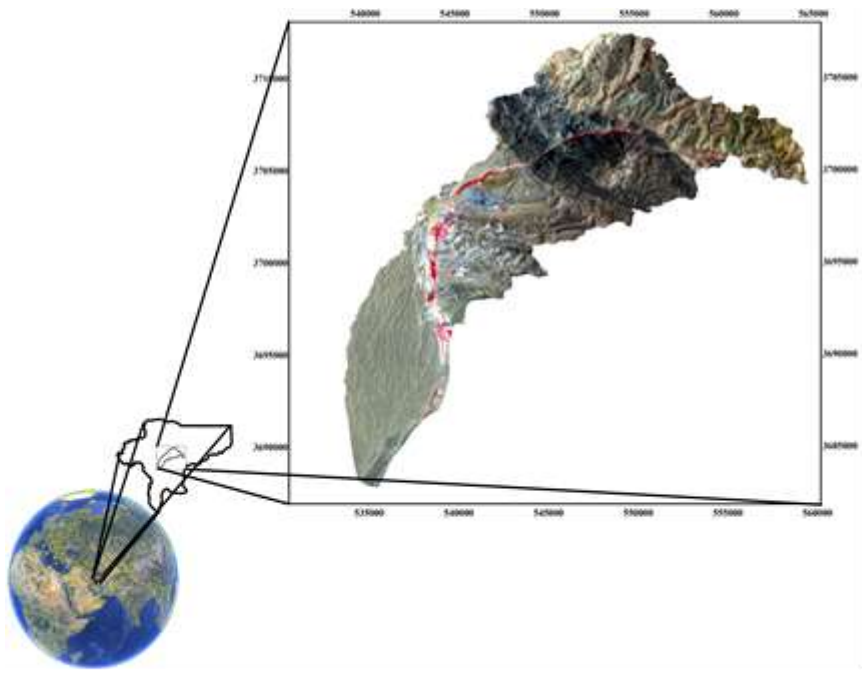


Figure 1. Location of the study area with a variety of Erosion-Sensitive Rock Units

2.2. The Study Area Geology

The study area is located in the northeast of the Sanandaj-Sirjan geological zone. The region stratigraphic sequence includes a wide variety of the Paleozoic to recent deposits. The oldest deposit includes dolerite rocks and red sandstone of upper red formation. Pabdeh (sandstone and dolomite), Bahram (limestone and dolomitic limestone), and Jamal (kaolinite sandstone, dark limestone, dolomitic limestone, and black siliceous dolomite) formations include Paleozoic deposits in the region.

Mesosoic deposits are widely spread in the region, Abyaneh (nodular shale and sandstone), Shotori (yellow dolomite), Nayband (black shale, sandstone, fossiliferous limestone), and Shemshak (alternation of shale and sandstone, conglomerate) formations contain marl and limestone related to the cretaceous era. Limestone, marl, conglomerate, tuff and marly limestones complex related to Qom formation consist Tertiary deposit series. Quaternary despites include travertine, old-alluvial deposits, young terraces deposits, and recent sediments.

2.3. The Method

A process of satellite image processing was used to determine erosion-sensitive rock units using geological, aerial photographs, and field operations. Each rock unit was investigated in 20 stations, and lithological characteristics, including rock type, weathering, and erosion susceptibility were recorded. Figure 2 shows the location of field points. These images were used to evaluate the processing accuracy of satellite images.

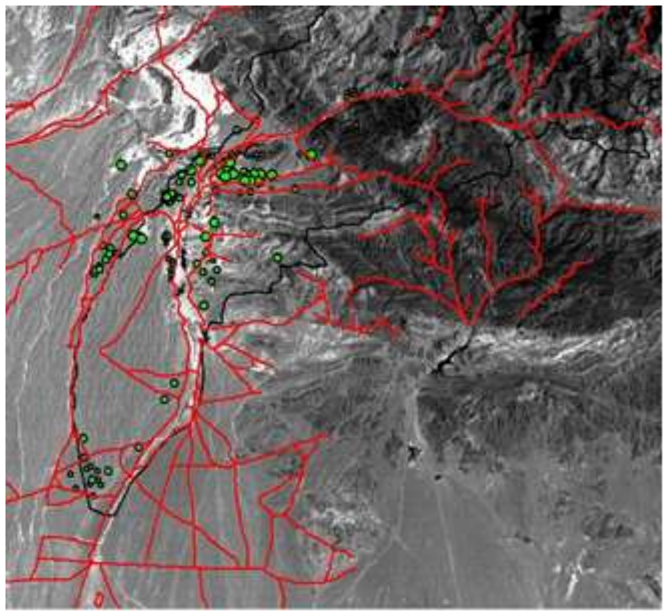


Figure 2. Field Form Registration Points

After preparing the data, ETM +/Landsat 7 satellite images (row 1364, path 137) were used for processing. All georeferenced bands of the same pixel size were re-sampled to include thermal band and the panchromatic band as well as to investigate the fusion bands. Regression analysis was the main method of data processing in this study. In this method, qualitative variables that were lithological units were used in the form of dummy variables. For this purpose, qualitative variables were studied in two steps. In the first step, these variables were entered in the role of the independent variable and the next step as a dependent variable in logistic regression.

Data Analysis Using a Dummy Independent Variable

Despite the numerous image processing methods commonly found in remote sensing software, new ones and new ideas are of interest to scholars in various fields of remote sensing. This method was used to determine the effect of rock material on the spectral reflection rate in different bands. First, the six bands of the ETM+ were analysed by principal component analysis. This analysis is very crucial in interpreting digital data. Collecting and integrating features information of different bands in several bands or fewer components is the most important efficiency of this analysis (Nilanchal & Rampal, 1992).

Parcharidis et al. (1998) examined the spectral reflectance of rock units, such as marl, with other rock units and found significant differences between them. Based on the average spectral reflection for each type of rock (lithological unit), these scientists recommended Equation (1). They also proposed Equation (2) to provide a suitable estimation model based on the mean spectral reflectance for each rock type.

$$Y_i = b_0 + b_1 X_{i1} + b_2 X_{i2} + \ldots + b_j X_{ij} + u_i \tag{1}$$

$$Y_i = b_0 + b_1 X_{i1} + b_2 X_{i2} + \ldots + b_j X_{ij} \tag{2}$$

In the model, Xij is rock units (dummy independent variable) at the sampling points, bi is the regression coefficient, and Yi is the dependent variable. These are the criteria for the spectral study of rock units (the first component of PCA analysis). This model investigates the spectral reflectance of rock units based on the changes of the first principal component (PC1), which has the most spectral information. In the above relations, if each point to be analyzed is of the desired rock material, the number one, otherwise the zero value is assigned to xij.

Data Analysis Using Dummy Dependent Variables

This method is suitable for examining qualitative variables such as different rocks that there are only two states, presence or absence, in each pixel or sample under study. Therefore, the dependent variable is a virtual variable with two values of 0 and 1. There are different methods for modeling the response function through the cumulative normal function to fit the response curve (Parcharidis et al. 1998). One of these methods is the use of the logistic functions.

The logistic function is defined as Equation 3 (Rimal et al, 2002; Tang 2001). The logistics function is nonlinear (Hosmer et al. 2013). When Y is a two-state dummy variable E (Y | X) = P; based on Austin and Merlo (2017), it is possible to convert it to a linear model using Equation (4). In the recent equations, E (Y | X), the change function of the dependent variable for each X, B0, and B1 are the coefficients of the variable X, and P* is the presence or absence of the dependent variable.

$$E(Y \mid X) = \frac{\exp(B_0 + B_1 X)}{1 + \exp(B_0 + B_1 X)} \tag{3}$$

$$P^* = B_0 + B_1 X \tag{4}$$

If spectral bands are examined to identify the marl lithological unit. The spectral reflectance rate (digital number) associated with 1, 2, bands, etc. can be considered as independent variables. In this model, the dependent variable can only have two states as with marl (1) and non-marl rock units (0).

3. Results

Early field surveys were based on nine rock units, including quaternary deposits, marl, tuff, shale, sandstone, limestone, dolomite, conglomerate, and dollarite volcanic rocks. The nine rock spectral reflectance is shown in Figure 3. As can be seen, different lithologies show a diverse spectral reflectance, especially in bands 3, 5, and 7.

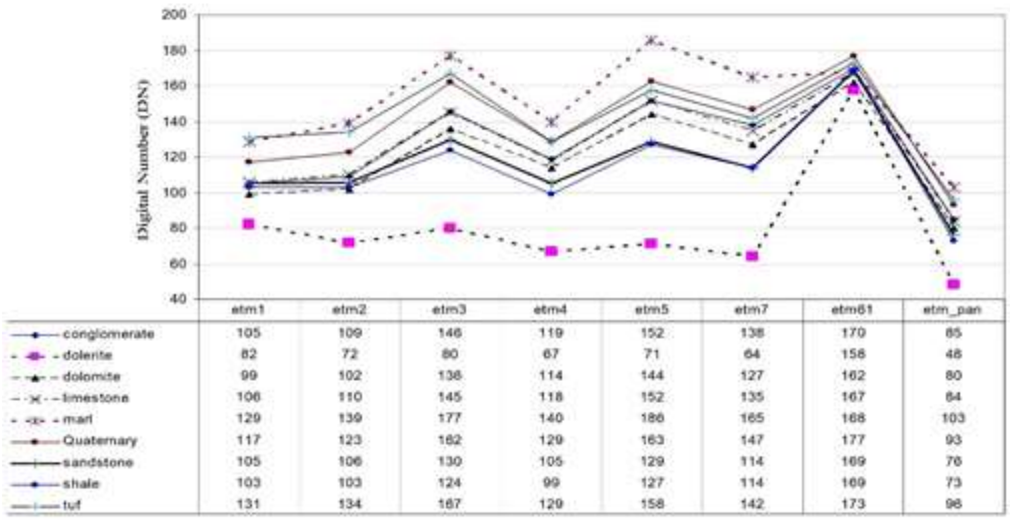


Figure 3. The Spectral Reflectance of NineRrock (Lithology) Units

As mentioned, the first principal component was considered as a predictor variable in this method. The result of the principal component analysis is presented in Table 1. The result shows that the first component with more than 94% variance represents most of the six-band data. Figure 4 shows the marl detection model using this method. In this figure, the marl is shown in black, and the other components of the image are less likely to have marl are in a lighter color. The result revealed the method is only able to identify the marl rock units. Other rock units could not be identified using the method.

Table1. Eigenvector Vector Matrix, Eigenvalue Representation, and Percentage of Variance for Reflective Bands in the First Six Components of PCA Analysis

ETM+ Bands / PCA Components	Band1	Band2	Band3	Band4	Band5	Band7	Special value	Percentage of variance
PC 1	0.20	0.29	0.47	0.37	0.54	0.48	2280.55	94.05
PC 2	0.37	0.41	0.44	0.21	-0.53	-0.42	85.87	3.54
PC 3	0.42	0.29	-0.01	-0.78	-0.08	0.35	36.32	1.50
PC 4	0.37	0.31	-0.47	0.04	0.53	-0.51	12.16	0.50
PC 5	0.32	0.08	-0.58	0.45	-0.37	0.46	7.92	0.33
PC 6	0.63	-0.75	0.16	0.03	0.07	-0.07	2.06	0.09

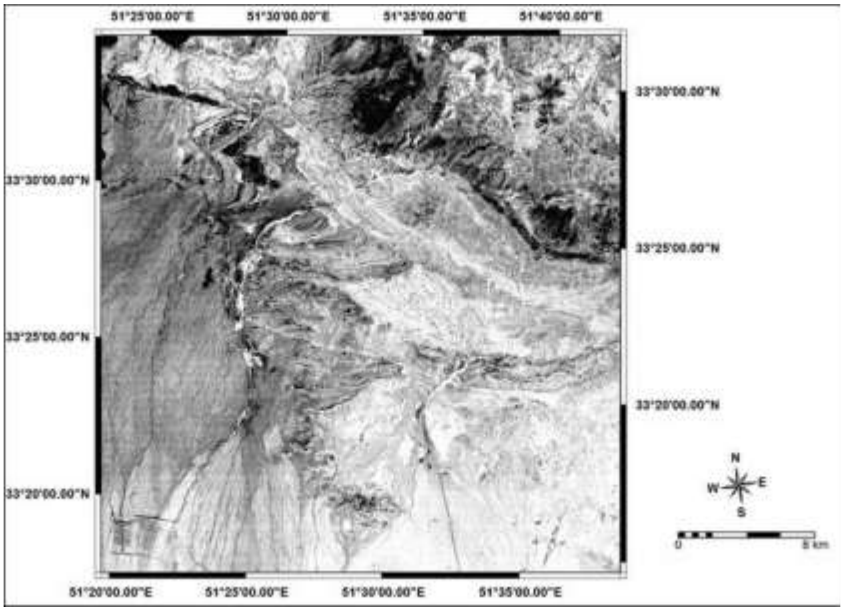


Figure 4. Marl Separating the Basin Model Using Dummy Variables

3.1. Data Analysis Results Using a Dummy Dependent Variable

The result of data analysis using a dummy dependent variable in the logistics function is presented in Table 2. The result shows that except for the model related to the limestone rock unit, the Chi-square index confirms the significance of the model for other rock units. The p-value also shows the relationship is acceptable at the 95% confidence level.

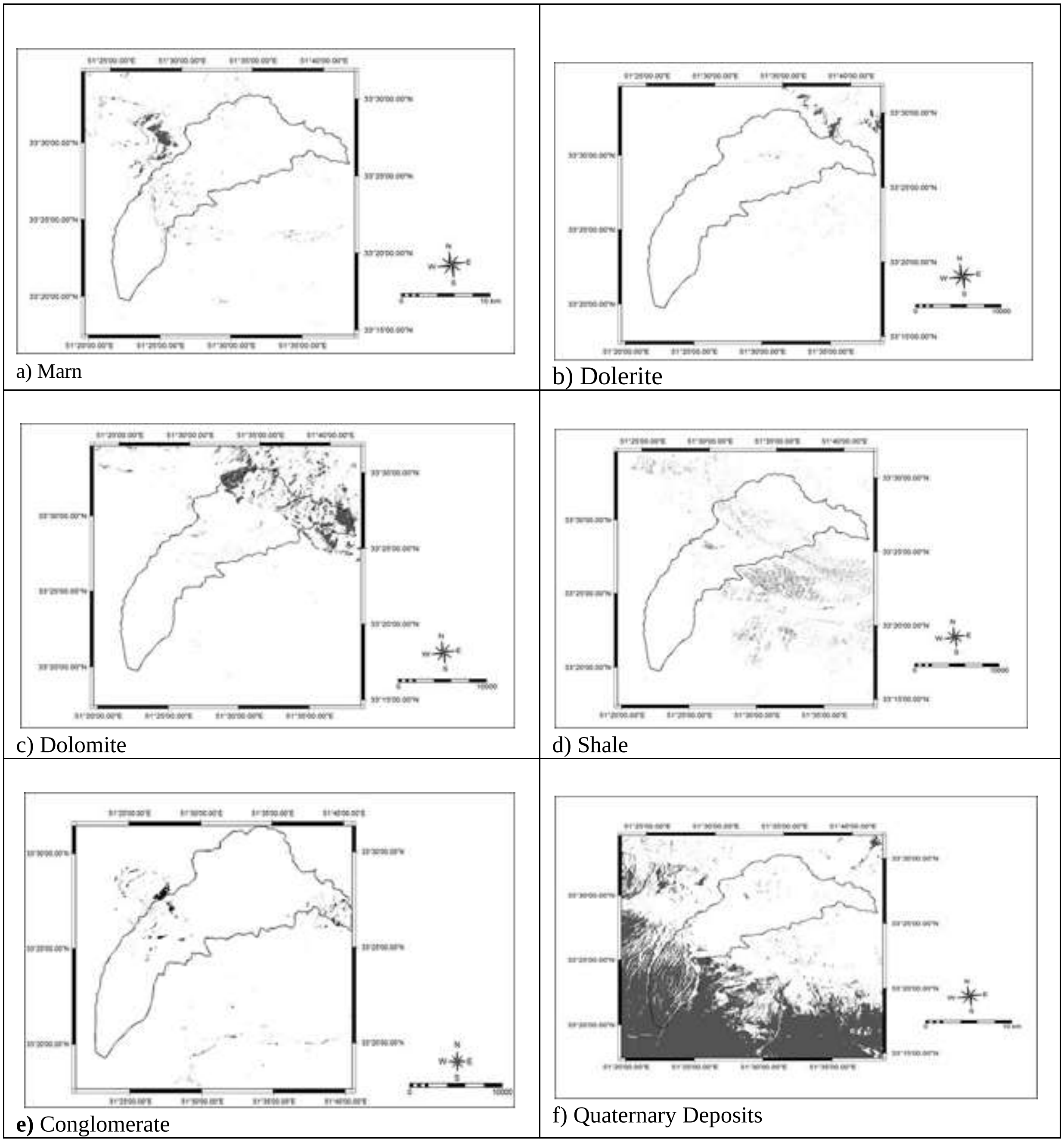
The identification model of marl, dolerite, dolomite, shale, conglomerate and quaternary rock (lithology) units is shown in Figure 5. It should be noted that since the outputs of the logistic model when calculated as a linear model are calculated based on the presence probability of a specific rock type for each component of the image, a probability of more than 50% was considered as the basis in the resolution map.

Table 2. Parameters of the Identification Model of Lithology Units Based on the Logistic Function

No.	Lithology	P-Value	Chi^2
1	Marl	0.0000	391.43
2	Dolerite	0.0000	270.59
3	Dolomite	0.0000	361.02
4	Limestone	0.00004*	32.305
4*	Limestone	0.00289	8.877
5	Shale	0.0000	223.4
6	Sandstone	0.0000	129.01
7	Tuff	0.0000	123.93
8	Conglomerate	0.0000	211.64
9	Quaternary deposits	0.0000	434.3

* Statistical parameters of combined application of indexing and regression for limestone unit

The possibility of the fine-grained deposit detection such as marl and clay rock types, which are transported downstream from different formations and are trapped in the rivers and drainages, was also investigated. For this purpose, some points were selected according to the spectral reflectance similarity and based on that, the identification model of fine-grained sediments was calculated using the logistic function. The model output shows a good correlation with the representing marl model and can be considered in identifying the sediment resource. Figure 6 shows the model development derived from Equation (5).



a) Marn
b) Dolerite
c) Dolomite
d) Shale
e) Conglomerate
f) Quaternary Deposits

Figure 5. Identification Model of Nine Lithological Units Using the Logistic Function

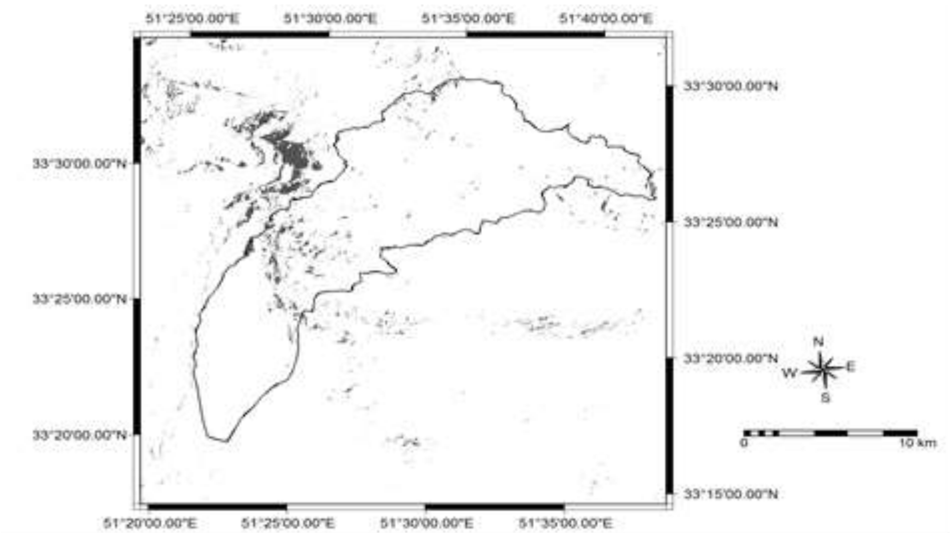


Figure 6. Fine-Grained Sediments Identification Model Using the Logistic Function

3.2. Indexing and Regression Combined Application

Since the logistic function, result to prepare the distribution map of the limestone rock unit was not acceptable, minor bands were eliminated in regression analysis. Therefore, the index was defined as Equation (5) for this rock unit based on the spectral behavior of limestone rock units in different bands.

$$LI = \frac{ETM7^2 - ETM4^2}{ETM7^2 + ETM4^2} \tag{5}$$

In which:

LI= Lithology Index

ETM4= 4^{th} band of ETM sensor

ETM7= 7^{th} band of ETM sensor

The index and recorded field data were analyzed. In correlation analysis, limestone rock unit as a dummy dependent variable and the index calculated with Equation (5) as an independent variable was subjected to logistic regression. Figure 7 shows the output map of the analysis. The final map resulting from the collection of detection maps of all rock units is shown in Figure 8. This map has been prepared based on the logistic regression analysis for each rock unit except lime. The limestone lithology unit, as stated, was obtained based on the new interbond analysis and the considering analysis in logistic regression analysis, entered in the final classification map. Unclassified areas are shown colorless in this image.

Based on field samples and the table presented by Feiznia (1995), rock units were classified according to their susceptibility to erosion. Data analysis was performed using dummy independent variables in SPSS software using multiple regression analysis. The overall accuracy coefficient was 0.66. The first component of PCA analysis of multispectral bands is the dependent variable in this model, and rock units (dummy variables) are the independent variable. As mentioned, this analysis yielded satisfactory results only for marl rock unit detection. The data analysis result using a dummy dependent variable based on logistic function showed that except for the limestone rock unit, the relationship was acceptable for other rock units at the 95% confidence level. Also, the index introduced for the limestone rock unit presented acceptable results. Although, the final classification accuracy and precision can be assessed based on the regression analyses statistical result used for each rock unit type; However, in order to increase the accuracy, the overall accuracy of the classification was obtained using 512 control points in the basin. The mean accuracy was 52.18%, and the overall accuracy was 56.8% which is an acceptable result considering the set of complexities in data analysis.

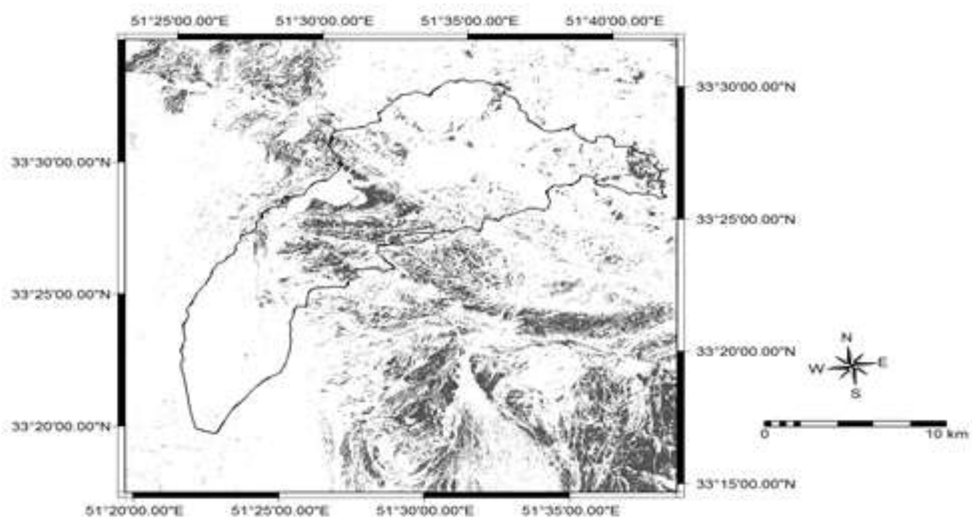


Figure 7. The Obtained Map Using the New Index for Lime

The conformity of the results with study area geological maps shows that the overall accuracy for these maps is 29.51% and 84.43%, respectively. Increasing spatial and thematic accuracy in these two Different mapping scales can cause such a significant difference in different scales of the map. The method presented in the paper can be used to study and identify rock units to verify geological maps. The verified lithological maps can be used in the preparation of large-scale maps of erosion susceptibility of rock units.

The results acquired from the classification of rock units based on their sensitivity coefficient showed that the lowest Sensitivity coefficient is related to sandstone, tuff, dolerite, and dolomite rock units with sensitivity coefficients of 0.75, 0.60, 0.55, and 0.50, respectively. The highest Sensitivity coefficient to shales, fine-grained sediments, marl, and Quaternary deposits are 0.20, 0.1, 0.07, and 0.05. Conglomerate and limestone rock units showed moderate values with values of 0.25 and 0.50. As can be seen in Figure 3, most of the sensitive units such as marl, shale, Quaternary deposits, and fine-grained sediments are located in the lower parts and near the outlet of the basin, and more resistant units are scattered in the middle and upper parts. This indicates the necessary strategy for comprehensive management of the watershed to reduce sediment and increase water productivity with the participation of watershed residents.

Table 3. Table of Rocks Susceptibility to Erosion

Lithology	Resistance coefficient (0-20)	Color
Conglomerate	5	
Dolerite	11	
Dolomite	10	
Limestone	8	
Marl	1.5	
Fine-grained sediments	2	
Quaternary deposits	1	
Sandstone	15	
Shale	4	
Tuff	12	

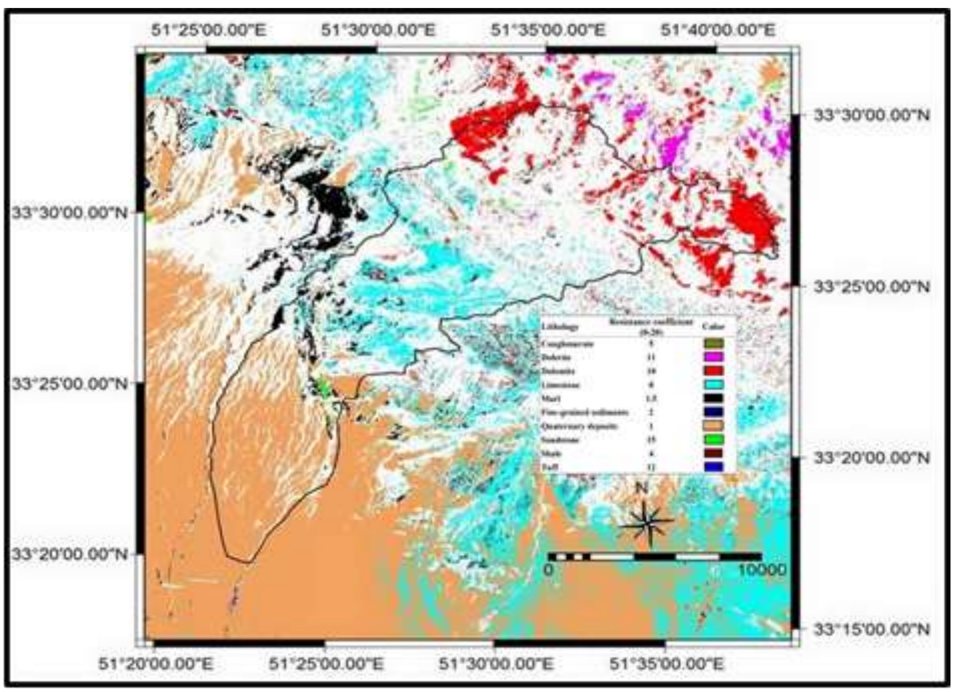


Figure 8. Rocks Susceptibility to Erosion (Unclassified Areas are Colorless).

4. Discussion and Conclusion

Barzegari dehaj et al. (2018) used Landsat 8 satellite images to compare the performance of different methods of detecting satellite images to isolate four geological units in the Taft watershed of Yazd. After processing the data, they processed the data and performed supervised and unsupervised classifications based on an updated geological map of the area. These scientists introduced the best analysis in their research with the b7 / b5 band ratio with kappa coefficient and overall accuracy of 78% and 87%. They considered the rock units KS, gd, Ktl, and Qal in the values of reflection accuracy of rock units in the observed and estimated ranges in the supervised classification map b7 / b5 for the four rock units studied in the field of research. The results of this study show a good agreement with our research.

Hashemi Tangestani and Shayghanpour (2019) used the band ratios of ester and sentinel 2 sensors to detect rock units in their study area. They affirmed that comparison of the results of this research with field observations and the results obtained from laboratory studies Showed that the simultaneous use of Aster and sentinel-2 data and the processing methods used, can be successful in separating the rock units of a metamorphic-sedimentary-volcanic complex. Therefore, the outcomes of this research agree with our research results. Accordingly, due to the good accuracy and confirmed results of the proposed method in this research; It can be used in watershed management and natural resource management.

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