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Assessment of ASTER Data for Soils Investigation Using Field Data and GIS in Damghan Playa

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Abstract

In order to assess the satellite data for soil investigation, ASTER digital data 20 June 2006, field study and phisio-chemical properties of soil, were analyzed. All landcover classes including soils are classified based on morphological and physico-chemical characteristics. Images were geocorrected and photomorphic units were selected based upon visual interpretation and sampling in study area. The images was classified using maximum likelihood algorithm; with eight approaches. The classified image was compared with the ground truth map. The lowest classification accuracy was achieved by optimum index factor (OIF) approaches and hence application of OIF for discrimination of soils was not effective way. The results showed that best index is not only efficient and other information such as DEM (digital elevation model) with the spectral combination increase the accuracy of classification and Kappa coefficient. Salinity Indexes (SI) and Normalized Soil Index (NDSI) and Brightness Index (BI) were useful for discrimination of the soils in the study area. Typic Haplocambids showed the maximum reflection due to bright color. In addition, the minimum value was related to the Typic Torriorthents class, because of dark gravels. The result showed ASTER data can differentiate Typic Haplocambids from Typic Torriorthents, Typic Haplosalids and Typic Haplogypsids in arid lands.

Keywords: ASTER; Soil; Maximum likelihood; Arid lands; Damghan; Iran

1. Introduction

The soil is an essential part of any terrestrial ecosystem as the product of interactions between parent material, biota, topography, and climate through time. As a result of human activities, the soil is also one of the most affected parts of the global ecosystem, (Flechsig, et al., 1995; Schiesinger, 1991). The first attempt to classify soils using a systematic approach was conducted in Russia in the 1880s. This rudimentary system was based on the identification of soil properties like texture and color that would lead to the creation of new and improved methods like the FAO system and Soil Taxonomy during the present century. These classification systems have traditionally involved field sampling and laboratory analysis that are time consuming, labor intensive, and destructive to the samples being analyzed. The use of remote sensing data, defined as the collection and interpretation of information about an object or feature from a distant point, is an alternative to classify soils. Remotely sensed methods are based on the measurements of the optical and spectral characteristics of the objects, i.e. their spectral reflectability. Each kind of object has its own specific spectral characteristics; type of the spectral curves and different values of the spectral reflectance coefficients in the different bands.

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Different soils in arid regions vary widely in the chemical characteristics and their reflectance contributes significantly to the overall spectral response from the surface area when vegetation cover is below 25- 35% (Vinogradov, 1984, Tueller, 1987).

Dwivedi (1992) studied the seasonal and annual salinity changes of soils. Another study in the field of salinity such as progress of salinity (1998) and role of the thermal band in the salinity studies (Alavi Panah et al., 2001) are carried out making use of the satellite data.

Karavanova (2000) used the remote sensing technique for the study and classification of the saline soils of Uzbekistan. Bands applied in this connection were green, red, and infrared bands. Making use of these bands, he classified the regional soils in 5 salinity classes with the 70 percent of precision. In the meantime, he concluded that regardless of soil humidity changes, the organic materials, carbonates and salt solved in water are the main factors affecting the spectral specification of the saline soils.

Martinez et al. (2002) evaluated Landsat TM data for classified soils in New Mexico. The results showed that the best differencing was gained when bands 2, 4, and 7 were present in classification, and the highest and lowest accuracy was related to Ustollic Paleargid soils and Typtic Torripsamment respectively.

Metternicht and Zink (2003) identified the salinity classes and Constraints on the use of remote sensing data for mapping saltaffected areas are shown related to the spectral behaviour of salt types, spatial distribution of salts on the terrain surface, temporal changes on salinity, interference of vegetation, and spectral confusions with other terrain surface.

Srivastava et al. (2004) applied the LISS_III (Linear Image Self-scanning) sensor data and panchromatic band with the spectral resolution of 5.8m for the generation of large-scale maps from the soils of Mahereshtrai region of India. With Hue-Intensity-Saturation (HIS) technique, they combined the panchromatic band with the LISS_III bands. With this technique, the map showed higher discrimination quality. Results of this study indicated that with the combination of images, topographic maps and field data, we can provide the large-scale soil maps (1:12500) in less time and low cost.

Matinfar et al. (2006) evaluated data from ASTER (Advance Spaceborne Thermal Emission and Reflection), LISIII, MSS (Multi Spectral Scanner), TM (Enhanced Thematic Mapper), and ETM_+ (Enhanced Thematic Mapper plus) sensors to identify soils of Kashan area in Iran. The results of this study indicate that ASTER, TM, and ETM_+ sensors classified soils in three classes: Typic Aquisalids, Typic Haplosalids, and Gypsic Aquisalids, due to capability of thermal band in discrimination between saline soil and Gypsic -saline soils.

Neild et al. (2006), using ETM images produced maps of Natric and Gypsic soils in America. They utilized band ratioing in order to get ideal results and finally recommended application of bands 5 and 7 for Gypsic soils. They recommend use of band ratios of 4 and 5 for identification of Natric soils.

The objective of this study is investigation of ASTER data efficiency for discrimination of soils and preparation of photomorphic map units and finally land cover map.

2. Materials and methods

2.1. Study area

The study area is marginal lands of playa of Damghan (Figure1). The selected area is located in the central Iranian deserts. This area is located in northeast of Iran between longitude 36° 09´ 26˝ to 36° 18´ 42˝and latitude of 54° 36´ 40˝ to 54° 49´ 02˝(Figure 2). The mean average of annual precipitation is 110 mm and temperature is 17^oC. The soil temperature regime is thermic and the soil moisture regime is aridic.

Fig. 1. Study area

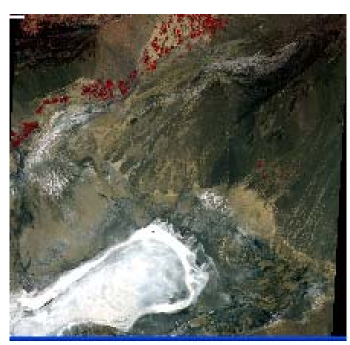
Fig. 2. Red-Green-Blue (RGB) color Composite of $ASTER_{321}$

ASTER data dated on June 20, 2006 (Table 1). The image was georefrenced to UTM map projection, zone 40 and datum of WGS84. In order to use of DEM in band combination pixel size must be same, thus image bands and DEM was resampled to 30 m for all bands.

Table 1. Statistical characteristics of ASTER Sensor bands in study area

Basic Stats	Min	Max	Mean	St dev
Band 1	6	181	82	17
Band 2	6	202	93	18
Band 3	6	229	117	16
Band 4	48	155	109	14
Band 5	57	150	108	13
Band 6	54	166	114	15
Band 7	51	160	108	15
Band 8	45	184	109	17
Band 9	51	172	96	12
Band 10	80	114	99	59
Band 11	88	123	108	58
Band 12	94	131	115	59
Band 13	110	150	135	91
Band 14	116	152	139	90

2.2. Field work and laboratory analysis

Upon field surveys and visual interpretation of false colors composite images, 17 homogeneous training classes were defined for the scope of investigation. Then profile was dug and soil sampling was performed in these classes. Soil factors such as pH (using pH meter), Ec (using Ec-meter), texture (determined by Bouyoucus hydrometer), Soluble calcium and magnesium (determined by titration with solution EDTA method), Soluble chlorine (determined by titration with $AgNO_3$), Soluble Carbonate and bicarbonate (determined by titration with H_2SO_4 using metilorange and phenolphthalein, respectively), Soluble Sodium and Potassium (determined by flame photometry method), Gypsum (determined by Aceton method) and lime (determined by collin's Calcimeter) are defined in laboratory. American comprehensive ordering system the U.S.D.A soil taxonomy 2003 was used for soils . The soils belonged to two orders of Aridisols and Entisols. Three sub-orders of solid, gypsid, and cambid that belonged to Typic HaplloSalid, Typic HaplloCambid and Typic HaplloGypsid.

2.3. Supervised classification process

The ground truth that was prepared for the comparison of the results of classification included all informational classes of the region (Figure 3 and Table 2). The Brightness Index (BI) and salinity indexes (SI) and Normalized Soil Index (NDSI) were calculated for the sake of the sensor data since it represented the lands impressed by salinity with remarkable clarity and it was classified and evaluated as a secondary image in a separate attitude along with the secondary image of the principle components. Calculation of the principle components indicated that more than 95 percent of the information is concentrated in the first up to third components. Therefore, the above components include useful information concerning phenomena capable of being extracted in the optimal and digital fashions. Reflection of the electromagnetic waves from the surface of soils depends on several factors such as frequency and size of the clay, sand, silt, particles, and detritus units, percentage of salt, color of the surface materials, quantity of humidity, rate of the organic traces, frequency and type of the plant species and the growth stages of plants.

If pixels of the red and infrared bands are plotted against each other, they will be distributed along one line (soil line) that means the positive correlation between the reflections of soil in red band with that in the infrared band. If such distribution is draw for a conical region with soil and plant covering, the above line will be called the "Soil Line" (Liang, 2004). This line composes a triangle in the top of which, pixels related to the green coating are, i.e. pixels having the higher brightness degree in the close infrared band and lowest brightness rate in the infrared band are related to the green and compact vegetation.

F1:Farm 1 F2:Farm 2 S1: Soil 1 S2: Soil 2 S3 : Soil 3 S4 :Soil 4 Ur : Urban S5: Soil 5 S6: Soil 6
S7 :Soil 7 Te : Terras OR: Orchard BL: Badland
R2: Range land 2 R3: Range land 3 R1: Range land 1 Ba: Bare land

Fig. 3. Ground truth map of study area and 17 information classes

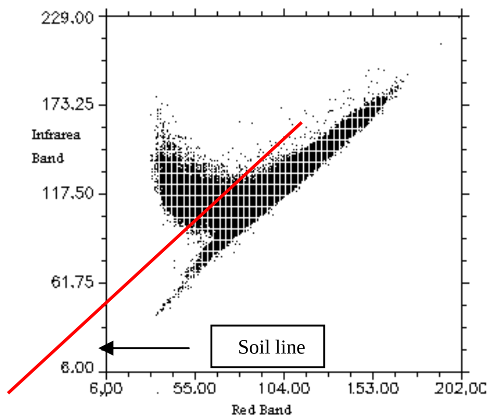

Fig. 4. Distribution of pixel values in red and infrared bands of the study area

Drawing of the distribution of the pixel values of the red band against the near infrared band for Damghan region (Figure 4) proves such concept and idea for the sake of the studied region, which is covered by vegetations, saline and gypsic soils, non-salinity soils, and sandy hills. This method of distributing pixels is considered as a criterion for identification of the distribution method of different spectrum classes.

2.4. Selection of classification algorithm

The algorithm selected for the supervised classification is the, maximum likelihood algorithm with the threshold of 20 that is one of the most common algorithms. Wilson (1986) presented the maximum probability method suitable for the supply of the topical maps from the satellite data. Alavipanah et al. (2001) compared different classification methods for the Mook region of Fars Province. This study showed that the highest precision in the maximum likelihood method is achieved, especially when the threshold limit is selected with the probability percentage of 20. The above-mentioned algorithm is applied for the classification of the sensor data.

2.5. Choosing the best bands combination

Because the ASTER image may be visually analyzed using only three bands at same time (assigned to red, green, and blue), we determined the three-band combination that had the greatest amount of variance within the scene by calculating the OIF (Jensen, 2005). The band combination with the highest OIF has the highest variance and lowest duplication for the scene, and thus contains the greatest amount of information about the scene. A Principle Component Analysis (PCA) was performed based on the correlation matrix. PCA is applied to 14ASTER bands. Therefore, the following eight approaches were used in this research:
First approach: ASTER 14 bands

Second approach: ASTER 14 bands plus DEM
Third approach: first rank PCA with indices of SI, BI, NDSI
Fourth approach: first rank OIF of 14 bands (band 14, 13, 12)
Fifth approach: first rank OIF of 14 bands (band 14, 13, 12)
Plus DEM
Sixth approach: first rank OIF of visible and SWIR bands (band 6, 7, 8)
Seventh approach: first rank OIF of visible and SWIR bands (band 6, 7, 8) plus DEM
Eighth approach: ASTER visible and SWIR bands

2.6. Selection of training classes

Based on the visual interpretation of the false color composite images, Aerial photograph, local information, and field observations, the homogeneous units from the image were identified on the monitor and the training samples were selected. The training classes for the classification of the ASTER sensor images are as follows:

Table 2. Summery of characteristics of trening classes of study area

Classes	Code of classes	Characteristic	Sub_group of soil (U.S.D.A)
Farm 1	Fa1	Fresh farming with density cover	....
Farm 2	Fa2	Dry- farming	....
Bad Land	BL	Vegetation less than 5%	....
Bare Land	Bad	Bare land with out vegetation	....
Soil 1	S1	Range land, surface pavement 70%	Typic HaploCambids
Orchard	OR	Pistachio orchards	....
Soil 2	S2	Hill ,desert pavement,	Typic HaploGypsids
Range Land 1	R1	Low density range land	....
Soil 3	S3	Very severe saline soil	Typic HaploSalids
Soil 4	S4	Saline soil with salt crust	Typic HaploSalids
Soil 5	S5	Saline soil with low gravel surface	Typic HaploSalids
Soil 6	S6	Saline soil	Typic HaploSalids
Range Land 2	R2	Range land with low vegetation	....
Range Land 3	R3	Eroded land , alluvial fan	....
Terras(Alluvial)	Te	Alluvial fan	....
Soil 7	S7	Surface pavement 70%,	Typic Torriorthent
Urban	Ur	Urban, village	....

3. Results and Discussion

3.1. Analysis of discrimination of information classes

The visual interpretation for the discrimination of phenomena is not solely reliable since it enjoys maximum spectral data of three bands and ignores the other spectral dimensions of phenomena but if it is combined with the statistical information such as mean and standard deviation and suitable band range is used, it can be used for the identification of training classes. Measurement of the statistical discrimination between model and a statistical parameter that is usually used for this purpose is a contrast since the weight distance of covariance is between the averages of classes.

The following matrix (Table 3) deals with discrimination of classes in visible bands approach it is based on Jeffries-Matusita distance and the amplitude of its figures is between zero and two, where zero indicates lack of discrimination and two indicates complete discrimination of classes in relation to one another. Reflectance of classes can be calculated for each pair of classes and can be shown in the form of matrix.

As indicated in the above matrix, S7 class has been completely discriminated from soil classes of S1. S6 and S2 that is due to different altitude position of soil classes and on the other hand, due to different reflectance of levels of this soil because the lowest DN value relates to S7 soil class that are due to dark detritus that exist at the soil level. This is well manifest. However, S1 and S6 soils have not been discriminated completely while these two classes have been completely discriminated in the position of ASTER band 14 plus DEM that seems to be due to introduction of thermal bands and DEM. Soil classes of S6 have not properly discriminated from class S4 that is because of similarity of surface cover of these two classes. In the approach of ASTER visible and intermediate bands, S6 has not completely discriminated from S1 but in position 14 of ASTER band where thermal bands have also been implemented, these two soil classes have discriminated. In position 14 of ASTER band, S7 has completely discriminated from all the three soils. In first time OIF of 14 bands of ASTER that are bands 12, 13, and 14 of ASTER sensor, S7 did not properly discriminate from S1 and S2 but S6 and S2 have completely discriminated that is indicative of positive role of thermal bands in discrimination of soils of S2 and S6. On the other hand, S6 has not completely discriminated from S1 in this approach. Given the above description, we can conclude that OIF index is not effective for discrimination of soil classes in an arid zone like Damghan (Table 3).

Table 3. Discrimination matrix of information classes in the second approach

	S7	S1	S6	S2	R2	S3	S4	S5	R1	Fa1	Fa2	Ur
S7	-											
S1	1.97	-										
S6	1.97	0.76	-									
S2	1.95	1.91	1.8	-								
R2	1.9	1.49	1.73	1.86	-							
S3	1.6	1.83	1.62	1.96	1.92	-						
S4	1.9	1.03	0.74	1.49	1.9	0.82	-					
S5	1.99	1.99	1.99	1.99	1.99	1.99	1.98	-				
R1	1.87	1.68	1.85	1.79	0.95	1.72	1.83	1.99	-			
Fa1	1.99	1.99	1.99	1.99	1.99	1.99	1.99	2	2	-		
Fa2	1.98	1.99	1.99	1.99	1.99	1.25	1.99	2	2	1.99	-	
Ur	1.62	0.71	1.18	1.58	1.44	1.99	1.02	1.98	1.99	2	2	-
OR	1.99	1.99	1.99	1.99	1.99	1.99	1.99	2	2	1.99	1.9	1/9

3.2. Statistical assessment of training classes

Study of statistical parameter showed quantities of SD (standard division) of gypsic soil (S2) is near 1, that reason for homogenty of S2 class , but other soil classes (S1, S3, S4, S5, S6, S7) have SD between 2.8 until 11.38, that reason for decrease of homogeneous of this classes and probability mixture spectral and mixed pixel (Tables 4-5).

Table 4. Quantities of SD (standard division) of training classes

	S1	S2	S3	S4	S5	S6	S7	Fa1	Fa2	OR
B 1	6.4	1.0	10.45	4.54	7.88	5.0	4.9	6.32	4.02	4.46
B 2	8.4	1.0	11.38	6.48	6.61	5.1	6.2	9.51	6.38	6.58
B 3	6.5	1.2	11.14	7.07	6.33	5.6	7.0	11.92	4.66	4.24
B 4	6.0	0.6	6.99	5.08	3.27	4.4	6.7	6.36	3.79	4.99
B 5	5.4	0.9	6.66	4.96	3.85	4.7	6.7	5.80	4.18	4.81
B 6	5.8	1.0	7.76	5.89	5.00	5.4	6.7	7.62	5.09	5.61
B 7	6.2	0.8	7.58	5.89	3.77	4.9	6.9	7.16	4.57	5.61
B 8	6.7	1.0	8.72	5.95	3.85	5.3	7.3	7.58	5.26	5.94
B 9	5.2	0.8	6.56	4.89	2.80	4.2	4.6	6.33	4.36	4.25

3.3. Soil classes of the study area

The following diagrams (figure 5 and figure 6) represent the spectral reflection of the studied regional soils. As one can see, the maximum reflection is related to S1 soil that is because of its bright surface. In addition, the minimum value of DN is related to the class of S7 Soil that is because of the grey gravels of it existing on earth in this soil class. Each of the soil classes is located in the thermal bands having similar status in which wave lengths have intense spectral overlaps. On the other side, as is observed through the figure, the S1 and S6 soils show almost single reflection.

Saline soils of the study region are classified in four classes i.e. S3, S4, S5 and S6 that are represented in Diagram 1. As one may discover form this diagram, the thermal bands result in the discrimination of S5 soil from the remainder saline soil classes. On the other side, the S4 and S6 soils have similar process.

3.4. Assessment of results of classification:

After classification (Figures 5-7) the map resulted from the classification was converged with training area (Table 5). On the basis of this convergence, error matrix of image classification was calculated and its results were utilized for calculation of overall accuracy and Kappa index. The important point that can be seen in the results acquired from classification is that Kappa index is lower than overall accuracy, that is due to reduction of the role of chance in calculation of this index because in addition to diagonal elements of error matrix, exterior elements of the matrix diameter also play a role in calculation of this index.

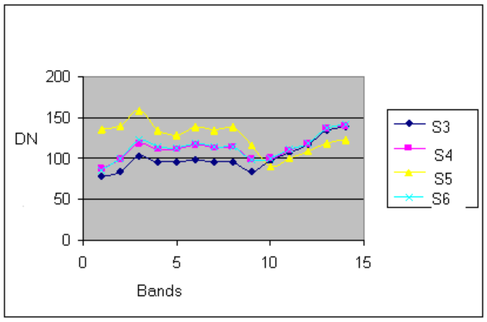

Fig. 5. Soil spectral reflectance study area

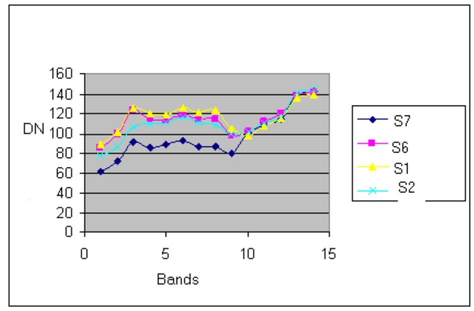

Fig. 6. Saline soils spectral classes in reflectance

Table 5. Overall accuracy and Kappa index in the approaches utilized in classification

Approach	Overall accuracy	Kappa index
First approach	75.08	73.
Second approach	78.71	77.
Third approach	72.06	70.
Fourth approach	60.49	58.
Fifth approach	69.9	68.
Sixth approach	53.7	50.
Seventh approach	72.2	71.
Eighth approach	77.22	75.

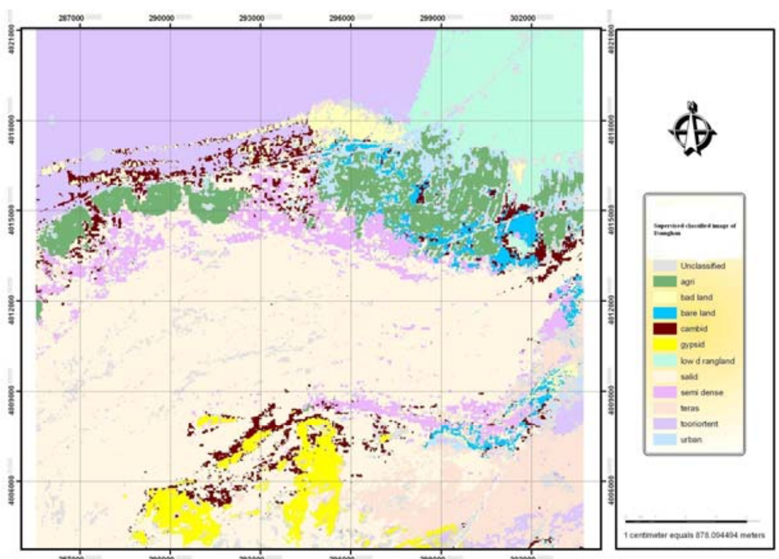

Fig. 7. Supervised classified image, using in second approach

3.5. Analysis of the impact of band composite on accuracy of classification

Eight approaches have been used for classification in the present study. The lowest overall accuracy relates to first rank OIF of visible and intermediate bands that is 53.7 but in the next approach where digital layer of altitude was added, the overall accuracy reached 72.2. This 20 percent increase in accuracy is due to involvement of DEM of altitude because information classes in the zone do not have the same altitudinal position. This result is in conformity with results of Matinfar (2006). Besides, in first time OIF approach resulting from all ASTER bands, accuracy of 60.49 was achieved but when digital layer of altitude was added, we witnessed a 9 percent increase in classification. The lowest classification accuracy was achieved in OIF approaches and hence application of OIF for discrimination of soils of this investigated zone was not found effective, that is in conformity with results of Matinfar (2006). Introduction of all spectral and spatial information appears to be a more important factor in increasing of classification than observance of ideal index as the criterion of selection of bands for classification of lands in arid zones. In the approach of application of visible and intermediate that includes the first 9 bands of ASTER sensor, 75 percent accuracy was achieved but in the next approach where thermal bands were added, accuracy increased to 77.22. This increase was due to thermal difference of information classes. The highest accuracy of classification (figure 7) relates to ASTER 14 bands approach plus DEM of the zone where accuracy of 78.71 was achieved. These results are in conformity with results of Weismller (1977), Dobos (2000), Zinck (2000), Martinez (2002), and Alavipanah (2001-2002). In the first time PCA approach of all bands plus salinity indexes SI, BI, and NDSI, 72 percent accuracy was achieved that indicates usefulness of these indices for discrimination of soils in the investigated zone. They are useful because in this zone, due to coverage of some part of it by salt, and difference of its brightness with other parts, these zones can be discriminated from other classes.

5. Conclusions

Based upon the results obtained through the eight approaches utilized, the Second approach, ASTER 14 bands plus DEM was selected as the best approach to classify soils in arid lands. Because information classes in the zone do not have the same altitudinal position, DEM was effective. The result showed ASTER data can differentiate Typic Haplocambids from Typic Torriorthents, Typic Haplosalids and Typic Haplogypsids in arid lands.

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