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Evaluation of ASTER images capability for identification of homogenous and heterogeneous soils in dry regions based on linear and non-linear relations Case Study: Khatam plain, Iran

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Abstract

Degree of homogeneity of soil particles is one of the major factors effecting soli spectral reflectance which is calculated based on the Geometric standard deviation of soil particles. This study evaluates the application of ASTER imagery for identification of homogenous and heterogeneous soils in dry regions with special reference to linear and non-linear equations in Khatam plain of Yazd province, Iran. To do this, soil samplings (76 samples) from the soil surface has been done in 2007/08/23 and were measured values of the texture fragments by using of the hydrometer method. Finally, Geometric standard deviations of soil particles were calculated for each sample point. After doing the geometric and radiometric corrections and applying of the average filters on the satellite images, some processing operations were done. Correlation coefficient between soil texture data and soil spectral reflectance for homogenous (Geometric standard deviation <10) and heterogeneous soil samples (Geometric standard deviation ≥ 10) were calculated based on the linear and non- *linear equations*. The results showed that the Near Infra Red (NIR) band of ASTER sensor can be effective on the spectral reflectance of homogenous soils and identification of clay texture of heterogeneous soils. Also, the results of this study indicated that Short Wave Infra Red (SWIR) has a remarkable effect on the soil spectral of sand and silt particles in heterogeneous soils.

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Introduction

Soil texture is an important land environmental variable because it plays a key role in soil degradation and water transport processes, controlling soil quality and its productivity (Hillel., 1980).In soil science, methods for mapping soil texture at various scales are needed for several applications. The complex and expensive conventional methods and field surveys are currently driving the scientific community to develop indirect estimation methods based on proximal and remote sensors (ground-based or airborne), including reflectance spectroscopy (Brown., *et al.*,2006;Ben-Dor *et al.*,2009).

Based on the soil-landscape model concept (Jenny, 1941), difficult to measure soil types and soil properties can be associated with some easily obtained soil forming factors. In the low relief areas, such as plains and gently undulating terrains, relatively easily obtained environmental factors such as landform and vegetation generally cannot effectively indicate soil spatial variation (Ding *et al.,* 1989; Mckenzie and Ryan., 1999; Zhu *et al.,* 2010). To overcome the difficulty of mapping soil texture in these regions, some attempts have been made to predict the variation of soil texture using multispectral remote sensing (Coleman *et al.,* 1993; Sullivan *et al.,* 2005). Dematte *et al (*2009) applied multiple spectral bands (TM2, TM5, and TM7) of Landsat Thematic Mapper imagery to estimate the variation of surface clay content in a bare soil area located in the region of Barra Bonita, Brazil. Legacherie *et al* (2008) used the data from laboratory, field and airborne hyperspectral measurements on bare soils to estimate topsoil clay.
Bragato (2004) explored the combination of detailed field soil sampling and spatial interpolation (linear regression and geo-statistics) to obtain the soil spatial distribution across flat flood -plains. Curcio *et al* (2012) indicated that a satisfactory level of prediction of soil texture can be obtained using only the PLSR technique, whereas a moderate level of prediction was obtained only for clay content using the CR approach.

Shirazi and Boersma (1984) claimed that the geometric standard deviation reflects soil homogeneity. Dwived *et al* (2001) concluded that spectral reflectiance obtained from the top soil represents some initial data which is helpful in understanding soil textutal properties. Casa *et al* (2013) highlighted the importance of middle infrared band for identification of clay, silt, and sand in the soil texture. Feng *et al* (2012) used MODIS images for preparation of soil textural map. Cozzolino *et al.*, (2003) concluded that there is the strong correlation (more than 0.8) between silt, sand, and clay particles and their spectral reflectance. Ebrahimi *et al* (2013) found that near infra red band of ASTER images Can be an effective role in determining the percentages of sand, silt, clay and geometric mean of soil particles. Shirazi *et al* (2011) indicated that using of the combination of near, middle and infrared bands of LISS-III with ASTER bands provide more accurate stratification of soil in the Damghan play a of Iran.

This study evaluates ASTER data with special respect to identification of homogenous and heterogeneous soils of dry regions via linear and non-linear functions in Khatam plains of Yazd province in Iran.

Materials and methods

Study area

Khatam plain is located in the southern-west of Yazd province of Iran. The study area covers approximately 713.5 km^2 (54.08°E- 54.3E° and 30.35°N – 30.51°N) (Fig. 1). Mean annual temperature is 18.6°C, and mean annual precipitation is 98mm. Based on modified Domartondryness index climate is between arid cold to hyper arid cold. Soil texture exhibits great spatial variation and varies from sands to clays.

Data and software used

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) is an imaging instrument onboard Terra. ASTER operates in the visible through thermal infrared portions of the electromagnetic spectrum. Of its 14 bands, three are in the visible and near-infrared (VNIR) between 05.-0.9 µm, six are in the short-wave infrared (SWIR) between 1.6-2.43 µm, and five are in the thermal infrared (TIR) between 8-12 µm. ASTER data products use combinations of VNIR, SWIR, and TIR and are important for cloud studies, surface mapping, soil and geologic studies, volcano monitoring, and investigations of land-use and vegetation patterns (ASTER Users Handbook).

So, In this study, we hypothesized that ASTER data with a high spatial resolution are useful to study homogenous and heterogeneous soils. Therefore, ASTER data (23/08/2007) is used to display the variation of soils. Geographical positioning system (GPS) was used for registration of points locations in the field survey, ENVI4.2 software was applied for image processing and SPSS-20 software was applicable for regression analysis.

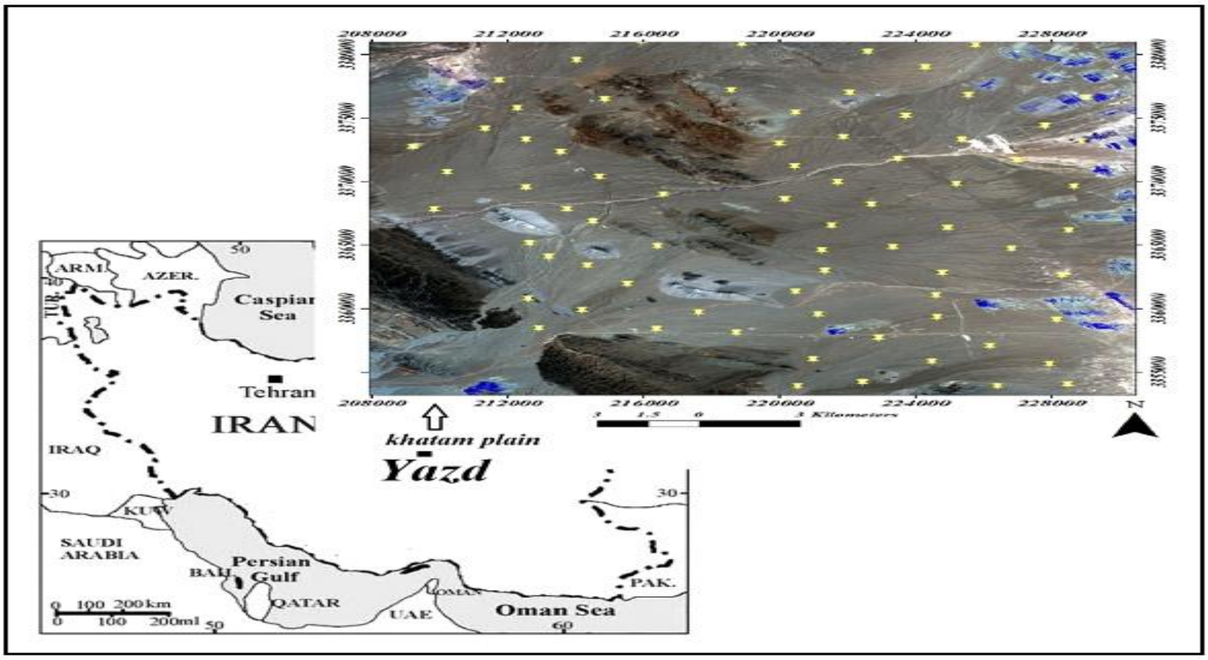

Fig. 1. Geographical location of Khatam plain in Yazd province – Iran.

Oil Field Sampling

In order to soil texture analysis (sand, silt, clay), Field survey including soil samples collection of the study area was undertaken in august 2007 which was overlapped in terms of time with the date of imagery. The soil samples (76 samples) were analyzed (Fig. 1) and soil texture was determined based on the hydrometric method (Soil Survey Staff, 1996).

Re-processing and Processing of the Satellite Imageries

In this research, in order to geometric registration, Image to image technique was applied. In this stage ETM geo-referenced image and ASTER image were considered as base and row images respectively. 68 control points were selected on the Base (ETM+) and Row (ASTER) images.

Then by using second-degree polynomial functions and the nearest neighborhood method, ASTER images were corrected with RMSE equals 0.45. In order to removing field sampling errors and atmospheric correction was applied average filtering of 3*3 and FLAASH algorithm respectively. Eventually some processes such as: Principal Component Analysis (PCA), Soil Line Euclidean Distance (SLED) and Normalized Difference Vegetation Index (NDVI) were done on the images. NDVI index was used for avoid of take sampling in the sites with dense vegetation. To produce of Soil Line Euclidean Distance (SLED) and Normalized Difference Vegetation Index (NDVI) were used following Equations (1 and 2) Bannari *et al.* (1995), Fox and Sabbagh (2002).

$$SLED = ((NIR - A)^2 + (R - B)\ )^{0.5} \quad \text{Equation 1}$$

$$NDVI = (NIR - R)/(NIR + R) \quad \text{Equation 2}$$

In these equations R and NIR represent ground surface reflection in red and near infrared. A and B represent the minimum spectral reflection in near infrared and red domain respectively. Although soil texture is only based on the average particles diameter and their abundance, but according soil textural triangle (Shirazi and Boersma, 1984),can obtain an important information regarding geometric particle diameter, soil texture mechanical analyses and soil homogenous (Bybordi, 2010). In order to differentiate of homogenous and heterogeneous soils in the study area by using of soil textural triangle, silt, Sand and clay portion of each sample was converted and calculated to geometric standard deviation of soil particles via equation(3) (Shirazi and Boersma, 1984).

Table 1. Correlations values between soil texture particles and spectral reflectance values in major and processed bands.

Band	Sand	Silt	Clay
b1	-.361**	.356**	.328**
b2	-.332**	.329**	.303**
b3b	-.60**	.531**	.657**
SLED	-.326**	.319**	.307**
b4	-.323**	.335**	.255*
b5	-.312**	.347**	.198
b6	-.289*	.331**	.158
b7	-.383**	.417**	.241*
b8	-.50**	.514**	.315**
b9	-.272*	.337**	.095
b10	-.085	.031	.173
b11	-.167	.120	.204
b12	-.243*	.182	.303**
b13	-.110	.057	.178
b14	-.113	.060	.178
pca1	.371**	-.354**	-.368**
pca2	-.195	.115	.361**
pca3	-.111	.080	.172

** 1% Significance level

* 5% Significance level.

$$a = 0.01\sum_{i}^{n} f_i \ln M_i \quad \text{Equation 3}$$

$$b^2 = 0.01\sum_{i=1}^{n} f_i \ln^2 M_I - a^2$$

$$\delta_g = Expb$$

In this equation δ_g, fi and Mi are respectively geometric standard deviation of soil particles, abundance percentage of each particle (silt, clay, sand) and numerical average particles diameter(Mi is 1.025mm for sand, 0.026mm for silt and 0.001mm for clay).After calculation δ_g ,all of 76 samples were divided in to two groups namely homogenous Samples (21 samples) with δ_g <10 and hetrogenous Samples (51 samples) with δ_g >10.

Spectral reflectance values of mentioned samples were extracted in 14 major bands of ASTER, SLED and Principal Component Analysis (PCA) layers. Then, correlation coefficients(R) between Spectral reflectance quantities of total samples, homogenous and heterogeneous samples with soil texture particles quantities (silt, sand and clay) were calculated .Finally, determination coefficients between soil data and remote sensing data for non-linear and linear functions was compared. Non-linear function was calculated based on the following equation.

Table 2. Correlations values of soil particles with major and processed bands in homogenous soils.

Band	Sand	Silt	Clay
b1	-.425	.446*	.378
b2	-.445*	.461*	.422
B3	-.815**	.729**	.902**
b4	-.402	.395	.429
SLED	-.424	.429	.455*
b5	-.357	.300	.449*
b6	-.448*	.446*	.378
b7	-.497*	.508*	.419
b8	-.608**	.524*	.60**
b9	-.422	.374	.358
b10	-.111	.045	.163
b11	-.057	-.037	.174
b12	-.519*	.444*	.528*
b13	-.439*	.423	.411
b14	-.185	.077	.196
pca1	.461*	-.456*	-.504*
pca2	-.226	.122	.557**
pca3	-.095	.087	.059

** 1% Significance level and * 5% Significance level.

Table 3. Correlations values of soil particles with major and processed bands in heterogeneous soils.

Band	Sand	Silt	Clay
b1	-.341*	.344*	.290*
b2	-.294*	.300*	.236
B3	-.420**	.360**	.490**
SLED	-.298*	.301*	.243
b4	-.257	.298*	.122
b5	-.234	.316*	.035
b6	-.212	.293*	.020
b7	-.320*	.386**	.137
b8	-.443**	.496**	.259
b9	-.177	.278*	-.029
b10	-.054	-.022	.239
b11	-.131	.063	.272*
b12	-.202	.118	.356**
b13	-.092	.013	.288*
b14	-.111	.032	.299*
pca1	.343*	-.335*	-.309*
pca2	-.192	.112	.331*
pca3	-.114	.070	.235

$= b_0 + b_1x + b_2x^2 + b_3x^3$ Equation 4

Results and discussion

Correlations values between soil texture particles and spectral reflectance values in major and processed bands (Geometric standard deviation of soil particles has been neglected) are presented in Table 1.

Based on the geometric standard deviation of soil particles, samples were divided in two classes: 1) homogenous soils with δ<10 and 2) heterogeneous soils with δ>10.

Assessment of Table (1)indicates that there is a significant relationship between sand and silt particles with spectral reflectance in VNIR and $PCA1_{(1-14)}$ at 1% and 5% significance levels. Although, as this table shows the highest correlation is established with bands 3 and 8 (R=-0.5 and R=-0.6).

Table 4. Determination coefficient between soil texture particles and major and processes bands in homogenous soils.

Band	Linear			Non-linear(Cubic)		
	Sand	Silt	Clay	Sand	Silt	Clay
b1	0.18	0.195	0.129	0.295	0.353	0.149
b2	0.19	0.212	0.159	0.399	0.453	0.221
b3	0.662	0.526	0.801	0.835	0.71	0.861
b4	0.183	0.167	0.187	0.52	0.602	0.256
b5	0.175	0.153	0.193	0.45	0.488	0.296
b6	0.166	0.157	0.134	0.362	0.415	0.202
b7	0.26	0.249	0.202	0.53	0.571	0.298
b8	0.389	0.38	0.252	0.662	0.695	0.353
b9	0.235	0.234	0.147	0.463	0.517	0.228
b10	0.06	0.039	0.046	0.066	0.045	0.074
b11	0.139	0.103	0.106	0.269	0.22	0.32
b12	0.192	0.143	0.18	0.489	0.445	0.451
b13	0.083	0.056	0.043	0.104	0.065	0.175
b14	0.085	0.058	0.045	0.125	0.08	0.202
SLED	0.182	0.187	0.193	0.463	0.514	0.229
Pc1	0.21	0.207	0.231	0.439	0.458	0.315
Pc2	0.051	0.017	0.31	0.057	0.026	0.342
Pc3	0.007	0.005	0.002	0.13	0.21	0.08

Table 5. Correlation coefficient between soil texture particles and major and processes bands in heterogeneous soils.

Band	Linear			Non-linear(Cubic)		
	Sand	Silt	Sand	Silt	Sand	Silt
b1	0.116	0.119	0.084	0.119	0.123	0.084
b2	0. 087	0.09	0.056	0.102	0.112	0.057
b3	0.176	0.13	0.24	0.178	0.13	0.243
b4	0.066	0.089	0.015	0.081	0.117	0.015
b5	0.055	0.1	0.001	0.12	0.193	0.006
b6	0.045	0.086	0.0001	0.114	0.185	0.005
b7	0.101	0.148	0.018	0.164	0.234	0.025
b8	0.197	0.247	0.067	0.229	0.293	0.07
b9	0.03	0.076	0.001	0.136	0.188	0.031
b10	0.003	0.001	0.057	0.003	0.009	0.092
b11	0.017	0.004	0.074	0.019	0.005	0.132
b12	0.041	0.014	0.127	0.066	0.02	0.24
b13	0.008	0.001	0.083	0.012	0.001	0.164
b14	0.012	0.001	0.089	0.017	0.001	0.169
SLED	0.089	0.091	0.059	0.0224	0.271	0.091
Pc1	0.118	0.112	0.095	0.222	0.256	0.154
Pc2	0.037	0.013	0.109	0.171	0.116	0.27
Pc3	0.013	0.005	0.055	0.022	0.008	0.111

The highest correlation of clay particles is established with band3and PCA1 (1-14) (0.66 and 0.368 respectively). There is also a significant relationship between clay particles and bands of VNIR and SWIR and The values of soil texture particles have a significant relationship with SLED (in level 1%).

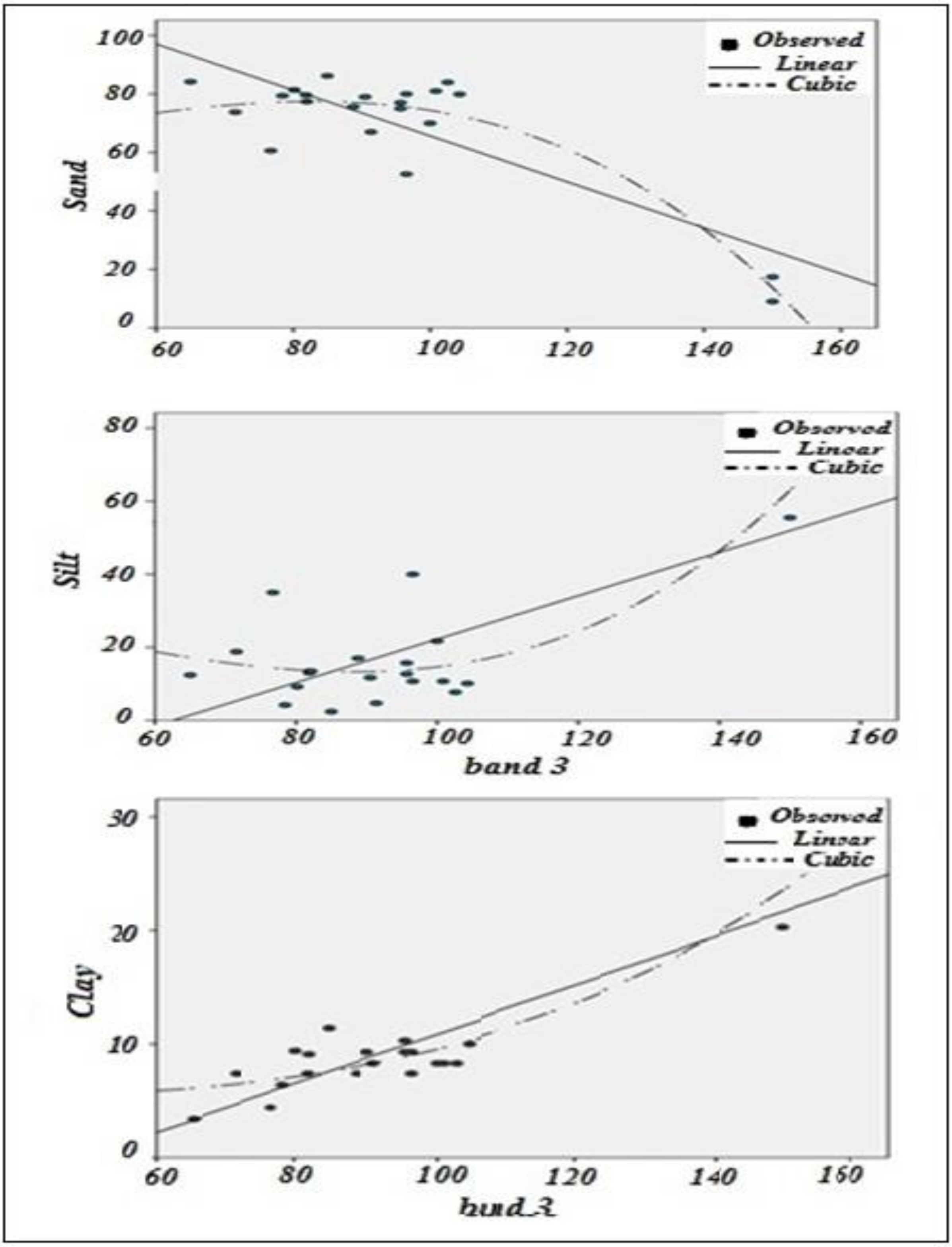

Fig. 2. Scatter plot between soil texture particles and spectral reflectance data for homogenous (left) and heterogeneous soils (right).

Correlation values of soil particles with major and processed bands are presented in Table 2 and 3. According to these tables, Although band 3 reflects the highest correlation with sand and silt particles, but the correlation coefficient of sand particles with spectral reflectance values was showed an increase of 0.21 in homogeneous soils than total samples and was recorded a remarkable decrease of 0.22 in homogeneous than heterogeneous samples. Also, the correlation coefficient of silt particles with spectral reflectance values showed an increase of 0.2 and decrease of 0.17 in homogenous and heterogeneous soils than total samples, respectively.

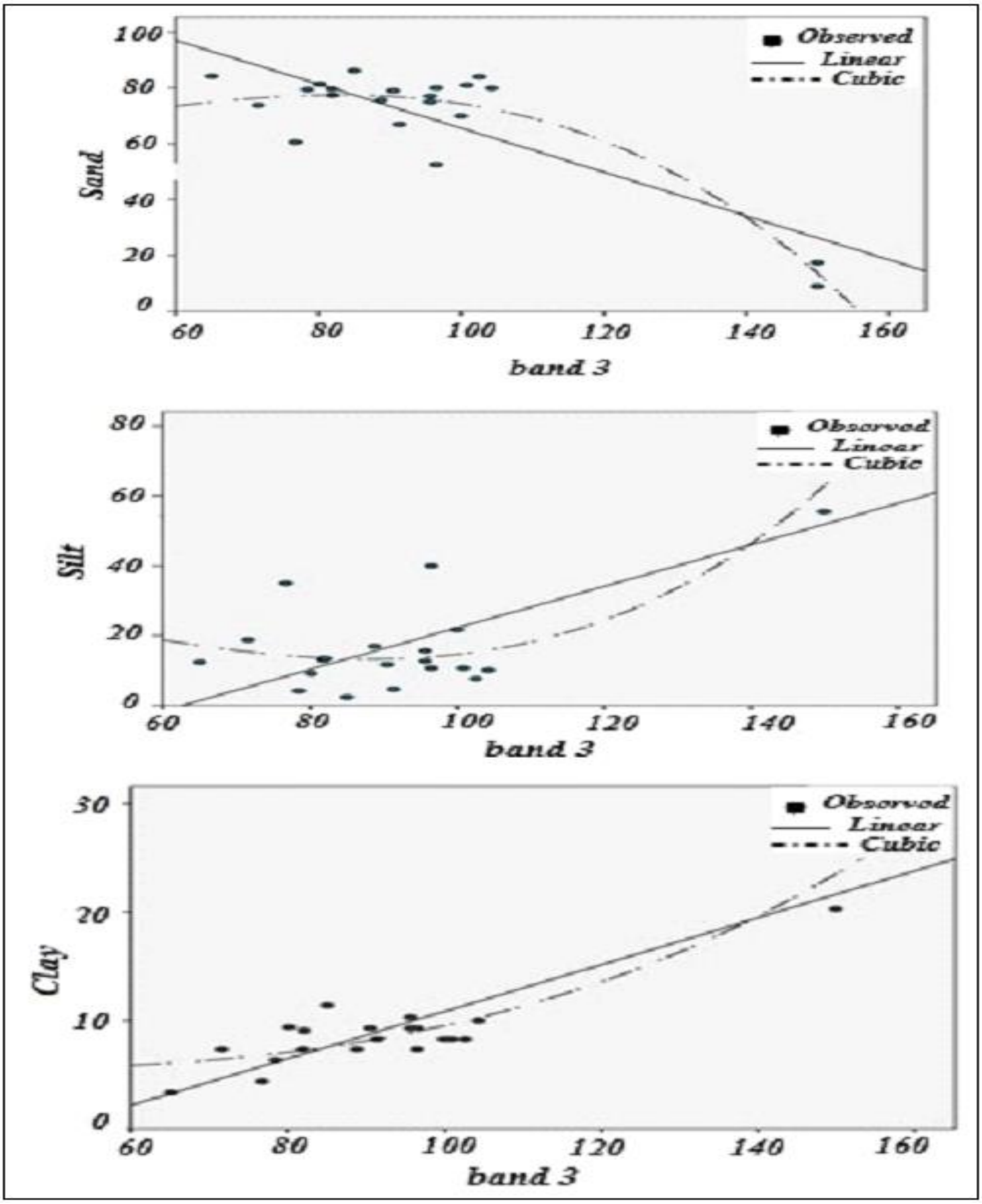

Fig. 3. Conformity of linear and non-linear graphs with scatter plot in homogenous soils.

Assessment of correlation coefficient between clay particles and spectral reflectance of near infrared band indicates a notable increase in the amount of 0.25 in the homogenous soils than total samples and also shows a notable decrease in the amount of 0.17 in the heterogeneous soils as compared to total samples. Therefore, based on these results it can be stated that the geometric standard deviation of soil particles has a significant effect on spectral reflection of soil texture in the study area.

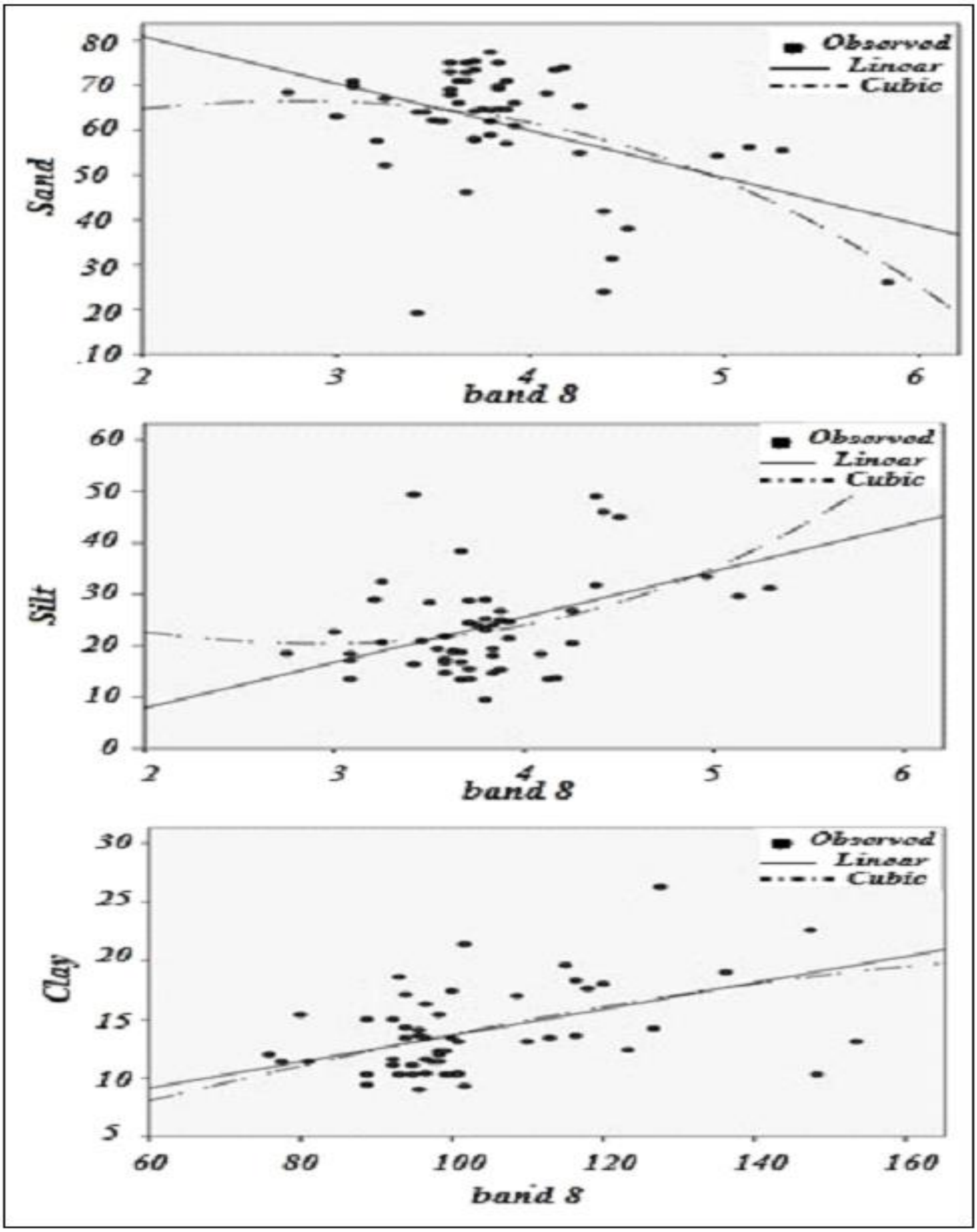

Fig. 4. Conformity of linear and non-linear graphs with scatter plot in heterogeneous soils.

The study of mentioned tables also shows that there is a significant correlation (5% significance level) between clay particles with Soil Line Euclidean Distance (SLED) in homogenous soils whereas there is no significant correlation between sand and silt particles with spectral reflectance values. Generally, it has been established a significant correlation (1% significance level) between soil texture particles in total condition (76 samples) with spectral reflectance data. Although in heterogeneous condition, no significant relationship has been established between clay particles with spectral data, but it has been recorded a significant correlation between sand and silt particles with remote sensing data (5% significance level).

Comparative scatter plot between soil texture particles and spectral reflectance data in the best condition for homogenous and heterogeneous soils is presented in Fig. 2.

The overall evaluation of scatter graphs illustrates a more regular distribution of data in homogenous soils than heterogeneous soils . In other words, it can be concluded that in homogenous soils, there is a stronger correlation between soil texture data and spectral reflectance values.

In the next stage, in order to assessment and comparison of linear and non-linear equations, determination coefficient (R2) between soil texture data in band(3), (because of higher correlation coefficient in linear equation) was calculated for both homogenous and heterogeneous soils. (Table 4 and 5). At the last, corresponding graphs was shown in the Fig. 3 and 4.

Based on tables (4 and 5) and Figures (3 and 4), it can be concluded that nonlinear functions show higher determination coefficient as compared with linear equations in homogenous soils having less geometric standard deviation than heterogeneous soils having more geometric standard deviation.

Conclusion

Generally, bases on results of this study it can be concluded that:

Geometric standard deviation of soil particles has significant effect on soil spectral reflectance and identification of homogenous and heterogeneous soils.

Correlation coefficient of soil texture data and field spectral reflectance in homogenous soils is more than general condition and in this case is more than heterogeneous soils

Near Infrared band of ASTER sensor has a remarkable impact on the spectral reflectance of homogenous soil particles and identification of heavy-textures soils in heterogeneous soils on arid regions, especially in the study area.

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