Evaluation of Landsat TM5 Multispectral Data for Automated Mapping of Surface Soil Texture and Organic Matter in GIS

Zaheer Ahmed* and Javed Iqbal

Institute of Geographical Information Systems, National University of Sciences and Technology (NUST), Sector H-12, Islamabad, Pakistan
*Corresponding author, e-mail address: zaheerahmed-2011@hotmail.com

Abstract
Mapping fine scale spatial variations of soil properties is important for site specific agriculture. The current study explores the potentials of remote sensing (RS) and geographical information system (GIS) techniques in studying the spatial variability of surface soil attributes. Around 170 surface (0-30 cm) soil samples collected from the soils of Shorkot Tehsil, Punjab, Pakistan were analyzed for surface soil texture and organic matter (O.M.). A multivariate linear regression (MLR) analysis technique was employed to relate surface soil variables with the spectral data from Landsat TM5 satellite. The MLR analysis showed significant (p<0.05) relationship of band 4 and band 6 with silt% (R² = 0.724) and clay% (R² = 0.509) while soil O.M. was best modeled using data from band 1, 6 and 7 (R² = 0.545). The resulting MLR equations were then used for the spatial modeling of these attributes for the entire study area. For developing surface soil texture map, the USDA textural triangle limits for clay% and silt% were used to develop a code in Visual Basic Language in ArcGIS environment. The results showed that ‘sandy clay loam’ was the most abundant textural class in the area followed by ‘sandy loam’ and ‘clay loam’ classes. Moreover, the status of O.M. in the entire study area soils was very poor (< 1%). The results indicate that RS and GIS techniques could be successfully used for fine scale mapping of soil texture and O.M. of a larger area.

Keywords: Soil, reflectance, Landsat, GIS.

Introduction
The major concern for soil scientists and environmental managers, over the last few decades, has been to study the soil properties effectively and timely. With the increasing demands of spatial and temporal resolution concerning soil properties in various precision agriculture applications, traditional laboratory methods are proving inadequate [Ehsani et al., 1999]. Moreover, the costs of soil analysis with precision agriculture systems are very expensive when compared to more traditional methods [Ge et al., 2007]. In this respect, the scope of
remote sensing can be explored as alternative methods for studying soil attributes [Galvao et al., 1997]. Remote sensing holds the potential for identifying fine-scale spatial patterns in soil properties across a field [Mulla et al., 2000]. The technology has helped speeding up the conventional soil survey work by reducing the field work to a considerable level [Manchanda et al., 2002]. Optical instruments such as aerial photography, multispectral scanners and hyper-spectral remote sensors can be used to record the reflectance spectra for studying topsoil properties, if the soils are not fully covered by dense shrubs and thick canopy trees [Jensen, 2000]. The spectral response of soil is influenced by a number of soil related properties such surface condition, particle size (texture), O.M., soil color, moisture content, iron and iron oxide content and mineralogy [Dwivedi, 2001].

**Background and objectives**

The use of spectral reflectance data to study soil properties started as early as in early 1980s. Krishnan et al. [1981] and Pitts et al. [1986] used the near infrared reflectance (NIR) to study soil O.M. Ben-Dor and Banin [1995] used NIR spectroscopy of soils for determining a number of soil properties namely clay content, specific surface area, cation-exchange capacity (CEC), hygroscopic moisture, calcium carbonate content, and O.M. Viscarra-Rossel and Mcbratney [1998] collected soil samples from a site in New South Wales, Australia and analyzed them for clay content, soil moisture and O.M. They used the reflectance spectra measured from 1300 to 2500 nm at 2 nm intervals for studying these properties and reported that clay and moisture contents were best predicted at 2100 nm while least accuracy for these variables was observed at 1600 nm. No significant relationship with O.M. was found with these wavelengths. The use of satellite remote sensing data has also been consistent in studying soil properties. Hong et al. [2002] investigated the ability of hyper-spectral data to provide estimates of soil EC and soil fertility levels by analyzing the relationships between spectral reflectance signatures and soil properties through statistical analyses, including simple correlation, multiple regressions, and principal component analysis (PCA) and related the satellite data to field-measured soil properties. The highest correlations to the hyper-spectral bands were found for Mg and CEC. Principal component analysis showed that PC 2 and PC 4 explained soil variability well for CEC, Mg, O.M., K, and pH. Shepherd and Walsh [2002] used spectral library in estimating soil properties. Their work was based on the analysis of diffusion reflectance spectroscopy. Nanni and Dematte [2006] used the soil satellite reflectance values from Landsat TM images to study the soil properties of tropical Brazilian soils. Samples collected from surface (0-20cm) and subsurface (80-100 cm) soils were chemically analyzed and the soil attributes observed were put into a statistical analysis with the soil reflectance values resulting in multiple regression equations. These regression equations were able to predict most of the soil attributes such as clay, oxides of iron (Fe₂O₃) and titanium dioxide (TiO₂). Hashemi et al. [2007] investigated a model for mapping soils by ETM+ satellite images and field data for Sarvestan plain, Iran using satellite images of the year 2002 and 63 soil samples (0 to 10 cm depth) collected using GPS. The study showed a strong correlation of band 6 with gypsiferous soil and spectral ratio (band3 – band4/band 2 – band4) with soil EC in the region. Supervised classification was carried out by using statistical procedures in ILWIS.
software. An overall accuracy of 80.56% and 78.57% was achieved for EC and gypsum maps respectively.

Soil texture is an important physical property of soil. It influences many other soil properties of great importance to crop production and field management [Brown, 2003]. The particle size distribution of soil has strong influence on its reflectance properties. Hoffer [1978] considered the silt content to be the key factor controlling the reflectance of soils. He noted that the soil reflectance decreases as the silt content decreases. Baumgardner et al. [1986] observed that a significant exponential increase is noted with a decrease in particle size for all wavelengths ranging from 0.4 to 1.0 μm. Palacios-Orueta and Ustin [1998] while studying the relationship between the soil properties and reflectance data collected with AVIRIS (Advanced Visible/Infrared Imaging Spectrometer) found that soil texture, soil O.M. and total iron contents were the main factors affecting the spectral curve of soil. Okin and Painter [2004] used the similar data to derive apparent surface reflectance for studying effective grain size of sand in sand plumes at a site in Mojave Desert. They found a strong negative correlation between the reflectance values and grain size of sand in plumes. The correlative analysis indicated short wave infrared as the most significant wavelength for prediction purpose.

Soil O.M. is a crucial indicator of soil fertility status and soil health. The presence of O.M. in soil significantly affects the soil color. Generally soil becomes darker as the percentage of O.M. increases and vice versa. A study carried out by Coleman and Montgomery [1987] showed that an increase in soil moisture and O.M. tends to decrease the reflectance values. They used a multiband radiometer having band configuration similar to the Landsat TM satellite sensor and found that O.M. is best predicted using band 1(450-520 nm) and band 4 (760-900 nm). Luo et al. [2008] calculated several soil color indices namely brightness index, coloration index, hue index, redness index and saturation index using Hyperion Hyperspectral data for statistical modeling of soil O.M. An overall accuracy of 76% was achieved showing the significance of the technique. Table 1 gives a review of literature showing the use of multivariate regression analysis and spectral reflectance in different regions of electromagnetic spectrum for quantitative prediction of soil O.M.

| Soil Property | Spectral Region | Spectral Range | R²  | Authors                  |
|--------------|----------------|----------------|-----|-------------------------|
| O.M. (%)     | UV–VIS–NIR     | 200–2500       | 0.53| [Palacios-Orueta and Ustin, 1998] |
|              | VIS–NIR        | 400–2400       | 0.65| [Shibusawa et al., 2001]  |
|              | MIR            | 2500–25,000    | 0.98| [Masserschmidt et al., 1999] |
|              | VIS–NIR        | 400–1190       | 0.59| [Daniel et al., 2004]     |
|              | NIR            | 1000–2500      | 0.92| [McCarty and Reeves, 2006] |
|              | NIR            | 1603–2598      | 0.79| [Hummel et al., 2001]     |
|              | VIS            | 400–680        | 0.68| [Stamatiadis et al., 2005] |

The literature review shows a consistent use of soil reflectance data in studying the top soil properties. However, the thermal response of the soil has not been taken into consideration. The purpose of the current study was to use both the reflectance and thermal properties of...
soil for mapping fine scale spatial variations of surface soil properties. The specific objectives of the study were to 1) evaluate Landsat TM5 data for statistical modeling of surface soil attributes 2) develop a GIS code for spatial modeling of soil texture using USDA textural classification triangle and 3) model spatial variation of surface soil texture and O.M.

**Materials and methods**

**Study area**

The study was conducted in Tehsil Shorkot of Punjab province, Pakistan. Figure 1 shows the location map of the study area.

![Location Map: Tehsil Shorkot](image)

**Figure 1 - Location map of the study area (Tehsil Shorkot, District Jhang, Punjab province, Pakistan).**

Shorkot is one of the four Tehsils municipal administrations (TMAs) of district Jhang, Punjab, Pakistan and is located along the river Chenab, 60km south of Jhang city. The area is among the largest wheat growing Tehsils of Jhang district [PMDFC, 2007]. The climate of the area is semi-arid subtropical continental. Rainfall varies between 200 and 350 mm per annum. The soil parent material observed mainly consists of mixed calcareous alluvium, originally derived from variety of rocks (e.g. calcareous sandstone, granites, shale and clays, schists, gneisses and slates etc) in the Hamalayas. The relief is generally level. Soil formation is mainly due to river alluvium in the old and young flood plains and is of late Pleistocene age. The area lies in the arid region where soil development is very slow due to low precipitation rates. [Shahid at al., 2009].
**Surface soil samples**
Around 170 surface (0-30 cm) soil samples were collected from the field using a stratified random sampling technique. Standard precautionary measures were adopted while performing sampling. The particle size distribution analysis of samples was carried out using the hydrometer method [Day, 1965]. Similarly, the soil O.M. content was determined using the Walkley-Black method [Walkley and Black, 1934].

**Satellite Imagery**
Multispectral Landsat TM5 data was used for remote sensing of surface soil attributes. The selection of spectral data was based on several factors. First, the images were checked for atmospheric disturbances. It was ensured that the entire study area was free of cloud, haze, and fog. Second, an attempt was made to get maximum bare soil pixels in the study area. The spectral behavior of soil is affected by the presence of vegetation, water bodies and other land features. To get the least vegetation cover, the satellite images were acquired for the month of May, 2010. This is the time frame between two cropping seasons (i.e. Rabbi and Kharif) and offers maximum fallow land.

**Data processing**
Figure 2 shows schematic representation of the processes adopted for remote sensing of surface soil properties.
**Data pre-processing**

Although the images acquired were of maximum fallow period, nearest neighborhood algorithm in Erdas Imagine software was implemented to suppress sparse vegetation pixels using majority bare soil pixels. Haze reduction was performed, as a spatial enhancement process, by subjecting the image to a 3x3 haze reduction filter. The radiometric calibration of band 1 to 5 and 7 was performed using the method suggested by Teillet et al. [2001]. The operational algorithm proposed by Gilabert et al. [1994] was used for atmospheric correction which produced reflectance images of band 1 to 5 and 7. The DN values in band 6 were also scaled from 0 to 100 in order to use them with the reflection values of the remaining bands.

**Extraction of vegetation and water pixels**

The vegetation pixels that remained after the application of Neighborhood Algorithm were extracted by applying the Normalized Difference Vegetation Index (NDVI). NDVI is a numerical indicator that utilizes the red and near-infrared reflections of the electromagnetic spectrum to detect live green vegetation. It is based on the observation that in actively growing plants, chlorophyll in leaf absorbs radiation in the visible (RED) region while the mesophyll structure of leaf reflects strongly in the near infrared region (NIR) of the spectrum. This difference in reflection is the key indicator of healthy vegetation. The formula for NDVI is given in equation [1] [Karaburun, 2010].

\[
NDVI = \frac{\lambda_{\text{NIR}} - \lambda_{\text{R}}}{\lambda_{\text{NIR}} + \lambda_{\text{R}}} \quad [1]
\]

where:
\[\lambda_{\text{NIR}} = \text{reflection in NIR region;}\]
\[\lambda_{\text{R}} = \text{reflection in RED region.}\]

Theoretically, the value of NDVI varies from -1 to +1. However, NDVI values of 0.2 and higher indicate the presence of vegetation.

For the extraction of water bodies, Normalized difference Water Index (NDWI) was used. The index uses the reflection values in visible and NIR region of the electromagnetic spectrum. Generally, reflection of water in NIR band is much lower as compared to visible (GREEN) band. This difference in reflection can be used to detect the presence of water bodies. The formula for NDWI is given in equation [2] [Baodong et al., 2008].

\[
NDWI = \frac{\lambda_{\text{GREEN}} - \lambda_{\text{NIR}}}{\lambda_{\text{GREEN}} + \lambda_{\text{NIR}}} \quad [2]
\]

where:
\[\lambda_{\text{GREEN}} = \text{reflection in green visible region.}\]

The value of NDWI also varies from -1 to +1. Values approaching to +1 indicate water bodies.
Preparing the non-analysis mask
The reflectance properties of soil are greatly affected by the presence of vegetation, water bodies and other land features. The reflection data from such land features may generate mixed spectra in the results. Thus, such permanent land features were excluded from the analysis by developing a non-analysis mask in ArcGIS. Natural vegetation and water bodies were extracted using NDVI and NDWI respectively. The accurate boundaries of the built-up areas in the study area were digitized from the Landuse maps prepared by the National survey organization (i.e. Survey of Pakistan). A non-analysis mask comprising of natural vegetation, water bodies, forest and built-up areas was thus prepared by combining these datasets.

Statistical Analysis
To develop the relationship between surface soil properties and remotely sensed spectral data in different wavelengths, a multivariate linear regression (MLR) analysis was carried out in SAS [SAS Institute Incorporation, 1999]. The predictor variables included in MLR analysis are often selected beforehand. It is important to restrict the set of predictor variables to variables with some potential physical link to the dependent variable(s) as including a large number of predictor variables can seriously bias the value of \( R^2 \) [Rencher and Pun, 1980]. The potential predictors for the particular dependent variable were identified by calculating the Pearson Product Moment Coefficient widely known as Pearson’s \( r \). The coefficient indicates the strength of association between two variables and gives a value between -1 and +1. Values approaching to extreme values indicate a strong negative / positive correlation. However, the significance of ‘\( r \)’ depends on the size of sample space and on the significance level [Lomax, 2007]. The predictor variables found significant were thereafter checked for Multicolinearity statistics. The term ‘Multicolinearity’ is used to describe a situation where the predictor variables are highly correlated with each other. Multicolinearity is a problem when contribution of individual predictor is to be determined. It can cause the variance of the regression co-efficient to inflate or the co-efficient may have wrong signs. [Greene, 2008]. As a result, any inference is not reliable and the confidence interval becomes wider. Multicolinearity can be detected by calculating the tolerance and variance inflation factor (VIF). The formulae for the two variables are given by the equation [3] and [4].

\[
tolerance = 1 - R_j^2 \quad [3]
\]

\[
VIF = \left( \frac{1}{tolerance} \right) \quad [4]
\]

where:
\( R_j^2 \) is the coefficient of determination of a regression of \( j^{th} \) predictor on all other predictor variables. Generally, if tolerance is less than 0.20 and/or if VIF is above 5, this indicates a multicolinearity problem [Peat and Barto, 2005].

Implementing USDA Textural Triangle in GIS
The resulting multivariate regression equations from the statistical analysis were used for spatial modeling of surface soil texture variables and soil OM. The surface soil texture map from the textural variables was prepared by implementing the USDA textural classification triangle in GIS environment. The process was achieved in following steps:
In the first step, the limits of textural variables of a particular textural class were specified. In the USDA textural triangle, the three textural variables specify the boundary conditions for each class. By applying the boundary conditions (or limiting values), we basically specify the area that a particular textural class holds within the textural triangle. Table 2 gives the limiting values of the three textural variables specifying the area of eight textural classes of the triangle.

| Textural Class    | Sand % | Silt % | Clay % |
|-------------------|--------|--------|--------|
| Clay              | 0 to 45| 0 to 40| 40 to 100 |
| Sandy clay        | 5 to 65| 0 to 20| 35 to 55 |
| Silty clay        | 0 to 20| 40 to 60| 40 to 60 |
| Sandy clay loam   | 45 to 80| 0 to 28| 20 to 60 |
| Clay loam         | 20 to 45| 14 to 53| 27 to 40 |
| Silty clay loam   | 0 to 20| 40 to 74| 27 to 40 |
| Loam              | 23 to 53| 28 to 50| 7 to 27 |
| Silt              | 0 to 20| 80 to 100| 0 to 12 |

However, there are certain classes for which the boundary lines show a behavior that is different from the regular diagonal lines of the textural variables passing through the triangle e.g. in the case of specifying the ‘sandy loam’ class. Figure 3 shows the area that has been specified for sandy loam class by the boundary conditions of the three textural variables.
It can be seen that some portions of other classes are also included in the specified area for sandy loam class. The reason for this is the deviating behavior of the boundary lines from the regular diagonal lines of percent sand passing within the triangle. Thus, to accurately specify the area of such textural classes, we need to study the deviating behaviors of the boundary lines. Similar problem appear while specifying the areas under ‘loamy sand’, ‘silt loam’ and ‘sand’ classes. The deviating behaviors of boundary lines in these classes were given numerical meanings as shown in Table 3.

Table 3 - Boundary conditions of soil textural classes in USDA textural triangle for special cases.

| Textural Class | Condition 1                                                                 | Condition 2                                                                 |
|----------------|------------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Sand           | a) sand(%) : ≥ 85                                                           | a) sand(%) : 70 – 85                                                         |
|                | b) [silt(%) + 1.5*clay(%)] ≤ 15                                             | b) [silt(%) + 2.0*clay(%)] ≤ 30                                             |
| Loamy sand     | a) sand(%) : 85 – 90                                                        | a) sand(%) : 70 – 85                                                         |
|                | b) [silt(%) + 1.5*clay(%)] ≥ 15                                             | b) [silt(%) + 2.0*clay(%)] ≤ 30                                             |
| Sandy loam     | a) clay(%) : ≤ 20                                                           | a) clay(%) : < 7                                                            |
|                | b) sand(%) : ≥ 52                                                          | b) silt(%) : < 50                                                           |
|                | c) [silt(%) + 2.0*clay(%)] ≤ 30                                             | c) sand(%) : 43 – 52                                                        |
| Silt loam      | a) silt(%) : ≥ 50                                                           | a) silt(%) : 50-80                                                          |
|                | b) clay(%) : 12 – 27                                                        | b) clay(%) : < 12                                                           |

Thereafter, the pixels from the variable raster surfaces [i.e. sand%, silt%, clay %, (silt% + 1.5*clay %) and (silt% + 2.0*clay %)] that satisfied the boundary conditions of a particular textural class were extracted.

- The next step was to select those pixels, from the extracted variable pixels, where all the boundary conditions of a particular textural class were satisfied. For this purpose, the Boolean operator ‘AND’ was used in ArcGIS software.
- To use the Boolean operator, the extracted variable pixels were first reclassified and were assigned a value ‘1’. Thereafter, the ‘AND’ operator was applied between the extracted reclassified variable pixels of a particular textural class. This resulted in only those pixels, with value ‘1’, i.e. only those pixels had a true value where all the variable pixels were true. The resulting pixels with ‘True’ value were assigned to that particular textural class for which the process had been done. In this way, pixels under all the textural classes were carefully examined.
- Finally pixels under each textural class were combined to form a single soil texture map. Final surface (0-30 cm) soil texture map was prepared in ArcGIS software by overlaying the remaining land features i.e. vegetation, water bodies and built up areas.

**Results and discussions**

**Statistical modeling**

Table 4 shows the results of Pearson correlation coefficient calculated for soil percent silt, clay and O.M. with the spectral values of Landsat TM 5 bands.
Table 4 - Pearson correlation coefficient (r) between Landsat TM5 bands spectral values and percent silt, clay and OM.

| Variables | SILT % | CLAY % | O.M. (%) |
|-----------|--------|--------|----------|
| Band1     | -0.102 | 0.026  | -0.701** |
| Band2     | -0.110 | 0.007  | -0.422*  |
| Band3     | -0.059 | 0.037  | -0.390*  |
| Band4     | 0.714**| 0.709**| -0.066   |
| Band5     | 0.018  | 0.057  | -0.150   |
| Band6     | -0.571**| -0.189*| -0.494*  |
| Band7     | -0.162 | -0.111 | -0.500** |

(Significance level: 0.05*, 0.01**).

The percent silt and clay variables showed a strong (p < 0.05) positive correlation with the reflection in near-infrared band (i.e. band 4) and a strong (p < 0.05) negative correlation with thermal band (i.e. band 6). Similar approach was adopted by Salisbury and D’ Aria [1992], Coleman et al. [1993] and Barnes and Baker [2000]. However, the percent O.M. showed strong (p < 0.05) negative correlations with soil reflections in visible (i.e. band 1, 2 & 3), thermal (i.e. band 6) and mid infrared band (i.e. band 7). The negative correlation of soil O.M. with each band is due to the fact that as the percentage of O.M. in soil increases, the soil becomes darker in color, decreasing the overall reflectance. Similar results were reported by Coleman and Montgomery [1987], Galvao and Vitorello [1998], Barnes et al. [2003] and Ladoni et al. [2010].

Table 5 shows the values of multicolinearity statistics namely tolerance and VIF calculated for the predictor variables of silt%, clay% and O.M.%.

Table 5 - Tolerance and Variance Inflation Factor (VIF) calculated for variables having significant correlations with the soil attributes under study.

| Variable | Silt % | Clay % | Soil O.M. |
|----------|--------|--------|-----------|
|          | VIF    | Tolerance | VIF    | Tolerance | VIF    | Tolerance |
| Band 1   | ---    | ---      | ---    | ---       | 3.585  | 0.279     |
| Band 2   | ---    | ---      | ---    | ---       | 6.406  | 0.156     |
| Band 3   | ---    | ---      | ---    | ---       | 5.739  | 0.174     |
| Band 4   | 1.022  | 0.978    | 1.022  | 0.978     | ---    | ---       |
| Band 5   | ---    | ---      | ---    | ---       | ---    | ---       |
| Band 6   | 1.022  | 0.978    | 1.022  | 0.978     | 1.363  | 0.734     |
| Band 7   | ---    | ---      | ---    | ---       | 3.132  | 0.319     |

(Values in bold exceed the threshold values).
The VIF and tolerance values for the predictor variable(s) of percent silt and clay were well within the threshold values. However, for soil O.M., the tolerance and VIF values calculated for band 2 and 3 violated the threshold values (values given in bold), indicating a multicollinearity problem. Thus, these variables were dropped from the analysis and the remaining variables were used for MLR analysis.

**Multivariate Linear Regression Equations**

The variables found free from multicollinearity problem were used as input in developing multiple linear regression equations. A ‘stepwise’ method [Hocking, 1976] was used in SAS for selection of variables. The resulting multivariate regression equations are given in Table 6.

| Variable | Equation                                      | $R^2$ | Adj. $R^2$ | RMSE |
|----------|-----------------------------------------------|-------|------------|------|
| Silt (%) | Silt(%) = 86.78 +1.26*(b4) - 1.91 *(b6)       | 0.724 | 0.720      | 4.215|
| Clay (%) | Clay(%) = -5.24 + 1.35*(b4) - 0.32*(b6)      | 0.509 | 0.501      | 5.021|
| O.M. (%) | O.M.(%) = 2.24 - 0.021*(b1) - 0.0165*(b6) + 0.0087*(b7) | 0.545 | 0.534      | 0.051|

The considerably high values of $R^2$ observed for the three soil attributes show the significance of Landsat TM5 data in modeling variations of surface soil properties. The difference between the values of $R^2$ and adjusted $R^2$ is also very low, indicating that the variations in dependent variables have been fully explained by the predictor variables. Nanni and Dematte [2006] conducted a similar study for studying soil attributes. Using the Landsat TM5 data, they also carried out an MLR analysis and observed an $R^2$ value of 0.675 and 0.508 for clay (%) and soil O.M. (%) respectively. Thomasson et al. [2001], Hong et al. [2002] and Maselli et al. [2008], also adopted similar statistical techniques for the modeling of soil attributes.

**Spatial Modeling**

The resulting multivariate regression equations for percent silt, clay & soil O.M. were used for spatial modeling of these variables. The results showed that the percent silt observed in the study area varied from 0 to 62 percent, clay from 1 to 61 percent, sand from 1 to 93 percent and soil O.M. from 0.1 to 0.8 which is considered as very low. Figure 4 shows the value distribution graphs for soil textural variables and soil O.M. values.

The range between the minimum and maximum values for each variable was divided into five equal intervals and was plotted against the pixel count. It can be observed that, for silt, the highest pixel count was observed for values ranged from 13 to 25 percent. For clay, the highest pixel count was observed for values ranged from 14 to 37 percent. Similarly for sand, the highest bar for pixel count was observed for values ranged from 57 to 75 percent. For soil O.M., it was observed that most abundant values in the area ranged from 0.53 to 0.66 percent. The spatial variation of soil O.M. is shown in Figure 5.
Figure 4 - Value distribution graphs for observed soil variables.

Figure 5 - Spatial distribution of surface soil O.M.
Figure 6 shows the soil texture map of the study area prepared by combining the textural variables. The values of pixel count for the observed textural classes showed that the ‘sandy clay loam’ class was the most abundant textural class in the study area followed by ‘sandy loam’ and ‘clay loam’ classes (Fig. 7).

Figure 6 - Spatial distribution of surface soil texture.

Figure 7 - Variation of soil textural classes.
**Accuracy Assessment**

To assess the accuracy of spatial modeling, 31 well-distributed surface soil samples (not included in the analysis) were collected for validation purposes. The values of the observed soil profile properties were compared with those of the predicted ones. RMS error was calculated for each of the modeled soil parameter. It was found that for percent silt, clay and O.M., the observed RMS errors were 2.21, 2.39 and 0.023, respectively.

**Conclusions**

Fine scale spatial variability analysis and modeling of surface soil properties of large area is possible using satellite remote sensing data as most of these soil properties e.g. soil texture and O.M., directly or indirectly, influence soil reflectance. The spectral reflectance data can be an alternative to the traditional methods for determining soil attributes

A Multivariate Linear regression approach has been adopted for studying the relationship between surface soil properties and soil reflectance which revealed bands 4 and 6 as the best predictors of percent silt and clay while O.M. is best predicted by bands 1, 6 and 7. Spatial modeling of soil texture has been performed by implementing the USDA textural triangle. The results revealed three main soil texture types in the study area namely ‘sandy clay loam’, ‘sandy loam’ and ‘clay loam’. Also, the O.M. status in the study area was found to be very poor (< 1%).

**References**

Baodong M., Lixin W., Shanjun L. (2008) - *Remote Sensing Detection of Subsidence-Resulted Water Body and Solid-Waste Dump In Coal Mine: Yanzhou Being a Case*. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37: 269-272.

Barnes E.M., Baker M.G. (2000) - *Multispectral Data For Mapping Soil Texture: Possibilities and Limitations*. Applied Engineering in Agriculture, 16 (6): 731-741. doi: http://dx.doi.org/10.13031/2013.5370.

Barnes E., Sudduth K., Hummel J., Lesch S., Corwin D., Yang C. (2003) - *Remote- and Ground-based Sensor Technologies to Map Soil Properties*. Photogrammetric Engineering and Remote Sensing, 69 (6): 619-630. doi: http://dx.doi.org/10.14358/PERS.69.6.619.

Baumgardner M.F., Silva L.F., Biehl L.L., Stoner E.R. (1986) - *Reflectance Properties of Soils*. Advances in Agronomy, 38: 1-44. doi: http://dx.doi.org/10.1016/S0065-2113(08)60672-0.

Ben-Dor E., Banin A. (1995) - *Near-infrared analysis as a rapid method to simultaneously evaluate several soil properties*. Soil Science Society of America Journal, 59: 364-372. doi: http://dx.doi.org/10.2136/sssaj1995.03615995005900020014x.

Brown R.B. (2003) - *Soil Texture [Fact Sheet]*. Retrieved from http://edis.ifas.ufl.edu/ss169.

Coleman T.L., Agbu P.A., Montgomery O.L. (1993) - *Spectral differentiation on surface soils and soil properties: Is it possible from space platforms?*. Soil Science, 155: 283-293. doi: http://dx.doi.org/10.1097/00010694-199304000-00007.

Coleman T., Montgomery O. (1987) - *Soil moisture, organic matter and iron content effect on spectral characteristics of selected Vertisols and Alfisols in Alabama*. Photogrammetric Engineering and Remote Sensing, 53: 1659-1663.
Daniel K.W., Tripathi N.K., Honda K., Apisit E. (2004) - *Analysis of VNIR (400-1100 nm) spectral signatures for estimation of soil organic matter in tropical soils of Thailand*. International Journal of Remote Sensing, 25: 643-652. doi: http://dx.doi.org/10.1080/0143116031000139944.

Day P.R. (1965) - *Particle Fractionation and Particle-Size Analysis*. In: Method of Soil Analysis, Black C.A. (Ed), PartI, Soil Science Society of America Journal.

Dwivedi R.S. (2001) - *Soil Resource Mapping: A Remote Sensing Perspective*. Remote Sensing Reviews, 20: 89-122. doi: http://dx.doi.org/10.1080/02757250109532430.

Ehsani M.R., Upadhyaya S.K., Slaughter D., Shafii S., Pelletier M. (1999) - *A NIR Technique for Rapid Determination of Soil Mineral Nitrogen*. Precision Agriculture, 1 (2): 217-234. doi: http://dx.doi.org/10.1023/A:1009916108990.

Galvao L.S., Vitorello I. (1998) - *Role of organic matter in obliterating the effects of iron on spectral reflectance and color of Brazilian tropical soils*. International Journal of Remote Sensing, 19 (10): 1969-1979. doi: http://dx.doi.org/10.1080/014311698215090.

Galvao L.S., Vitorello I., Roberto A. (1997) - *Relationships of spectral reflectance and color among surface and subsurface horizons of tropical soil profiles*. Remote Sensing of Environment, 61 (1): 24-33. doi: http://dx.doi.org/10.1016/S0034-4257(96)00219-2.

Ge Y., Thomasson J.A., Morgan C.L., Searcy S.W. (2007) - *VNIR diffuse reflectance spectroscopy for agricultural soil property determination based on regression-kriging*. Transactions of the American Society of Agricultural and Biological Engineers, 50 (3): 1081-1092.

Gilabert M.A., Conese C., Maselli F. (1994) - *An atmospheric correction method for the automatic retrieval of surface reflectances from TM images*. International Journal of Remote Sensing, 15: 2065-2086. doi: http://dx.doi.org/10.1080/01431169408954228.

Greene W.H. (2008) - *Econometric Analysis*. Fourth edition, New Delhi: Dorling Kindersley, India, pp. 56-61.

Hashemi S.S., Baghernejad M., Pakparvar M. (2007) - *GIS Classification Assessment for Mapping Soils by Satellite Images*. In: 4th Middle East Spatial Technologies Conference and Exhibition, 10-12 December 2007, Bahrein.

Hocking R.R. (1976) - *The analysis and selection of variables in linear regression*. Biometrics, 32: 1-49. doi: http://dx.doi.org/10.2307/2529336.

Hoffer R. (1978) - *Biological and physical considerations in application computer aided analysis techniques to remote sensing*. In: Remote Sensing: The Quantitative Approach, Swain P.H., & Davis S.M. (Eds.), pp. 237-286 (New York: McGraw-Hill).

Hong S.Y., Sadduth K.A., Kitchen N.R., Drummond S.T., Palm H.L., Wiebold W.J. (2002) - *Estimating Within-Field Variations In Soil Properties From Airborne Hyperspectral Images*. In: Pecora 15/Land Satellite Information IV Conference, 10-15 November, (Colorado: ASPRS), pp. 10-15.

Hummel J.W., Sadduth K.A., Hollinger S.E. (2001) - *Soil moisture and organic matter prediction of surface and subsurface soils using an NIR soil sensor*. Computers and Electronics in Agriculture, 32 (2): 149-165. doi: http://dx.doi.org/10.1016/S0168-1699(01)00163-6.

Jensen J.R. (2000) - *Remote Sensing of The Environment*. Singapore: Pearson Education, pp. 507-515.

Karaburun A. (2010) - *Estimation of C factor for soil erosion modeling using NDVI in
**Buyukcekmece watershed.** Ozean Journal of Applied Sciences, 3 (1): 77-85.

Krishnan P., Butler B.J., Hummel J.W. (1981) - *Close-range sensing of soil organic matter.* Transactions of the American Society of Agricultural Engineers (ASAE), 24 (2): 306-311. doi: http://dx.doi.org/10.13031/2013.34246.

Ladoni M., Bahrami H.A., Alavipanah S.K., Norouzi A.A. (2010) - *Estimating soil organic carbon from soil reflectance: a review.* Precision Agriculture, 11 (1): 82-99. doi: http://dx.doi.org/10.1007/s11119-009-9123-3.

Lomax R.G. (2007) - *An introduction to statistical concepts.* New Jersey: Lawrence Erlbaum Associates, pp. 182-188.

Luo Z., Yaolin L., Jian W., Jing, W. (2008) - *Quantitative mapping of soil organic material using field spectrometer and hyperspectral remote sensing.* The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 37: 901-906.

Manchanda M.L., Kudrat M., Tiwari A.K. (2002) - *Soil survey and mapping using remote sensing.* Tropical Ecology, 43 (1): 61-74.

Maselli F., Gardin L., Bottai L. (2008) - *Automatic mapping of soil texture through the integration of ground, satellite and ancillary data.* International Journal of Remote Sensing, 29 (19): 5555-5569. doi: http://dx.doi.org/10.1080/01431160802029651.

Masserschmidt I., Cuelbas C.J., Poppi R.J., De Andrade J.C., De Abreu C.A., Davanzo C.U. (1999) - *Determination of organic matter in soils by FTIR/diffuse reflectance and multivariate calibration.* Journal of Chemometrics, 13: 265-273. doi: http://dx.doi.org/10.1002/(SICI)1099-128X(199905/08)13:3/4<265::AID-CEM552>3.0.CO;2-E.

Mccarty G.W., Reeves J.B. (2006) - *Comparisons of near infrared and mid infrared diffuse reflectance spectroscopy for field-scale measurement of soil fertility parameters.* Soil Science, 171 (2): 94-102. doi: http://dx.doi.org/10.1097/01.ss.0000187377.84391.54.

Mulla D.J., Sekely A.C., Beatty M. (2000) - *Evaluation of remote sensing and targeted soil sampling for variable rate application of lime.* In: Proceedings of the 5th International Conference on Precision Agriculture, 16-19 July 2000, Bloomington, pp. 1-14.

Nanni M.R., Dematte J.A. (2006) - *Spectral Reflectance Methodology in Comparison to Traditional Soil Analysis.* Soil Science Society of America Journal, 70 (2): 393-407. doi: http://dx.doi.org/10.2136/sssaj2003.0285.

Okin G.S., Painter T.H. (2004) - *Effect of grain size on remotely sensed spectral reflectance of sandy desert surfaces.* Remote Sensing of Environment, 89: 272-280. doi: http://dx.doi.org/10.1016/j.rse.2003.10.008.

Palacios-Orueta A., Ustin S.L. (1998) - *Remote Sensing of Soil Properties in the Santa Monica Mountains I. Spectral Analysis.* Remote Sensing of Environment, 65 (2): 170-183. doi: http://dx.doi.org/10.1016/S0034-4257(98)00024-8.

Peat J.K., Barto B. (2005) - *Medical statistics: a guide to data analysis and critical appraisal.* Oxford: Blackwell Publishing Ltd., pp. 172-173. doi: http://dx.doi.org/10.1002/9780470755945.

Pitts M.J., Hummel J.W., Butler B.J. (1986) - *Sensors utilizing light reflection to measure soil organic matter.* Transactions of the American Society of Agricultural Engineers (ASAE), 29 (2): 422-428. doi: http://dx.doi.org/10.13031/2013.30166.

PMDFC (2007) - *Planning Report Shorkot.* Lahore: Punjab Municipal Development Fund Company, pp. 13.

Rencher A.C., Pun F.C. (1980) - *Inflation of R² in Best Subset Regression.* Technometrics,
Salisbury J.W., D’Aria D.M. (1992) - *Infrared (8-14 µm) Remote Sensing of Soil Particle Size*. Remote Sensing Environmental, 42: 157-165. doi: http://dx.doi.org/10.2307/1268382.

SAS Institute Incorporation (1999) - *SAS/STAT User’s Guide, Version 8*, Cary, NC : SAS Institute Incorporation.

Shahid S.A., Aslam Z., Hashmi Z.H., Mufti K.A. (2009) - *Baseline Soil Information and Management of a Salt-Tolerant Forage Project Site in Pakistan*. European Journal of Scientific Research, 27 (1): 16-28.

Shepherd K., Walsh M. (2002) - *Development of reflectance spectral libraries for characterization of soil properties*. Soil Science Society of America Journal, 66: 988-998. doi: http://dx.doi.org/10.2136/sssaj2002.0988.

Shibusawa S., Imade Anom S.W., Sato S., Sasao A., Hirako S. (2001) - *Soil mapping using the realtime soil spectrophotometer*. Precision agriculture, 1: 497-508.

Stamatiadis S., Christofides C., Tsadilas C., Samaras V., Schepers J.S., Francis D. (2005) - *Groundsensor soil reflectance as related to soil properties and crop response in a cotton field*. Precision Agriculture, 6 (4): 399-411. doi: http://dx.doi.org/10.1007/s11119-005-2326-3.

Teillet P.M., Barker J.L., Markham B.L., Irish R.R., Feodosejevs G., Storey J.C. (2001) - *Radiometric cross-calibration of the Landsat-7 ETM+ and Landsat-5 TM sensors based on tandem data sets*. Remote Sensing of Environment, 78: 39-54. doi: http://dx.doi.org/10.1016/S0034-4257(01)00248-6.

Thomasson J.A., Sui R., Cox M.S., Al–Rajehy A. (2001) - *Soil Reflectance Sensing For Determining Soil Properties In Precision Agriculture*. Transactions of the American Society of Agricultural Engineers, 44: 1445-1453. doi: http://dx.doi.org/10.13031/2013.7002.

Viscarra-Rossel R.A., Mcbratney A.B. (1998) - *Laboratory evaluation of a proximal sensing technique for simultaneous measurement of soil clay and water content*. Geoderma, A Global Journal of Soil Science, 85 (1): 19-39.

Walkley A., Black I.A. (1934) - An examination of Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. Soil Science, 37: 29-37. doi: http://dx.doi.org/10.1097/00010694-193401000-00003.

© 2014 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).