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RESEARCH PAPER

Estimation of soil moisture using multispectral and FTIR techniques

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LST

Abstract Soil moisture is a key capricious in hydrological process, the accessibility of moisture content in soil reins the mechanism amid the land surface and atmospheric progression. Precise soil moisture determination is influential in the weather forecast, drought monitoring, hydrological modeling, agriculture management and policy making. The aims of the study were to estimate soil moisture through remotely sensed data (FTIR & optical) and establishment of the results with field measured soil moisture data. The ground measurements were carried out in 0–15 cm depth. Permutation of normalized difference vegetation index (NDVI) and land surface temperature (LST) were taken to derive temperature vegetation dryness index (TVDI) for assessment of surface soil moisture. Correlation and regression analysis was conceded to narrate the TVDI with *in situ* calculated soil moisture. The spatial pattern of TVDI shows that generally low moisture distribution over study area. A significant ($p < 0.05$) negative correlation of $r = 0.79$ was found between TVDI and *in situ* soil moisture. The TVDI was also found adequate in temporal variation of surface soil moisture. The triangle method (TVDI) confers consistent appraisal of moisture situation and consequently can be used to evaluate the wet conditions. Furthermore, the appraisal of soil moisture using the triangular method (TVDI) was possible at medium spatial resolutions because the relationship of soil moisture with LST and NDVI lends an eloquent number of representative pixels for developing a triangular scatter plot.

1. Introduction

Soil water content is a key biophysical constraint which is used as an interface between surface and atmosphere, also an important utter variable in hydrology and climate (Gao et al., 2014). It plays an intrinsic role in understanding the hydrology agriculture, climate and environmental peculiars of a region (Akkuzu et al., 2013). It also clinches contraceptive energy exchanges between soil and air. It is an exigent aspect

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affecting the budgeting of hydrological cycles pointedly by disuniting the rainfall into runoff, surface infiltration and evapotranspiration (Choi et al., 2011; Pollacco and Mohanty, 2012). The expertise of soil moisture level and the phenomena of defining the apportionment of water content are always being compelling in many ways. In the past with the advent of agriculture in human history, knowledge about soil moisture is imperative in a much wider area, e.g. hydrology, meteorology and climatology, ecology, land surface modeling and current studies on global climate changes. There is increase in the issues related to environment, so the demand for information on environmental parameters grows simultaneously. Soil analysis craves development of less time and overwhelming techniques. People were going for brisk and predictive soil data to be applied in environmental monitoring, land quality assessment, as considerably as in both precision agriculture and forestry (Engman, 1991). The validation of accuracy farming, which is incorporated among the expedient cultivating frameworks, suits regular monitoring of whole agriculture system and environment (Dutta et al., 2015). The studies carried on the spatial and temporal variability of soil moisture at regional level embroil in hydrological application, river flow forecasting, irrigation management, soil conversation measures, agriculture development, and meteorology (Haq et al., 2012). The knowledge about soil water content is kernel element for crops. The development and productivity of crops will deleteriously affect if the crop is not supplied with ample soil moisture content. The legitimate monitoring of soil water content concedes better information than precipitation or the weather forecast, which helps farmers in better crop production and decision making (Akkuzu et al., 2013). The decrease in soil water content to assertive level leads to decline in crop production and yield, resulting agriculture drought. In peoples' day to day life, agriculture is a key component as well as in the country's economy, so recurring drought events put sustainable development at great risk (Ali and Shalaby, 2012). Using soil moisture information helps in early detection of drought and evaluating its impact on agriculture.

Soil moisture interaction with environmental factors needs eloquent measurements. The progression in technology and precise apparatus determines soil water content and describes its variability only at specified locations (Ali and Abd El-hady, 2012). The temporal and spatial variability of soil water content over large extent is not possible to measure using such advanced equipment. The method of interpolation between conventional points does not yield precise results because the method does not examine the surface roughness, topography, vegetation condition, and other essential conditions (Ali and Moghanm, 2013). The cost and efforts involved during *in situ* measurements appeal to think about a free and easily accessible data source (remote sensing). This has become a main reason to clinch scientists' brains to investigate other techniques such as remote sensing to presume surface soil moisture status and information about its spatial and temporal distribution (Al-Jassar and Rao, 2010; Albergel et al., 2013; Bezerra et al., 2013; Brosinsky et al., 2014; Nemani et al., 1992). Soil moisture is commonly estimated using the point based method (gravimetric method) by collecting soil samples, but this method is overwhelming and sturdy. It is unable to describe the behavior of its spatial and temporal distribution. Also the ground measurement of soil water content in general is laborious and cannot be easily carried out on a daily basis.

In modern epoch technological advancement has presented that soil water content can be estimated by a number of remote sensing methods. Especially the techniques in optical/IR and microwave have engrossed more consideration (Vinnikov et al., 1999). The channel frequency and spatial resolution of microwave radiometer are not ideal for land remote sensing because of practical problems in supporting a large low recurrence antenna in space (Blumberg et al., 2002).

Hence the swivel task was to use the novel optical/IR approach based on the triangular method proposed by Gruhier et al. (2008). Land-sat data appear to be fine for monitoring the soil water content over large area. Various methodologies are used for determination of soil moisture using remote sensing, which includes, thermal inertia method, normalized vegetation index approach, crop water stress index method, crop water deficit index model. In this study the renowned temperature vegetation dryness index method which is derived from satellite data is used to estimate soil moisture content (Iqbal and Khan, 2014; Chen et al., 2011; Sandholt et al., 2002; Wang et al., 2004). In the last decade, a number of researchers have studied the relationship between vegetation indices and land surface temperature. This method was based on the Ts/NDVI triangulation. The interpretation of trapezoid relationship between (NDVI) and LST will help out in the calculation of TVDI/soil moisture content (Ismail and Yacoub, 2012; Atchley and Maxwell, 2011; Dall'Amico et al., 2013; Fan and van den Dool, 2011; Hejazi and Woodbury, 2011; Holzman et al., 2014; Liu et al., 2012; Lopes et al., 2011; Mei and Wang, 2011; Ridler et al., 2012; Song et al., 2014; Srivastava et al., 2013; Sun et al., 2012; Tennant and Beare, 2014;Wu et al., 2011; Zhao and Li, 2013). Moran et al. (1994) described a method based on the Ts/NDVI trapezoid. The TVDI is calculated based on the interpretation of the relationship between vegetation indices (NDVI) and LST (TS).

The objectives of this study were to estimate surface soil moisture by linking the temperature vegetation dryness index (TVDI) with ground observation and Fourier Transform Infrared Technique (FTIR) and validation of the results with field measured soil moisture data in the laboratory.

2. Materials and methods

2.1. Study area

The National Agricultural Research Centre (NARC), Islamabad (latitude 33° 43′ N, longitude 73° 04′ E, with altitude 490 Msl) was selected as a study area (Fig. 1). The total area of NARC is approximately 556 hectares and located near Rawal Lake, six kilometers southeast of Islamabad. The site contains Nabipur soil series, was classified as *Typic Camborthid* (Calcaric Fluvisols). It is developed from a mixed, calcareous alluvium, and is weakly differentiated, they are generally medium textured to clay-loam with native organic matter as low as $< 2.5\ g\ kg^{-1}$ (Khanzada, 1976). The study area has a typical climate version of humid subtropical, a specialty of covering all the five major seasons: Spring (March–April), summer (May–June), rainy monsoon (July–August) autumn (September–October), and winter (Nov–Feb). June is the warmest of all months, and average maximum temperature exceeds 38 °C. The humidity is very high during July, having thunderstorms and huge rainfalls. The cold prevails during

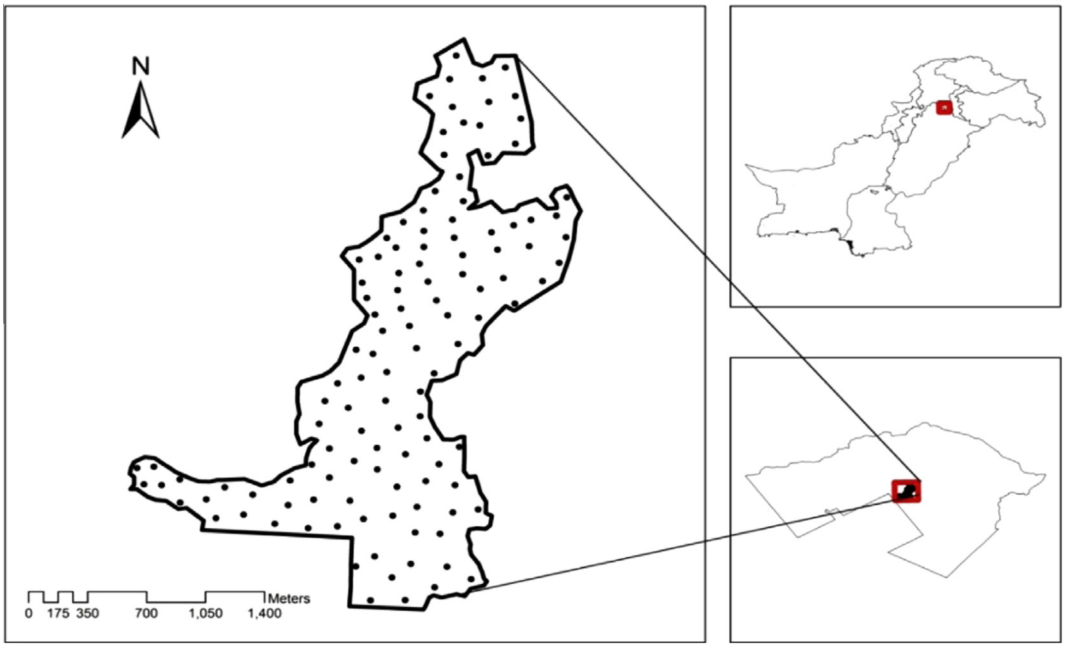

Figure 1 Study area national agriculture research center Islamabad.

January; with low climates varying by location. Islamabad temperatures change from cool to gentle often going beneath zero. There is meager snowfall in hilly territories. The average low and high temperature is 2–38 °C.

2.2. Field work

The field work was performed in March 2013 to collect the primary soil moisture data. The main activity during the field was to measure soil moisture using the direct method. For this purpose 120 soil samples were collected using the randomized sampling technique from the study area by using a soil auger at 0–15 cm depth. The spatial distribution of the soil samples collected is shown in the above figure. Each sampling point was georeferenced using a handheld GPS system. Samples were placed in sealed polyethylene bags and transferred to a soil laboratory for moisture and soil texture analysis.

2.3. Soil texture analysis

The dispersion of mineral particles (or its related pore volume), is a standout among the most imperative measures of a soil in light of the fact that finely separated soil particles have a much more prominent surface area per unit mass or volume than do coarse particles. Soil texture has an important role in defining the soil moisture retention and its redistribution in the soil profile. Therefore the texture of all the samples was analyzed using the hydrometer method (Bouyoucos, 1962).

2.4. Soil moisture measurement using gravimetric method

Soil samples were dried, crushed, sieved and finally bagged for further lab analysis. In the lab for analysis of gravimetric soil moisture content a 50 g sample was placed in oven at 105 °C for 24 h (Gardner, 1986). The dried soil samples were weighed using a Mettler balance and the percent gravimetric soil moisture was calculated using Eq. (1):

$$\text{Moisture } (\%) = \frac{\text{Wt. of soil (g)} - \text{Drysoil (g)}}{\text{Drysoil}} * 100 \tag{1}$$

2.5. FTIR spectroscopy analysis

Fourier Transform Infra-Red spectroscopy is the most used technique of infrared spectroscopy. When IR radiations passed from a sample, some of it is absorbed by the sample and the remaining passed through. A spectrometer of full range (500–2500) nanometer was used to acquire reflectance signatures of samples in laboratory. The first step was to calculate the effect of reflectance on the oven dried soil samples; after that distilled water was put into the same sample using pipette to saturate the sample. Again spectral signatures were recorded frequently till the condition of soil moisture returned to its starting value (will take 1-h). For the determination of soil water content mass measurements were recorded during the experiment, and mathematically expressed on a volumetric basis (Lobell and Asner, 2002). Spectral measurements of soil water content were calculated using the following equation:

$$\frac{m - m_\theta/\rho_w}{m_\theta/\rho_b} \times 100 \tag{2}$$

where m = mass of the soil sample by weight, m_θ = dry mass of soil sample on initial stage, ρ_w = water density (1.0 g/cm^3), ρ_b = soil bulk density.

2.6. Remote sensing of soil moisture

For remote sensing approach Landsat-8 imagery was used whose general introduction is already mentioned. To estimate surface soil water content the triangulation method was used which was used in previous studies. The method combines visible, infrared and thermal datasets. The knowledge related to surface energy and moisture status through developing the relationship among remotely sensed land surface temperature (LST) and normalized difference vegetation index (NDVI) has been reported by many researchers. The correlation between thermal and visible/NIR has determined to be useful for appropriate monitoring of vegetation and water stress. The method lies in the interpretation of the pixel distribution in Ts-NDVI space. If an image contains a large space of soil water content and green vegetation, the space presents a triangle. The triangle formed because the surface temperature decreases as vegetation cover increases. Scatter plot between NDVI and LST is termed as the Ts-NDVI space which is closely associated with surface evapo-transpiration and moisture etc., (Fig. 2). The method of mapping, soil moisture using LST and NDVI is called TVDI.

3. Results and discussions

3.1. Soil moisture and texture analysis

The conventional method was carried out to determine the soil water content status of the study area. The soil moisture was determined in the laboratory of each soil sample. The results showed a range of 2–10% soil moisture of the study area. The most common method used for soil texture determination involves soil texture triangle to distinguish the textural classes. The classification depends on the amount of percent sand, silt, and clay in a given sample. Soil texture plays an important role in retention of soil moisture as clay soils have more water holding capacity than silt and sand. The results showed 4 texture classes, i.e. silt, clay, clay loam, loam and silt clay loam (Fig. 3).

3.2. FTIR analysis

FTIR is a technique which is used to determine the reflectance in a given sample. In this method samples were placed under a full range spectrometer (500–2500 nm). Soil samples were arranged on the basis of texture classes and 5 composite samples were taken from each texture class which was representative of the whole study area. The study quantify changes in soil reflectance as a soil proceeded from wet to dry states and to determine the dependence of these changes on soil type and wavelength. These results will develop a significant relationship between the reflectance and soil water content that can also reduce differences among soil types to be used in practical retrieval algorithms of moisture and canopy radiative transfer models. Reflectance decreases with increasing moisture in all soils as shown in (Fig. 4a) for silt, clay loam (Fig. 4b) for loam (Fig. 4c) for clay loam and (Fig. 4d) for silt, clay below, except there was a certain region of SWIR where the behavior of the curve went higher because of the absorption region for water molecules (Muller and Decamps, 2001).

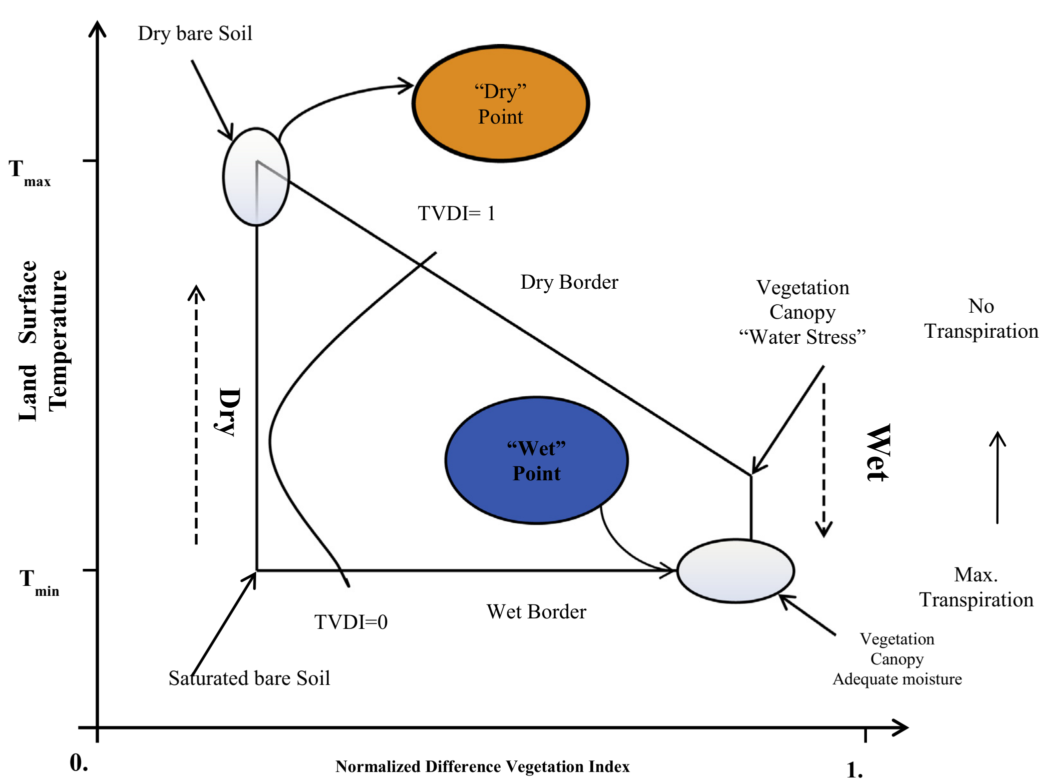

Figure 2 Land surface temperature and normalized difference vegetation index graph.

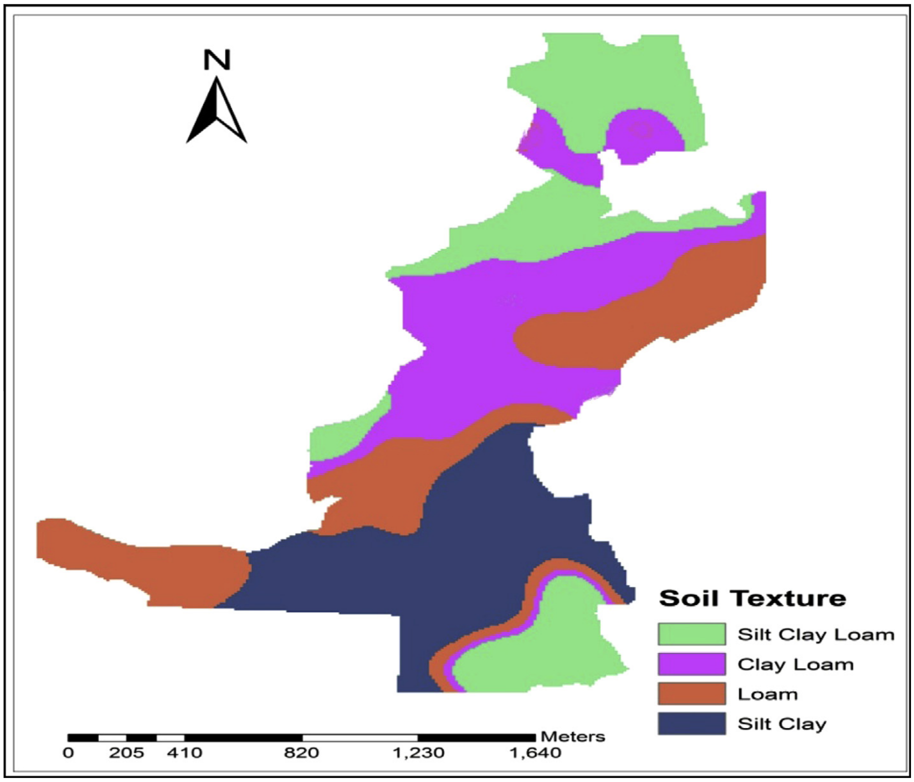

Figure 3 Textural classes of the study area.

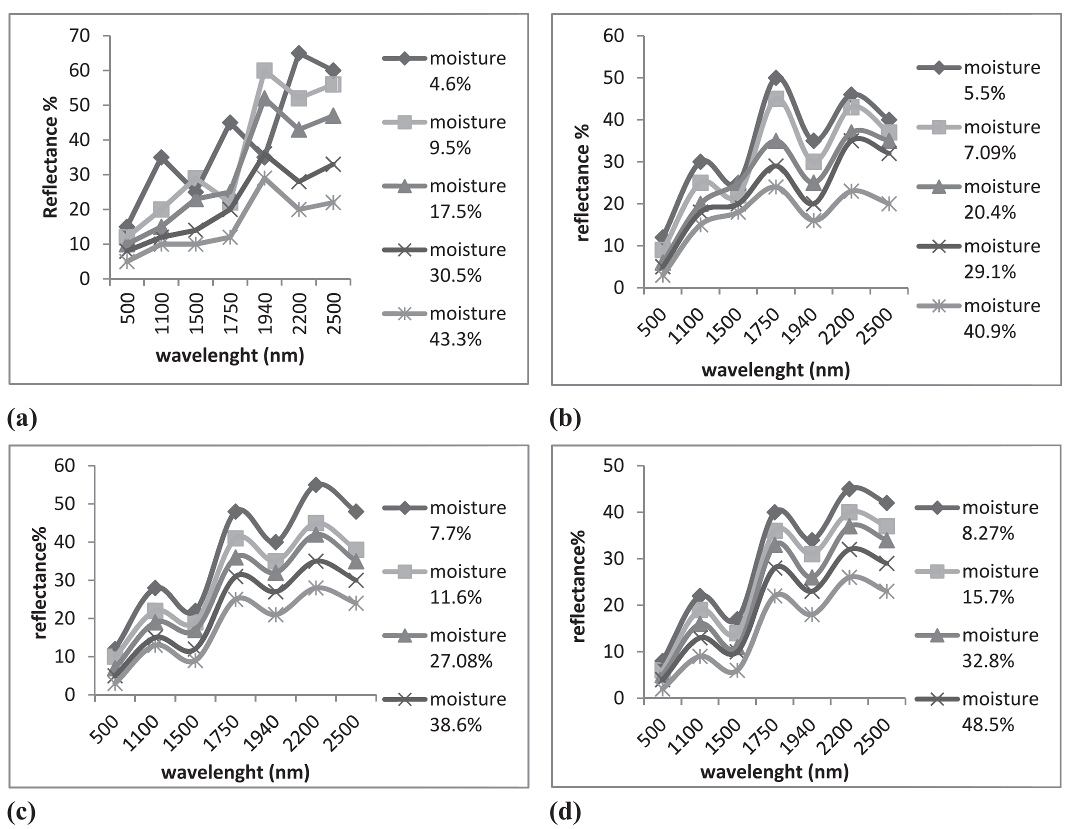

Figure 4 Relationship of soil moisture and reflectance (a) silt clay loam (b) loam (c) clay loam and (d) silt clay.

3.3. Normalized difference vegetation index

Vegetation indices are based on reflection characteristics of plant leaves in visible (VIS) and near-infrared (NIR) portion of light. Low reflectance of visible light (0.4–0.7 μm) was found for healthy vegetation because it is strongly absorbed for photosynthesis. On the other hand near-infrared light (0.7–1.1 μm) shows high reflectance for healthy vegetation. NDVI can be calculated by the ratio between visible and near-infrared bands of the satellite image. Mathematically it can be written as follows,

$$\mathrm{NDVI} = \frac{\mathrm{Ref(NIR)} - \mathrm{Ref(Red)}}{\mathrm{Ref(NIR)} + \mathrm{Ref(Red)}} \tag{3}$$

The formula was applied by using Erdas Imagine, a model builder. NDVI values are always lying between −1 and 1. The value of NDVI ranges from 0.02 to 0.54 of study areas. The map of NDVI is shown in Fig. 5. Hosseini and Saradjian (2011) studied four different soil water content estimation models, which were NDVI–LST, EVI–LST, NDVI–LST–NDWI and EVI–LST–NDWI; they want to assess the accuracies of these models. Statistically it was proved that when EVI was replaced with NDVI in the model it increases the accuracy of soil moisture estimation.

3.4. Land surface temperature

Land surface temperature is also the surface atmosphere interaction energy fluxes between ground and the atmosphere on earth, including thermal emission from the landscape surface which includes top of the canopy for vegetated surfaces as well as the other surfaces such as bare soil. Surface temperature was calculated from satellite image's thermal band. In Landsat 8 there are 2 thermal bands. The brightness of both bands was calculated and then the average was taken as LST of the study area. To obtain actual surface temperature information, first convert the DNs to top-of-the-atmosphere (ToA) radiance values, and secondly convert the ToA radiance values to ToA brightness temperature in Kelvin. The (Eq. (4)) was used to convert Digital Numbers into ToA radiance values.

$$L_\lambda = (M_L * Q_{cal}) + A_L \tag{4}$$

where L_λ = ToA spectral radiance, M_L = band-specific multiplicative rescaling factor, A_L = band-specific additive rescaling factor, Q_{cal} = quantized and calibrated standard product pixel values (DN).

After getting the radiance values these were converted into temperature brightness by using the following (Eq. (5)):

$$T = K_2/(ln(K_1/L_\lambda + 1)) \tag{5}$$

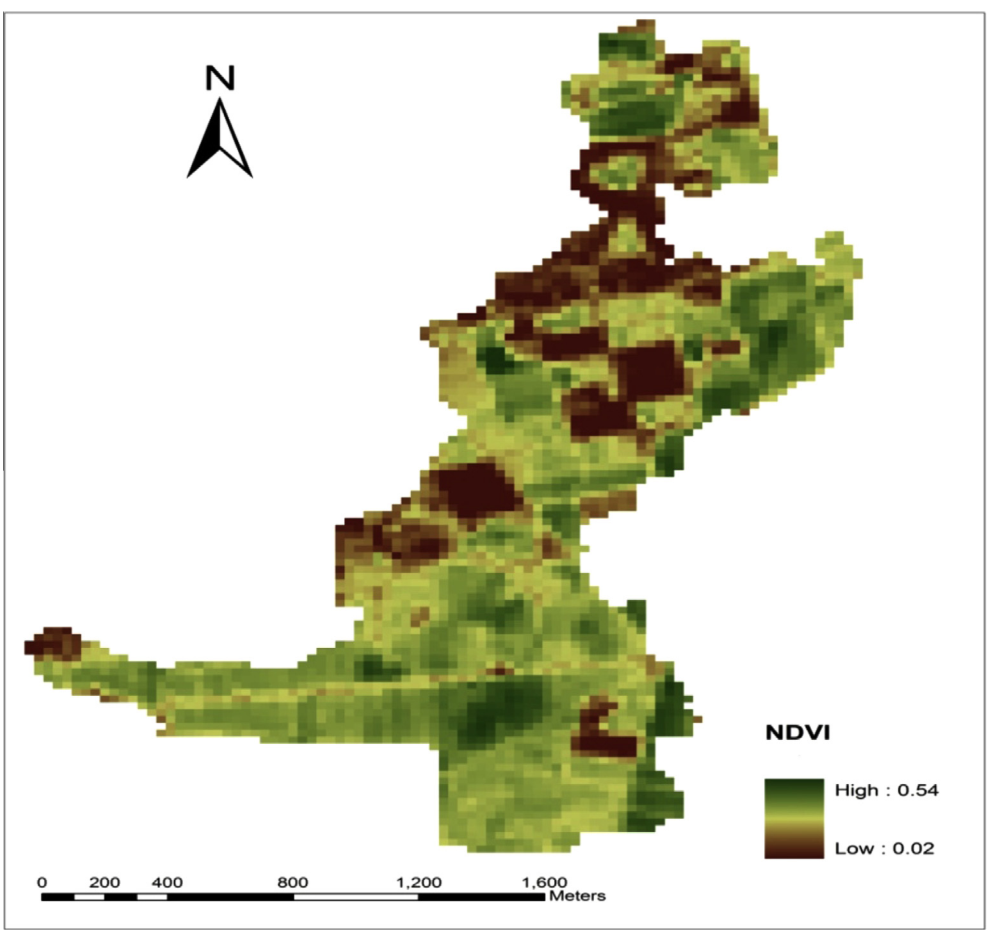

Figure 5 Normalized difference vegetation index of study area.

where T = brightness temperature (K), L_λ = spectral radiance, K_1 = band-specific thermal conversion constant, K_2 = band-specific thermal conversion constant.

The temperature values result in Kelvin, which were then converted into degree Celsius by applying simple equation (C = K-273). The temperature values of LST range from 33.19 to 40.57. A map was created by using Arcgis which shows the variation in temperature among the study areas (Fig. 6).

3.5. Temperature vegetation dryness index

TVDI was calculated through the estimated values of LST and NDVI. The values of both were rounded to two decimals and exported to dbf files. They were plotted against each other in excel sheet to identify the regression lines defining the upper and lower edges of the triangle. The Ts-NDVI space was created to identify the dry and wet edges of the area. The procedure was applied to the image from which wet and dry edges were identified by the pixel distribution of LST and NDVI. Sandholt et al., 2002 analyzed the triangle formed by the scatter plot of two parameters LST and NDVI representing Ts-NDVI space and used this space for the definition of TVDI. After this the TVDI can be calculated by using Eq. (6):

$$\mathrm{TVDI} = \frac{T_s - T_{smin}}{T_{smax} - T_{smin}} \tag{6}$$

where T_s = land surface temperature of any pixel, T_{smin} = minimum land surface temperature, T_{smax} = maximum land surface temperature.

There was a strong correlation between LST and NDVI. In Fig. 7 the y-axis represents the land surface temperature and x-axis shows normalized difference vegetation index. The LST and NDVI relationship slope could be effectively determined during the growing season with a certain level of NDVI. The derived T/NDVI slope from image windows was significantly correlated to *in situ* soil moisture (Xin et al., 2006). The relationship between LST and NDVI shows decreasing temperature with increasing vegetation and increasing temperature with decreasing vegetation. After getting the dry and wet edges the values were exported in Arcgis to draw TVDI map. The TVDI values range from 0 to 1 and the map of TVDI is shown in Fig. 8.

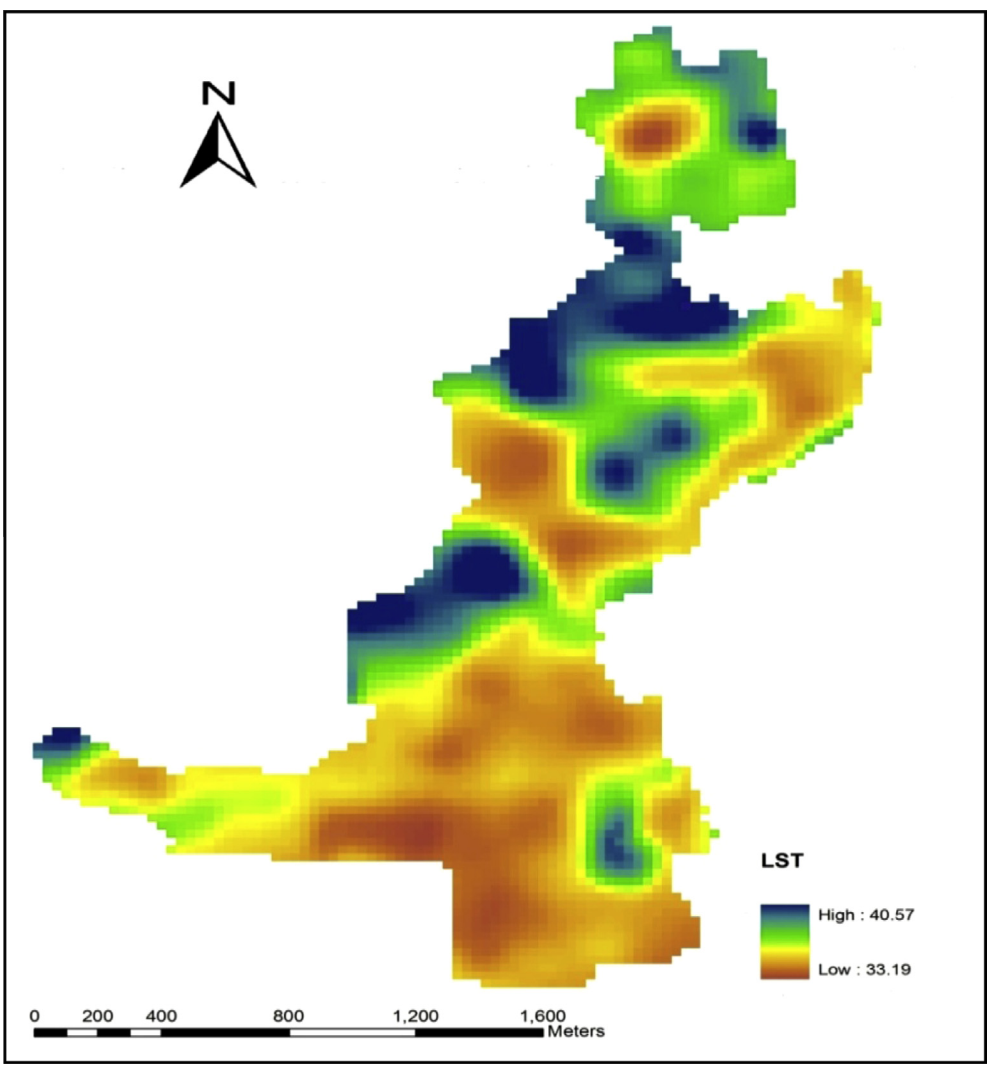

Figure 6 Land surface temperature of study area (°C).

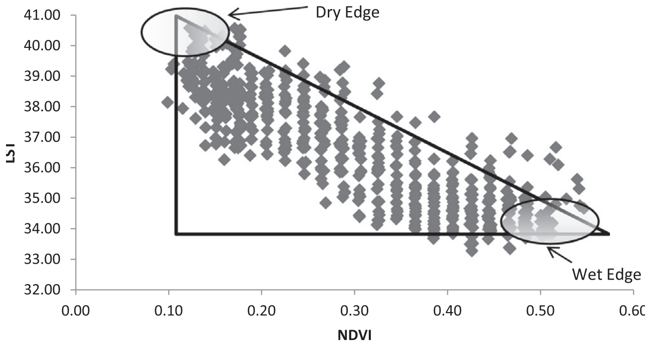

Figure 7 Land surface temperature and normalized difference vegetation distribution of sample points.

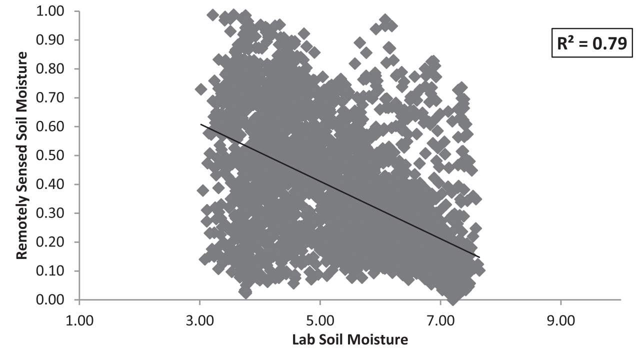

Figure 9 Correlation between remotely sensed soil moisture and lab soil moisture.

3.6. Validation of remote sense derived soil moisture data with gravimetric soil moisture content

After getting the TVDI surface, it was compared with physically measured soil moisture. The values of satellite measured soil moisture in the form of TVDI were exported to dbf format to perform correlation analysis. The result shows that as the TVDI value decreases the physically measured moisture increases and vice versa (Fig. 9). So it was concluded that there was a moderately strong negative correlation between TVDI and actual soil moisture. The RMS value recorded was 0.79. The study reveals that the probability of TVDI from MODIS data in estimating soil water content was observed. The correlation and regression analysis was done to check the relation of TVDI against *in situ* soil moisture measurement data during winter wheat/summer maize main growth stages. A significant negative correlation exists between the TVDI and *in situ* measurements at various soil depths (Chen et al., 2011). While the

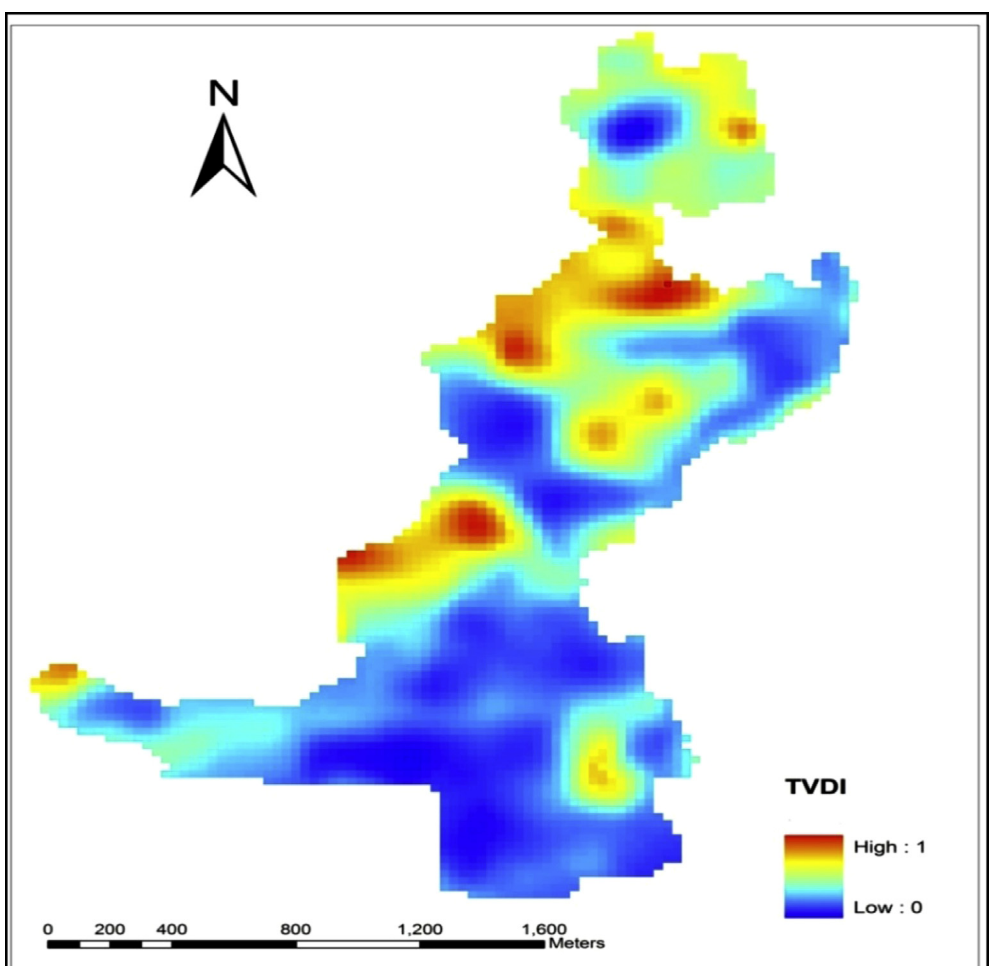

Figure 8 Temperature vegetation dryness index of study area.

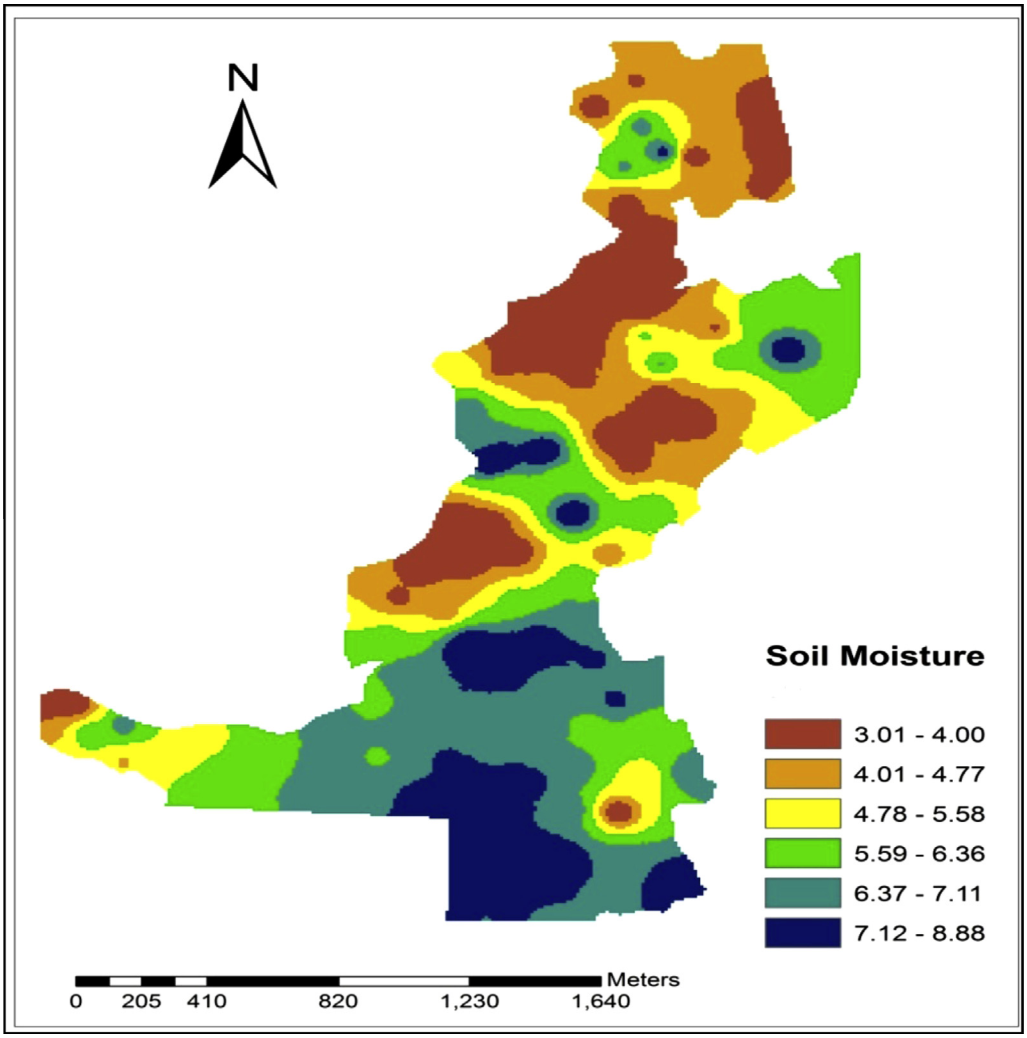

Figure 10 Final soil moisture map of study area.

surface temperature was more responsive than NDVI to TVDI, the drought information can better reveal from LST than NDVI. The capability of TVDI with the drought index that was surmise from Ts alone, was named as crop water stress index (CWSI). The TVDI has a more strong relation than CWSI to soil moisture measured *in situ*. TVDI in view of a mix of Ts and NDVI is more exact than CWSI construct exclusively in light of Ts in provincial dry spell assessment (Wang et al., 2004). The results of the study by Patel et al. (2009) reveal that a significantly strong and negative relationship exists between the TVDI and *in situ* soil moisture, particularly when vegetation cover is sparse. The dryness index was also found satisfactory to capture the temporal variation in the surface moisture status in terms of antecedent precipitation index. The final map of soil moisture of the study area is shown in Fig. 10.

4. Conclusions

The study investigated different methods for estimation of surface soil moisture. *In situ* measurements were taken from study area located in NARC Islamabad. The samples were analyzed for moisture determination by using traditional methods. FTIR analysis was carried out to the effect of the reflectance on different moisture conditions. A general trend was found that as the moisture increases reflectance from soil decreases and vice versa. The FTIR analysis should be more precise as repeated measurements should be taken by applying different types of soils under various moisture conditions. This will form standard criteria to estimate soil moisture directly by using FTIR spectroscopy. The third method was remotely sensed soil moisture estimation. Landsat 8 imagery of the study area was used for estimation. The triangulation method was applied, which was found good for appropriate estimation of soil moisture. A strong correlation was found between LST & NDVI which results in the formation of TVDI surface by using regression analysis. TVDI surface was then correlated with *in situ* soil measurements. The results had shown a moderately strong correlation. So from the above study it is concluded that remotely sensed data can be used for the estimation of surface soil moisture as it is less time and resource consuming. It can be applied on a large scale. Regular monitoring of soil moisture can be made for agriculture management, drought management, decision making. It can also be used in hydrological modeling where soil moisture is a key component.

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