Influence of soil texture on the estimation of bare soil moisture content using MODIS images

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ABSTRACT
Spectral behaviour of soil is strongly influenced by the soil texture as well as its nutrient content. Many attempts have so far been made to assess the soil moisture using soil reflectance in different bands of satellite images. In this paper, the investigations showed that the coarse texture soils did not show a profound relationship with the reflectance values that was in part due to its weak water storage capacity. Fine texture soils, on the contrary, showed better results which could be attributed to their higher water storage capacity and the capillary phenomenon. Finally, a linear regression model made of a combination of Land Surface Temperature (LST), Normalized Difference Water Index (NDWI) and Visible and Short-wave infrared Drought Index (VSDI) indices was proposed. The suggested method has improved the accuracy of the soil moisture content estimation up to 1% in general and the medium texture soil in particular. The results were compared with the performance of seven conventional soil moisture estimators method all using the Moderate Resolution Imaging Spectroradiometer (MODIS) data.

Introduction
Generally, soil moisture content (SMC) is expressed either by volumetric (cm$^3$/cm$^3$) or gravimetric (gram/ gram) unit. Constantly measuring and monitoring of this parameter plays an important role in various studies such as estimation and prediction of plants evapotranspiration, analysis of atmospheric parameters, drought condition and surface runoffs (Goward, Xue, & Czajkowski, 2002; Khanna et al., 2007; Paloscia, Pampaloni, Pettinato, & Santi, 2008).

Remote sensing (RS) is considered as an effective tool for monitoring soil parameters over wide areas and is believed to be more cost effective compared to in situ measurements (Wagner, Lemoine, & Rott, 1999).

The SMC along with parameters such as colour, texture, roughness, temperature, vegetation cover, organic matter can influence the RS observations (Weidong et al., 2002). Consequently, separate assessment of each of these parameters using RS data requires the development of a particular algorithm in which the effects of the other factors are reduced. In other words, the SMC estimation using RS observations requires an understanding of the behaviour of this parameter in interaction with electromagnetic spectrum.

Since 1970s, various methods for the SMC estimation using a variety of electromagnetic spectral bands from visible to microwave wavelength regions have been developed (Carlson, 2007; Mallick, Bhattacharya, & Patel, 2009; Petropoulos, Carlson, Wooster, & Islam, 2009; Sandholt, Rasmussen, & Andersen, 2002). In general, these methods can be classified into three categories: passive and active microwave RS, optical and thermal passive RS and hybrid downscaling methods (Nichols, Zhang, & Ahmad, 2011; Sabaghy, Walker, Renzullo, & Jackson, 2018). Each of these methods has its own limitations. The critical challenging disadvantages of these methods are the low spatial resolution of passive microwave RS, low temporal resolution of active microwave RS and the more dependence of the results of optical and thermal RS methods on the atmospheric conditions and land surface properties. The combined active and passive (hybrid) methods take advantages of high spatial resolution of the active sensors and the sensing accuracy of the passive sensors. The average accuracies for SMC estimation achieved in different studies are as follow: a – about 4% in models based on passive microwave, b – between 2–4% in methods based on active microwave and c – between 2–6% for the methods in which optical/thermal images are used (Choker et al., 2017; Jin et al., 2017; Paloscia, Pettinato, & Santi, 2012; Rahimzadeh-Bajgiran, Berg, Champagne, & Omasa, 2013; Sabaghy et al., 2018; Sahebi, Bonn, & Gwyn, 2003; Zhang, Chen, Zhao, Li, & Chen, 2018).
The SMC is highly variable both spatially and temporally (Lacava et al., 2012). Generating time series of this parameter is very important for the applications, such as drought indices assessment, detection of dust hotspots, monitoring of evapotranspiration and proper scheduling of irrigation on regional scales. This requires RS data with high temporal resolution.

For the soil related studies at the regional scales, Moderate Resolution Imaging Spectroradiometer (MODIS), among the other operational optical and thermal sensors, is highly applicable for several reasons. These are: free near real-time data availability, various calibrated products, high temporal resolution and high spectral resolution i.e. 36 optical and thermal bands (Gardin et al., 2014; Hosseini & Saradjian, 2011; Pablos et al., 2016; Rahimzadeh-Bajgiran et al., 2013; Wang & Qu, 2007; N. Zhang, Hong, Qin, & Liu, 2013; Zhao et al., 2010).

As mentioned above, the soil texture is one of the important factors in the estimation of SMC by means of RS data especially optical and thermal data. In this study, the effect of soil texture on the SMC estimation has been investigated using MODIS images.

From the theoretical point of view, it is believed that the water capacity of soils depends on the soil texture and soil porosity. In other words, the soil water content is a function of the pore size and volume of the pore space (Kurucu, Sanli, Esetlili, Bolca, & Goksel, 2009). In Figure 1, the SMC is plotted as a function of the soil texture (Kaufmann & Cleveland, 2008).

As seen in Figure 1, the range of the SMC variations in the coarse texture soils are less than for fine texture ones. This phenomenon can be justified by the high flow of gravitational water in the coarse texture soils. On the contrary, due to the low volume and high density of porous spaces in the fine texture soils, molecular absorption of the water by the soil particles overcomes the gravity and consequently a high level of water content in these soils is maintained.

Furthermore, the length of capillary rise for the medium texture soils is greater than coarse texture ones (Weil and Brady, 2016). Figure 2 shows the length of capillary rise for different types of soil. As seen, the length of capillary rise for loamy soils increases over time compared to the sandy soils.

The differences between physical behaviour of different types of soils have motivated these authors to study the effects of soil texture on estimation of SMC from optical and thermal bands and compare the results with the methods suggested by other authors so far.

In this study, the data collected in Soil Climate Analysis Network of the United States (US-SCAN) stations whom distributed throughout the USA, have been used. Due to the vast spatial distribution of the SCAN stations, it is likely to have variety of soil texture in our field study region.

The main objective of this study is to investigate the effects of different soil texture on the estimation of SMC using the well-established US-SCAN data and MODIS images. Also a modified regression model will be worked out in order to improve the accuracy of the estimated SMC.

Data preparation

Study area and in situ data

The data used in this study are those collected in US-SCAN stations. As asserted in the US-SCAN website

![Figure 1. Soil texture and soil water. Source: (Kaufmann & Cleveland, 2008).](image-url)
The purpose of these data collection is drought monitoring, agricultural water management, calibration and assessment of the SMC models through satellite images. These data are being routinely collected in more than 220 stations. The parameters collected in these stations are soil moisture, temperature at different depths, soil salinity, soil electrical conductivity, air relative humidity, precipitation, solar irradiance and wind speed. The sensor used for SMC measurement is Hydra Probe.

To minimize the uncertainties involved with some parameters, the criteria for the selection of suitable stations for this study were:

a. Absence of water bodies closer than 1 km to each station;
b. At least 75% of the soil texture should be from one type; based on USDA soil maps.
c. Absence of dense vegetation cover and evergreen plants around the station.
d. Visual inspection of area around each station for the minimal presence of impervious surfaces and man-made structures (asphalt, concrete etc.) using Google Earth.
e. Absence of extreme topography that could result in large shadows. Stations located at the mountainous area were not used.

All the US-SCAN stations did not meet our criteria to be used in this study. Therefore, in a strict decision-making process, 173 stations have not met these criteria. Those stations suitable stations for this research are referred to as Ground Reference Stations (GRS) and are marked by circles in Figure 3.

Taking into account the above-mentioned criteria, due to the relative surface cover homogeneity around each of the selected stations, it is anticipated to be able to extend the field measurements to a larger area around each station. However, there is still some uncertainty involved with the results and should not be expected to be as accurate as the field measurements.

Hourly time series of field volumetric SMC collected data at 0–5 cm depth from 2012 to 2015 were downloaded for the 47 GRSs. The information regarding 47 GRSs and the number of SMC collected data used in this study are given in Table 1.

Due to the necessity of simultaneously collecting ground data and acquiring image, it is tried to utilize in situ data whose time of collection be as close as possible to the image acquisition time. In general, the difference between image acquisition time and time of in situ measurements was less than half an hour.

Pre-processing of satellite images

In this study, in order to find suitable images, all images acquired by MODIS sensors on board of both TERRA and AQUA platforms for the period 2012–2015, were checked for all selected GRSs. The criteria considered image selection were:

a. Cloudless conditions for GRS containing pixels using MOD35/MYD35 products.
b. Selecting those images where GRS pixels are close to the scene centre lines in order to minimize the effects of atmosphere and any other geometrical effects.
c. Using daytime and snow free pixels by applying the well-known Normalized Difference Snow Index (NDSI).
d. Minimum vegetation covered GRSs containing pixels using Normalized Difference Vegetation Index (NDVI) for values between 0–0.15.

Based on these criteria, 50 images were selected. The products used in this work were MOD09/MYD09 and MOD11/MYD11, where the necessary atmospheric corrections and georeferencing have been carried out by the provider.
Methodology

The structure of this study is based on two main objectives: investigating the influence of soil texture on the SMC estimation and developing a modified procedure to improve the accuracy for the SMC estimation.

This methodology section consists of 4 sub-sections. In section 3.1, the frequently used models (here called conventional models) for the SMC estimation using optical and thermal data are introduced. In section 3.2, all GRSs are classified based on soil texture and the results were compared by the results of conventional models. In section 3.3, a modified model for SMC estimation has been proposed and its performance was compared to the conventional models. Finally in the last part of this section, method used for accuracy assessment was described. All these procedures are shown in Figure 4.

Conventional SMC estimation models

As described in the introduction section, various models were developed to estimate the SMC using active/passive microwave, and optical/thermal RS data. Since in this study, it is intended to use MODIS products in optical and thermal regions, this section is especially devoted to the similar methods in the optical/thermal regions.

Various models have been developed for SMC estimation all using optical/thermal RS data (Leng, Song, Duan, & Li, 2016; Mobasher & Amani, 2016; Petropoulos, Ireland, & Barrett, 2015; Rahimzadeh-Bajgiran et al., 2013; Sadeghi, Babaeian, Tuller, & Jones, 2017). Generally, these methods can be categorized in three groups:

1. Methods based on soil moisture indices where the most important indices are: Normalized Multi-band Drought Index (NMDI),
Table 1. Main features of the 47 SCAN sites used in this study.

| Station Name           | Location                  | (Lat, Lon)       | Number of SMC Data | Dominant Soil Texture |
|------------------------|---------------------------|------------------|--------------------|-----------------------|
| Orchard Range Site     | Idaho, Ada                | (43.32, −116)    | 18                 | Sandy Loam            |
| Sheldon                | Nevada, Washoe            | (41.9, −119.44)  | 9                  | Loam                  |
| Adams Ranch #1         | New Mexico, Lincoln       | (34.25, −105.42) | 10                 | Loam                  |
| Nunn #1                | Colorado, Weld            | (40.87, −104.73) | 11                 | Sandy Loam            |
| Torrington #1          | Wyoming, Goshen           | (42.07, −104.13) | 8                  | Sand                  |
| Lind #1                | Washington, Adams         | (47, −118.57)    | 3                  | Silty Loam            |
| Level #1               | Texas, Hockley            | (33.55, −102.17) | 5                  | Sandy Loam            |
| Crossroads             | New Mexico, Lea           | (33.54, −103.24) | 6                  | Sandy Loam            |
| Willow Wells           | New Mexico, Lea           | (33.53, −103.63) | 5                  | Loamy Sand            |
| Lovelock NNR           | Nevada, Pershing          | (40.03, −118.18) | 16                 | Silty Loam            |
| Circleville            | Utah, Piute               | (38.15, −112.25) | 39                 | Loam                  |
| Ephraim                | Utah, Sanpete             | (39.42, −111.57) | 45                 | Sandy Loam            |
| Holden                 | Utah, Millard             | (39.19, −112.4)  | 43                 | Loam                  |
| Enterprise             | Utah, Iron                | (37.63, −113.64) | 40                 | Sandy Loam            |
| Eastland               | Utah, San Juan            | (37.78, −109.17) | 39                 | Sandy Loam            |
| Price                  | Utah, Carbon              | (39.53, −110.81) | 48                 | Loam                  |
| Blue Creek             | Utah, Box Elder           | (41.94, −112.43) | 37                 | Silty Loam            |
| Nephi                  | Utah, Juab                | (39.65, −111.87) | 45                 | Silty Loam            |
| Alkaline Mesa          | Utah, San Juan            | (37.67, −109.36) | 40                 | Sandy Loam            |
| West Summit            | Utah, San Juan            | (38.01, −109.13) | 38                 | Loam                  |
| McCracken Mesa         | Utah, San Juan            | (37.45, −109.34) | 41                 | Sandy Loam            |
| Trough Springs         | Nevada, Clark             | (36.37, −115.79) | 26                 | Loam                  |
| Pine Nut               | Nevada, Clark             | (36.57, −115.2)  | 27                 | Sandy Loam            |
| Jordan Valley-Cwmca    | Idaho, Owyhee             | (42.95, −117.01) | 18                 | Silty Loam            |
| Marble Creek           | California, Mono          | (37.78, −118.42) | 15                 | Sandy Loam            |
| Chicken Ridge          | Utah, Morgan              | (41.33, −111.3)  | 44                 | Loam                  |
| Buffalo Jump           | Utah, Morgan              | (41.34, −111.19) | 45                 | Loam                  |
| Park Valley            | Utah, Box Elder           | (41.77, −113.26) | 35                 | Loam                  |
| Manderfield            | Utah, Beaver              | (38.37, −112.64) | 41                 | Loam                  |
| Spooky                 | Utah, Kane                | (37.51, −111.26) | 47                 | Loamy Sand            |
| Sand Hollow            | Utah, Washington          | (37.1, −108.34)  | 38                 | Loamy Sand            |
| Vermillion             | Utah, Kane                | (37.19, −112.19) | 42                 | Loamy Sand            |
| Tule Valley            | Utah, Millard             | (39.24, −113.46) | 41                 | Loam                  |
| Hals Canyon            | Utah, Millard             | (38.59, −113.75) | 41                 | Sandy Loam            |
| Goshtute               | Utah, Tooele              | (39.99, −114)    | 41                 | Sandy Loam            |
| Harms Way              | Utah, San Juan            | (38.31, −109.24) | 36                 | Sandy Loam            |
| Dugway                 | Utah, Tooele              | (40.17, −113.02) | 38                 | Silty Loam            |
| Los Lunas PMC          | New Mexico, Valencia      | (34.77, −106.76) | 14                 | Loam                  |
| Sevilleta              | New Mexico, Socorro       | (34.36, −106.69) | 14                 | Loamy Sand            |
| Desert Center          | California, Riverside     | (33.8, −115.31)  | 19                 | Sandy Loam            |
| Ford Dry Lake          | California, Riverside     | (33.65, −115.1)  | 17                 | Sand                  |
| Essex                  | California, San Bernardino| (34.67, −115.17) | 23                 | Loamy Sand            |
| Shadow Mtns            | California, San Bernardino| (35.47, −115.72) | 25                 | Loamy Sand            |
| Deep Springs           | California, Inyo          | (37.37, −117.97) | 15                 | Sandy Loam            |
| Death Valley Jct       | California, Inyo          | (36.33, −110.34) | 23                 | Sandy Loam            |
| Doe Ridge              | California, Mono          | (37.63, −118.83) | 11                 | Loamy Sand            |
| CPER                   | Colorado, Weld            | (40.82, −104.71) | 6                  | Sandy Loam            |
| Total: 1415            |                           |                  |                    |                      |

Perpendicular Drought Index (PDI), Normalized Difference Water index (NDWI) and Visible and Shortwave infrared Drought Index (VSDI). These indices use reflectance values in the reflective part of the electromagnetic spectrum especially in SWIR bands.

(2) Methods based on LST and some vegetation indices: These methods use feature spaces escalating by LST and different vegetation indices one of which is triangular/trapezoidal shape in the feature space in Temperature Vegetation Dryness Index (TVDI) used to estimate SMC on regional scale. The most severe limitation of these methods is the identification of the shape of triangular/trapezoidal in the pixel distribution and it requires a flat surface and a large number of pixels over an area with a wide range of soil wetness and fractional vegetation cover (Carlson, 2007).

(3) Regression models in which a combination two or more optical/thermal bands are deployed. Carlson (2007) proposed a second degree polynomial regression model using LST and NDVI. In addition to LST and NDVI, Chauhan, Miller, and Ardanuy (2003) added the surface albedo to the regression equation. Due to the uncertainty involved with angular dependence in the estimation of albedo, Sobrino, Franch, Mattar, Jiménez-Muñoz, and Corbari (2012) replaced the albedo by the surface emissivity where the results of this substitution were reported an improvement in the SMC estimation. Mobasher and Amani (2016) proposed a linear regression using the distance of each pixel from the origin in the Red/NIR space, bare soil fraction and LST. An acceptable accuracy was reported using Landsat 8 images and data collected in
the US-SCAN campaign. Hosseini and Saradjian (2011) proposed two linear regression models with NDVI-LST-enhanced vegetation index (EVI) and NDVI-LST-NDWI using MODIS images where acceptable accuracies was reported for both models.

Due to the versatility of regression method in utilizing different parameters and indices as variables, many studies have used this method for SMC estimation compared to other methods. This method have also been applied in this study, where different parameters and indices all supplied from satellite images in thermal and reflective band are used as independent variables detail of which will be explained shortly.

In this study, seven known conventional regression models have been presented Table 2. The indices deployed in these models are defined in Table 3. Model no. 1 is one of the widely used regression model for SMC estimation in which two variables of LST and NDVI are involved. The accuracy of this model was reported to be better than 2% where the NOAA Advanced Very High Resolution Radiometer (AVHRR) images are used (Carlson, 2007). The accuracy of the model no. 2 in SMC estimation using the same images was reported to be better than 5% (Chauhan et al., 2003). The accuracy of Model no. 3 where MODIS images are used is claimed to be better than 2% (Ray, Jacobs, & Cosh, 2010). Model no. 4 was applied on two sets of data; Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and the Airborne Hyperspectral Scanner (AHS) images and the achieved accuracies in SMC estimation was reported to be 6 and 5%, respectively (Sobrino et al., 2012). The accuracy claimed by model no. 5 was reported to be close to 4% where MODIS image are used (Zhang, Tang, Tang, Wu, & Li, 2015). Finally, the accuracy claimed by model no. 6 and 7 was reported to be

![Flowchart illustrating the study procedure.](image)

**Figure 4.** Flowchart illustrating the study procedure.

**Table 2.** Seven conventional models for SMC estimation.

| Name   | Model                                                                 | Reference                  |
|--------|----------------------------------------------------------------------|---------------------------|
| Model 1| \( SMC = \sum_{i=1}^{2} \sum_{j=1}^{2} a_{ij}NDVI^{(i)}LST^{(j)} \)   | (T. Carlson, 2007)        |
| Model 2| \( SMC = \sum_{i=1}^{2} \sum_{j=1}^{2} a_{ij}NDVI^{(i)}LST^{(j)}A^{(k)} \) | (Chauhan et al., 2003)   |
| Model 3| \( SMC = \sum_{i=1}^{2} \sum_{j=1}^{2} a_{ij}NDVI^{(i)}LST^{(j)}A^{(k)} \) | (Ray et al., 2010)        |
| Model 4| \( SMC = \sum_{i=1}^{2} \sum_{j=1}^{2} a_{ij}NDVI^{(i)}LST^{(j)}\varepsilon^{(k)} \) | (Sobrino et al., 2012)   |
| Model 5| \( SMC = \sum \sum a_{ijk}FVC^{(i)}LST^{(j)} \)                       | (D. Zhang et al., 2015)   |
| Model 6| \( SMC = aLST + bNDVI + cNDWI + d \)                                | (Hosseini & Saradjian, 2011) |
| Model 7| \( SMC = aLST + bEVI + cNDWI + d \)                                 | (Hosseini & Saradjian, 2011) |

\( a_{ij}, a, b, c \) and \( d \) are constant coefficients to be determined using known in situ measured data. SMC, soil moisture; LST, Land Surface Temperature; LST/Δ3, Normalized LST; NDVI/Δ3, Normalized NDVI; \( \alpha^{c} \), Normalized Albedo; \( \varepsilon^{c} \), Normalized Emissivity; FVC, Fractional Vegetation Cover; NDWI, Normalized Difference Water Index.
### Table 3. Definition of multispectral indices.

| Acronym | Name                        | Index                                                                 | Reference |
|---------|-----------------------------|----------------------------------------------------------------------|-----------|
| NDVI    | Normalized Difference       | $\frac{\rho_i - \rho_0}{\rho_i + \rho_0}$                         | (Rouse Jr, Haas, Schell, & Deering, 1973) |
| EVI     | Enhanced Vegetation Index   | $\frac{2.5(\rho_6 - \rho_7) + 3(\rho_7 - \rho_8)}{\rho_6 + \rho_7 + 7.5\rho_8}$ | (Hyete, Liu, Batchly, & Van Leeuwen, 1997) |
| NDWI    | Normalized Difference Water | $\frac{\rho_i - \rho_0}{\rho_i + \rho_0}$                         | (Gao, 1996) |
| VSDI    | Visible and Shortwave infrared Drought Index | $1 - \left(\rho_b - \rho_s\right) + \left(\rho_i - \rho_5\right)$ | (N. Zhang et al., 2013) |
| Albedo  | Broad-band reflectance      | $0.16\rho_i + 0.291\rho_2 + 0.243\rho_3 + 0.116\rho_4 + 0.112\rho_5 + 0.081\rho_7 - 0.0015$ | (Liang et al., 2003) |
| FVC     | Fractional vegetation cover | $f_i = \left(\frac{NDVI_{max} - NDVI}{NDVI_{max} - NDVI_{min}}\right)^2$ | (T. Carlson, 2007) |

$\rho_i$ is the surface reflectance in different MODIS bands.

### Classification of the GRSs based on soil texture

According to the United State Department of Agriculture (USDA), the texture of soils is classified into five general classes: coarse, moderately coarse, medium, moderately fine and fine textures (Weil, R. R. & Brady, N. C., 2016). In this study, the class of the soil in each station was determined based on soil map data available by US Soil Survey website (https://web soilsurvey.sc.egov.usda.gov). Dominant soil texture of all GRSs used in this study were medium, moderately coarse and coarse textures and were located in 19, 18 and 10 stations, respectively Table 4. Last column of Table 1 shows dominant soil texture of each of GRSs appropriate to spatial resolution of MODIS images.

### Proposed model (3index_SMC)

Since in this study, bare soil SMC assessment is the goal, it is decided to use VSDI (Zhang et al., 2013) instead of using NDVI. The VSDI index has been developed by using the reflectance differences in three bands located in the blue, red and SWIR regions as is defined by Equation 1 below:

$$VSDI = 1 - \left[\left(\rho_{SWIR} - \rho_{blue}\right) + \left(\rho_{red} - \rho_{blue}\right)\right]$$  \hspace{1cm} (1)

Here, $\rho_{SWIR}$, $\rho_{blue}$ and $\rho_{red}$ are the reflectance in SWIR, blue and red band, respectively.

The red and SWIR bands are sensitive to moisture in soil while blue is less sensitive to moisture variation and consequently this band can be used as a benchmark. Therefore, the Euclidian distance between the blue reflectance and the reflectance in red and SWIR may found to be sensitive to SMC Equation 1. In this study, a model similar to model no. 6 is suggested where NDVI is replaced by VSDI to read:

$$3index_{SMC} = a * LST + b * NDWI + c * VSDI + d$$  \hspace{1cm} (2)

The coefficients a, b, c, and d can be calculated by applying the least square method on training data.

### Model evaluation

The accuracy of the models were calibrated using 60% of all in situ measured SMC data for model training and remaining 40% for model evaluation. To evaluate the accuracy of the models, the coefficient of determination ($R^2$), Root Mean Square Error (RMSE), and percentage of relative RMSE (i.e. $RRMSE = \frac{RMSE}{Mean(\text{observed})} * 100$) were used. The output of the model was compared with the field measured data. High values of $R^2$ and low values of RMSE and RRMSE represent an acceptable accuracy.

### Results and discussion

In order to investigate the effect of the soil texture on the SMC estimation, the ability of seven conventional

### Table 4. USDA particle-size classification (Weil and Brady, 2016).

| Common Names of Soils (General Texture) | Sand (%) | Silt (%) | Clay (%) | Textural Class | Number of Stations |
|----------------------------------------|----------|----------|----------|----------------|-------------------|
| Sandy soils (Coarse texture)           | 86–100   | 0–14     | 0–10     | Sand           | 2                 |
| Loamy soils (Moderately coarse texture) | 70–86    | 0–30     | 0–15     | Sand loam      | 8                 |
| Loamy soils (Medium texture)           | 50–70    | 0–50     | 0–20     | Sandy loam     | 18                |
| Loamy soils (Moderately fine texture)  | 23–52    | 28–50    | 7–27     | Loam           | 13                |
| Loamy soils (Moderately fine texture)  | 20–50    | 74–88    | 0–27     | Silty loam     | 6                 |
| Clayey soils (Fine texture)            | 0–20     | 88–100   | 0–12     | Silt           | No data           |
| Clayey soils (Fine texture)            | 20–45    | 15–52    | 27–40    | Clay loam      | No data           |
| Clayey soils (Fine texture)            | 45–80    | 0–28     | 20–35    | Sandy clay loam| No data           |
| Clayey soils (Fine texture)            | 0–20     | 40–60    | 40–60    | Silty clay     | No data           |
| Clayey soils (Fine texture)            | 0–45     | 40–40    | 40–100   | Clay           | No data           |
| Total                                  |          |          |          |                | 47                |
optical/thermal regression models along with proposed 3index_SMC were evaluated. These models were applied to the 3 aforementioned soil texture categories i.e. medium texture soil, moderately coarse texture soil and coarse texture soil datasets using MODIS images and their accuracies were compared.

The results that are presented in Table 5, show the suitability of each of 7 models. As can be seen, they do not show an acceptable accuracy when using all soil categories. However, the accuracy increases significantly for the finer soil particle size. The values of $R^2$ and RRMSE for medium texture soils are greater than the other two classes. The accuracy of all 7 models for the sandy soils is very poor. As expected, the accuracy of 7 models meaningfully decreases from medium texture to coarse texture.

The coefficients of 3index_SMC model were calculated using the least square method. The calculated coefficients for different soil texture category are shown in Table 6. The differences between in situ SMC and estimated ones are shown in Figure 5 using different dataset than those for modelling. As can be seen the accuracy of the 3index_SMC model decreases for the coarse texture soils. But the improvement for the medium texture soils is considerable. The results show that by using VSDI instead of NDVI index, the accuracy in the estimation of SMC improves when the soils are classified especially for the medium soil texture class.

As mentioned in the introduction section, the average uncertainties in all methods including passive microwave, active microwave and optical/thermal reported by different studies is between 2–6%. However, what is achieved in this study is the

### Table 5. The results of evaluation of 7 conventional models mentioned in Table 2.

| Model Name | All soil categories | Medium texture | Moderately coarse | Coarse texture |
|------------|---------------------|----------------|-------------------|---------------|
|            | $R^2$  | RMSE | RRMSE | $R^2$  | RMSE | RRMSE | $R^2$  | RMSE | RRMSE |
| Model 1    | 0.33  | 0.05 | 81    | 0.58  | 0.044| 38    | 0.43  | 0.017| 58    | 0.15  | 0.031| 73    |
| Model 2    | 0.36  | 0.054| 84    | 0.69  | 0.039| 34    | 0.37  | 0.018| 62    | 0.16  | 0.011| 94    |
| Model 3    | 0.34  | 0.055| 85    | 0.59  | 0.042| 37    | 0.36  | 0.02  | 62    | 0.02  | 0.036| 70    |
| Model 4    | 0.21  | 0.05 | 85    | 0.61  | 0.045| 40    | 0.29  | 0.026| 82    | 0.16  | 0.046| 89    |
| Model 5    | 0.32  | 0.058| 89    | 0.63  | 0.041| 36    | 0.36  | 0.023| 72    | 0.03  | 0.04  | 76    |
| Model 6    | 0.23  | 0.06 | 92    | 0.5   | 0.05 | 45    | 0.39  | 0.022| 69    | 0.12  | 0.028| 84    |
| Model 7    | 0.3   | 0.055| 85    | 0.65  | 0.046| 40    | 0.36  | 0.02  | 70    | 0.17  | 0.027| 82    |

### Table 6. Calculated coefficients of Equation (2) in the 3index_SMC model for different soils.

| Soil texture          | a     | b     | c    | d     |
|-----------------------|-------|-------|------|-------|
| All soil categories   | −0.046| −0.25 | 0.11 | 0.03  |
| Medium texture soil   | −0.0269| −1.37 | 0.1632| 0.1    |
| Moderately coarse texture soil | −0.054| −0.18 | 0.082 | 0.02  |
| Coarse texture soil   | −0.053| −0.11 | −0.16 | 0.18   |

### Figure 5. SMC values measured in situ versus those estimated by 3 index_SMC model using (a) all soil categories (b) Medium texture soil (c) Moderately coarse texture soil (d) Coarse texture soil.
accuracy between 3–5%. Considering the low cost and daily availability of MODIS images, it is believed that this method is more applicable.

**Conclusion**

In this study, the effects of soil texture on the SMC estimation were investigated. Seven different well-known regression models were evaluated on the three different soil categories datasets. Among three soil texture categories of medium texture, moderately coarse texture and coarse texture soils, the highest correlation with the *in situ* measured SMC values was for medium texture soil. In relation with the electromagnetic waves, the effect of particle-size and the soil texture was the most influential factor on the saturation level of soil moisture. The results showed an inverse relationship between the accuracy in the SMC estimation and the soil particle size. In other words, the accuracy of the SMC models decreased by the increase of soil particle size. In the case of medium texture soils, better response to the SMC estimation have seen in optical bands. Coarse texture soils such as sandy soil, because of porosity, water penetrates rapidly and freely inside the soil due to the force of gravity and show a lower water content capacity. On the contrary, medium texture soils have the ability to retain more water in their textures and the length of capillary rise in these soils is greater than those of coarse texture soils. Thus, moisture variations in this type of soils have a greater effect on the soil spectral responses compared to coarse texture soils where the results of the SMC modelling for loamy medium texture soils approves this.

The other objective of this study was to propose a modified linear regression model with three variables of LST, NDWI1 and VSDI indices. This is done in 3index_SMC model. The results showed that the accuracy of this model for non-classified soils have not improved significantly compared to the previous models. However, 3index_SMC model for the medium texture soils the accuracy was improved close to 1%. This result can be due to the high sensitivity of SWIR bands to the SMC variations and high water storage capacity of the medium texture soils.

**Future works**

The mismatch between the SMC field measurements and the pixel size of image is one of the most important challenges in the field of modelling and calibration of SMC using low spatial resolution images such as MODIS. In this research, to overcome this challenge, we tried to precisely select homogenous stations for the field measurements so that the uncertainty related to this mismatch is minimized. However, some uncertainty might also be involved with the results.

Radiometric cross-calibration between high and low spatial resolution images like Sentinel 2 and MODIS could be considered as a solution to reduce this uncertainty. In other words, SMC could be produced by high spatial resolution images and then used to calibrate low spatial resolution images such as MODIS. This procedure could be an effective solution to use the potential of high spatial/temporal images. This method has been proposed as a further work to the current research.

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No potential conflict of interest was reported by the authors.

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