Final Report

Remote Sensing Techniques for Soil Moisture and Drought Monitoring

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1. Project Objectives

Soil moisture is one of the key variables in controlling the exchange of water and heat energy between land surface and atmosphere. However, widespread and/or continuous measurement of soil moisture is all but nonexistent. Direct observations of soil moisture are currently restricted to discrete measurements at specific locations, and such point-based measurements do not reveal large-scale soil moisture and are therefore inadequate to carry out regional and global studies. Satellite remote sensing offers a means of measuring soil moisture across a wide area continuously over time (Engman 1990), while techniques in the microwave and optical/IR frequency regimes have attracted more attention (Chauhan 2003). Microwave remote sensing technology has demonstrated a quantitative ability to retrieve soil moisture physically for most ranges of vegetation cover (Njoku et al. 2002). However, current microwave technology limits the spatial resolution of soil moisture measurements. Optical/IR techniques can provide fine spatial resolution for soil moisture estimation (Idso et al. 1975, Price 1977), but it is difficult to decouple signals from vegetation and soil. In addition, satellite remote sensing can only provide soil moisture measurements for the top few centimeters of the soil profile (Engman et al. 1995), while the complete soil moisture profile in the unsaturated zone is more useful for hydrologic, climatic and agricultural studies (Jackson 1980, Mancini et al. 1995, and Newton et al. 1983).

Therefore, to establish robust algorithms for soil moisture estimation, further efforts are still needed to study the physical principles so as to identify the quantitative relationships between soil moisture content and remote sensing variables, and the feasibility and capability of soil moisture retrieval from space need to be assessed in more details.

The objectives of this proposed research are:

(1) To estimate soil moisture by combining the strengths of multi-sensor and ground measurements to achieve higher accuracy and spatial resolution.

(2) To investigate the potentials of using a combination of multiple solar spectral signatures to minimize the vegetation effects for soil moisture estimation.

(3) To retrieve soil moisture profile in the unsaturated zone by solving the Richards equation, which governs the vertical water infiltration in layered soil profiles.

(4) To generate daily soil moisture and drought index products and test/validate those products using NOAA/NWS measurements or model simulations.

2. Project Accomplishments and Findings

2.1 Study Area and Period

We conducted soil moisture study over the Montana state for the period of year 2007-2010. The total land area of Montana is about 93.1 million acres, and approximately 66% of the total land areas are dedicated to farmland or agriculture. Soil observations and analysis in Montana are very helpful for farmers and government agencies in agricultural planning, drought relief, irrigation management, and water resource management.

2.2 Data Collection and Processing

Ground Observation

We used in-situ measurements from the Soil Climate Analysis network (SCAN).

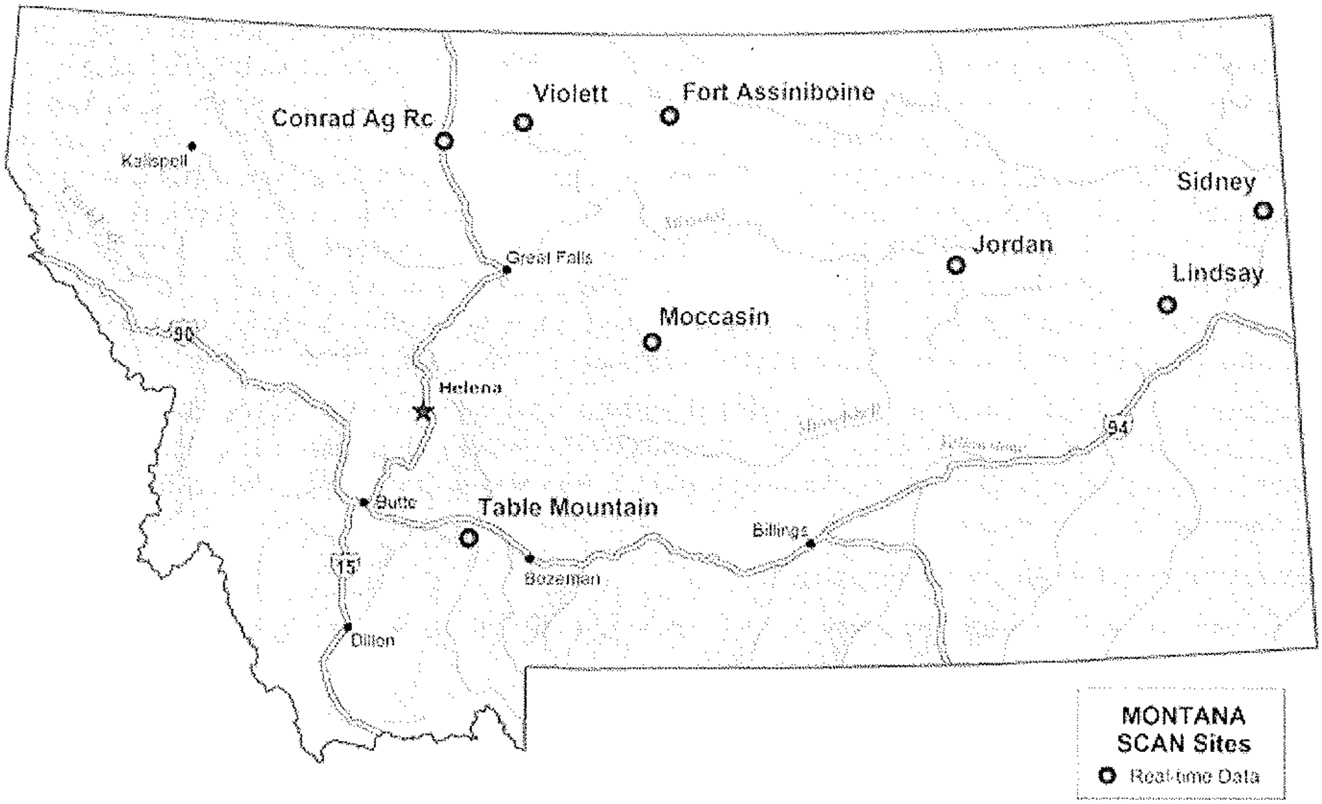

Fig. 1 SCAN sites in Montana
(From http://www.wcc.nrcs.usda.gov/scan/Montana/montana.html)

The SCAN sites provide observations of soil moisture (at 2", 4", 8", 20", and 40"), soil temperature, air temperature, and precipitation etc. Figure 1 shows the SCAN sites in Montana. We collected daily soil moisture and precipitation data from year 2006 to 2010 at the 8 SCAN sites.

Satellite Remote Sensing Measurements

MODIS instrument onboard NASA EOS satellites Terra and Aqua has high potential for better estimation of land surface parameters. To investigate the feasibility of soil moisture retrieval with MODIS measurements, we adapted the triangle method to MODIS measurements, and validated with ground measurements at SCAN sites in Montana. We collected Terra MODIS daily surface reflectance and surface temperature products from year 2007 to 2010 in this study. Large volume of remote sensing datasets, over 1200 MODIS surface reflectance data files and over 1200 MODIS surface temperature data files are collected, with a total size around 108 gigabytes.

Based on geolocation, MODIS daily surface reflectance and surface temperature data at the 8 SCAN sites are extracted from the MODIS data products, and merged with the daily ground measurements. Finally, a table of integrated daily datasets is generated, including year, month, day, soil moisture at 2”, 4”, 8”, 20”, and 40”, precipitation amount, surface reflectance at MODIS bands 1-7, and surface temperature. Since MODIS visible and infrared bands only can sense the Earth’s surface during clear days, data records with precipitation>0, or invalid LST, or invalid surface reflectance are filtered out. The following steps are based on valid data only. And, NDVI and other spectral indices are calculated based on surface reflectance data.

2.3 Technical Methods

Universal Triangle Method

Vegetation and land surface temperature have a complicated dependence on soil moisture. The unique relationship among soil moisture M, land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) for a given region, referred as the ‘Universal Triangle’ (Carlson et al. 1994, Gillies et al. 1997) can be expressed through a regression formula such as:

$$M = \sum_{i=0}^{i=n}\sum_{j=0}^{j=n} \mathrm{a}_{\mathrm{ij}} NDVI^{*(i)} T^{*(j)},$$

where $T^* = \frac{T - T_0}{T_s - T_0}$, $NDVI^* = \frac{NDVI - NDVI_0}{NDVI_s - NDVI_0}$, T and NDVI are observed LST and NDVI, respectively. For n=2, the polynomial model can be written as:

$$M = a_{00} + a_{10} NDVI^* + a_{20} NDVI^{*2} + a_{01} T^* + a_{02} T^{*2} + a_{11} NDVI^* T^* + a_{22} NDVI^{*2} T^{*2} + a_{12} NDVI^* T^{*2} + a_{21} NDVI^{*2} T^*.$$

Our early study has demonstrated that soil moisture can be estimated at MODIS 1km resolution based on the above polynomial equation (Wang et al. 2007). The flowchart of the soil moisture estimation is given in figure 2.

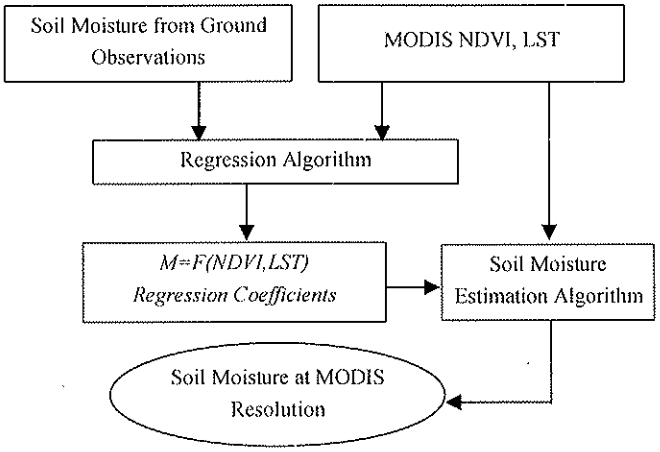

Fig. 2 Schematic flow diagram for estimating soil moisture.

First, the regression relationships are identified by combining the ground measurements of soil moisture and MODIS NDVI and LST. By applying these regression relations to MODIS measurements, daily soil moisture data at MODIS resolution can be obtained. In situ soil moisture is compared against the predictions.

Spectral indices using multiple MODIS RSB measurements

Based on the soil and vegetation spectral signatures, the Normalized Multi-band Drought Index (NMDI) is proposed by using three wavelengths, one in the NIR centered approximately at 860 nm, and two in the SWIR centered at 1640 nm and 2130 nm, respectively. The usefulness of NMDI has been validated by using the bare soil spectra under various soil water contents as well as satellite data. Results show that strong differences between two water absorption bands in response to soil and leaf water content give this combination capability to estimate water content for both soil and vegetations (Wang and Qu 2007). NMDI has demonstrated the potential to monitor dry soil status for the bare soil, while for heavily vegetated areas, NMDI turns to a complete vegetation water index like NDWI, rather than a soil moisture index.

In this study, MODIS spectral indices were compared with the SCAN soil moisture observations.

2.4 Results and Analysis

Universal Triangle Method

The universal triangle methods were applied to 8 SCAN sites in Montana to check the performance of the approach with 2nd order polynomial model. Data of year 2007, 2008 and 2009 were used to calibrate the soil moisture model, while the data of year 2010 were used for validation.

Since visible and infrared channels only can sense a very thin layer of the surface, we investigated the 2nd order model with MODIS data and 2" soil moisture data. Figures 3-10 demonstrates the results of modeling and validation of soil moisture at 2" depth. Although the results are not perfect, they are typical in soil moisture retrieval with remote sensing technology. The determinant coefficients (R^2) are from 0.29 to 0.48, with RMSE at reasonable range for most sites. Why the determinant coefficients (R^2) are not very high? There are several reasons:

(1) The SCAN system uses automatic sensor to detect soil moisture. The accuracy of SCAN soil moisture data depends on sensor calibration. In our previous studies, we noticed that manually measurements of soil moisture usually could get very good results (Wang et al. 2007), while for automatic instruments, the extra error source from instrument calibration could affect the performance of the model.

(2) Uncertainties in atmospheric correction and surface temperature retrieval of MODIS data products may also introduce errors and effect model performance.

For regional applications of soil moisture estimation with MODIS measurements, more details about land cover type, fractional vegetation cover, and soil type are necessary. Different soil types and different vegetation types have different response to water content change. And, in case of dense vegetation cover, satellite instrument may not be able to sense signals from soil effectively.

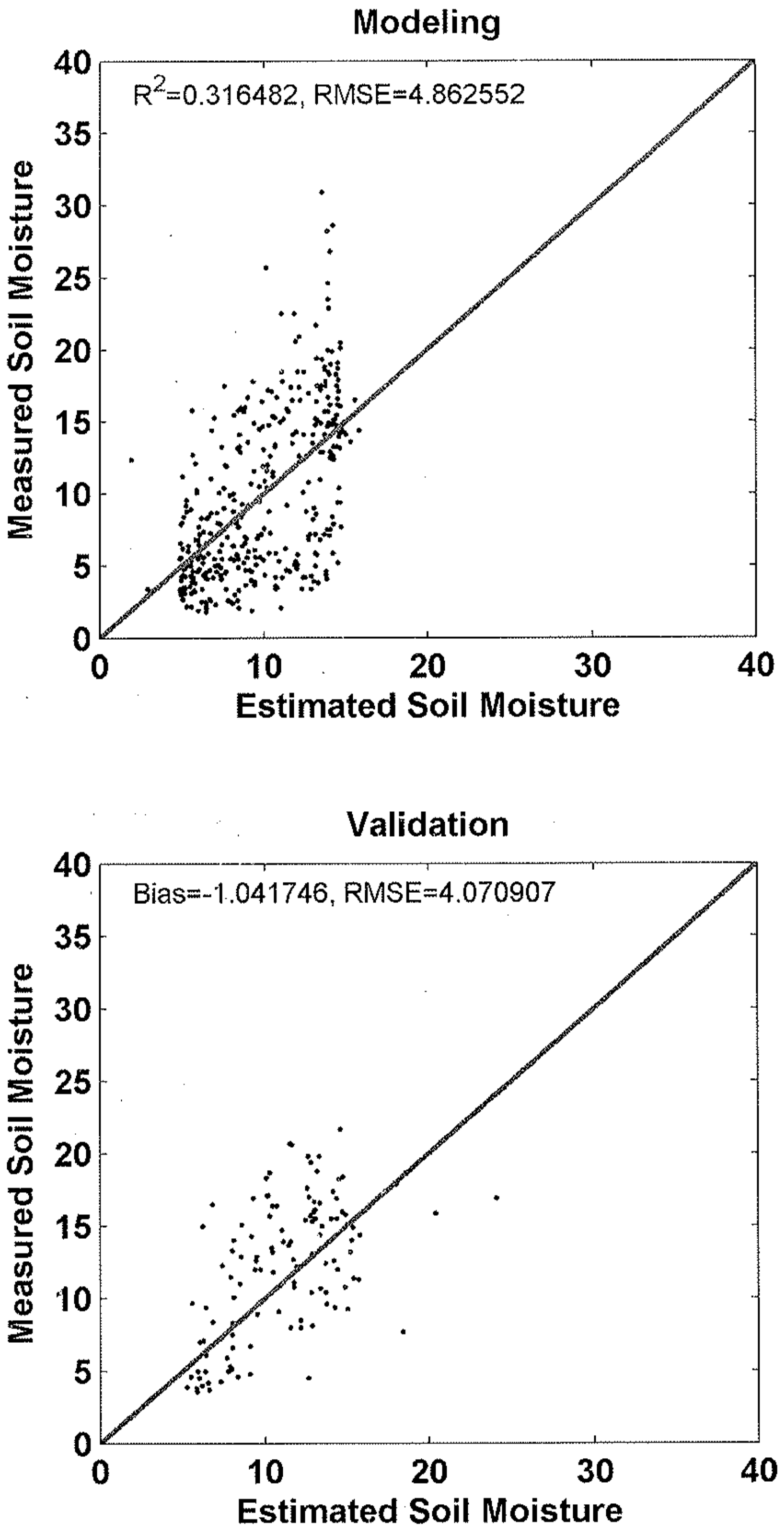

Figure 3: Modeling and validation results of SCAN site 581.

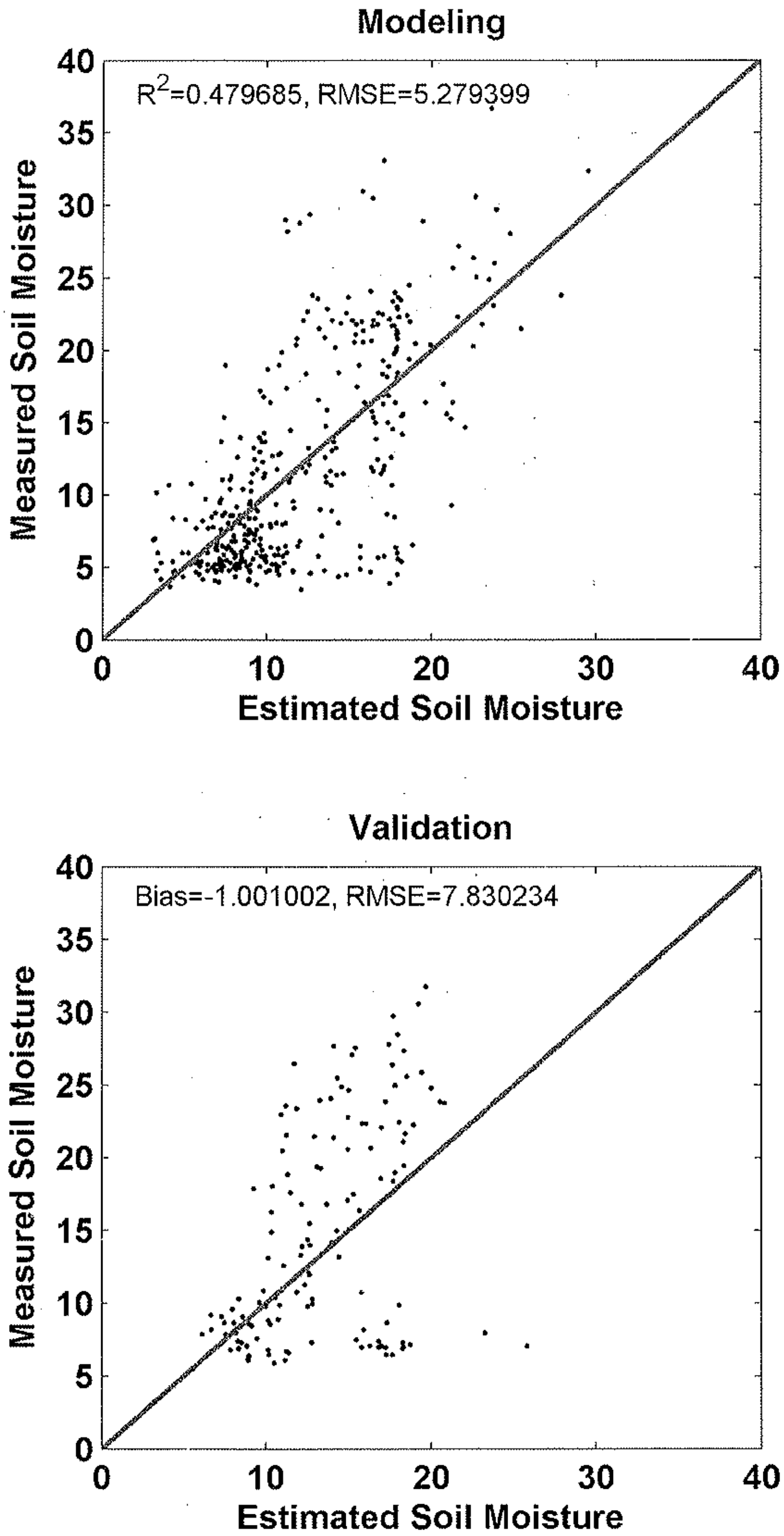

Figure 4: Modeling and validation results of SCAN site 808.

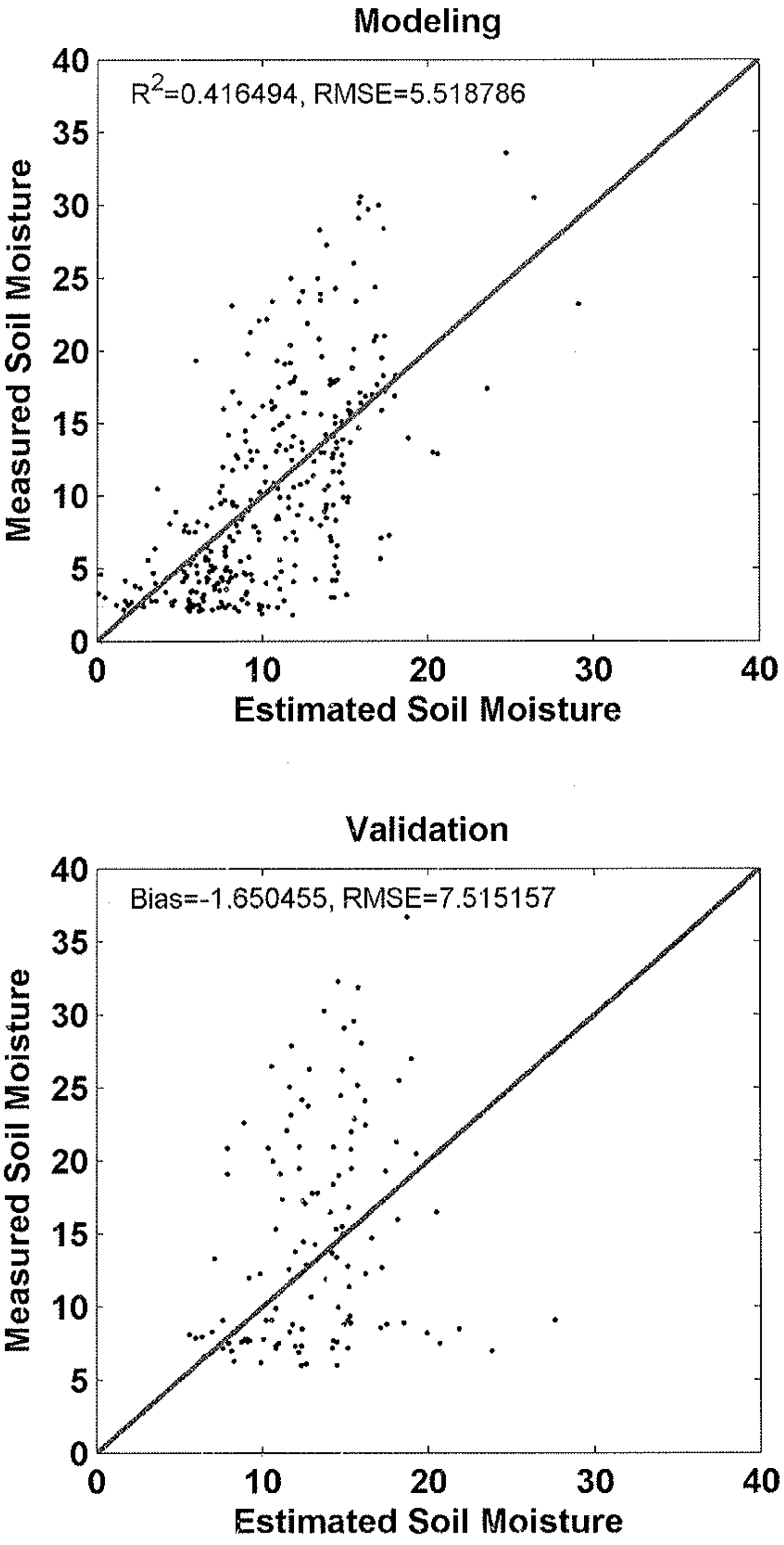

Figure 5: Modeling and validation results of SCAN site 2019.

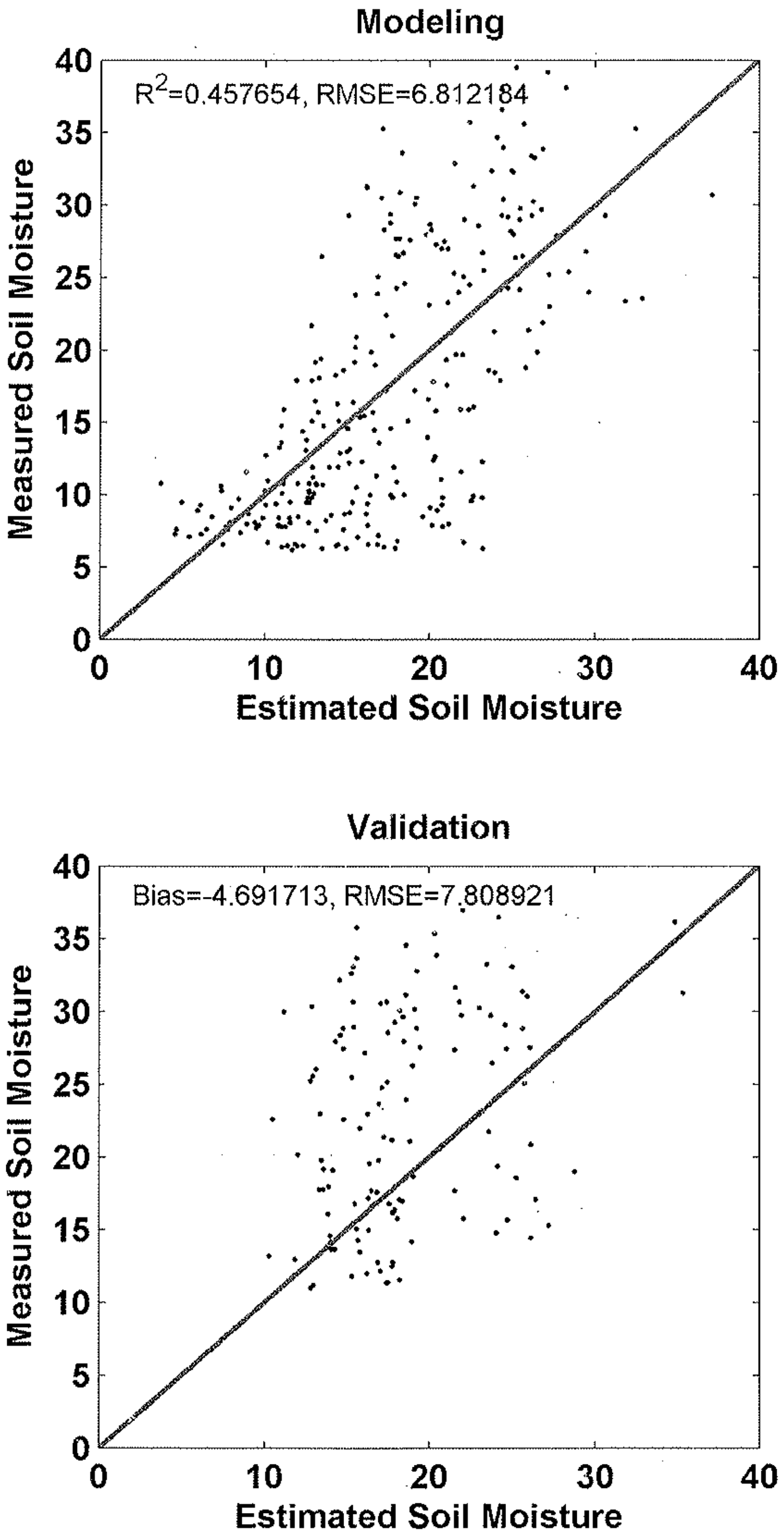

Figure 6: Modeling and validation results of SCAN site 2117.

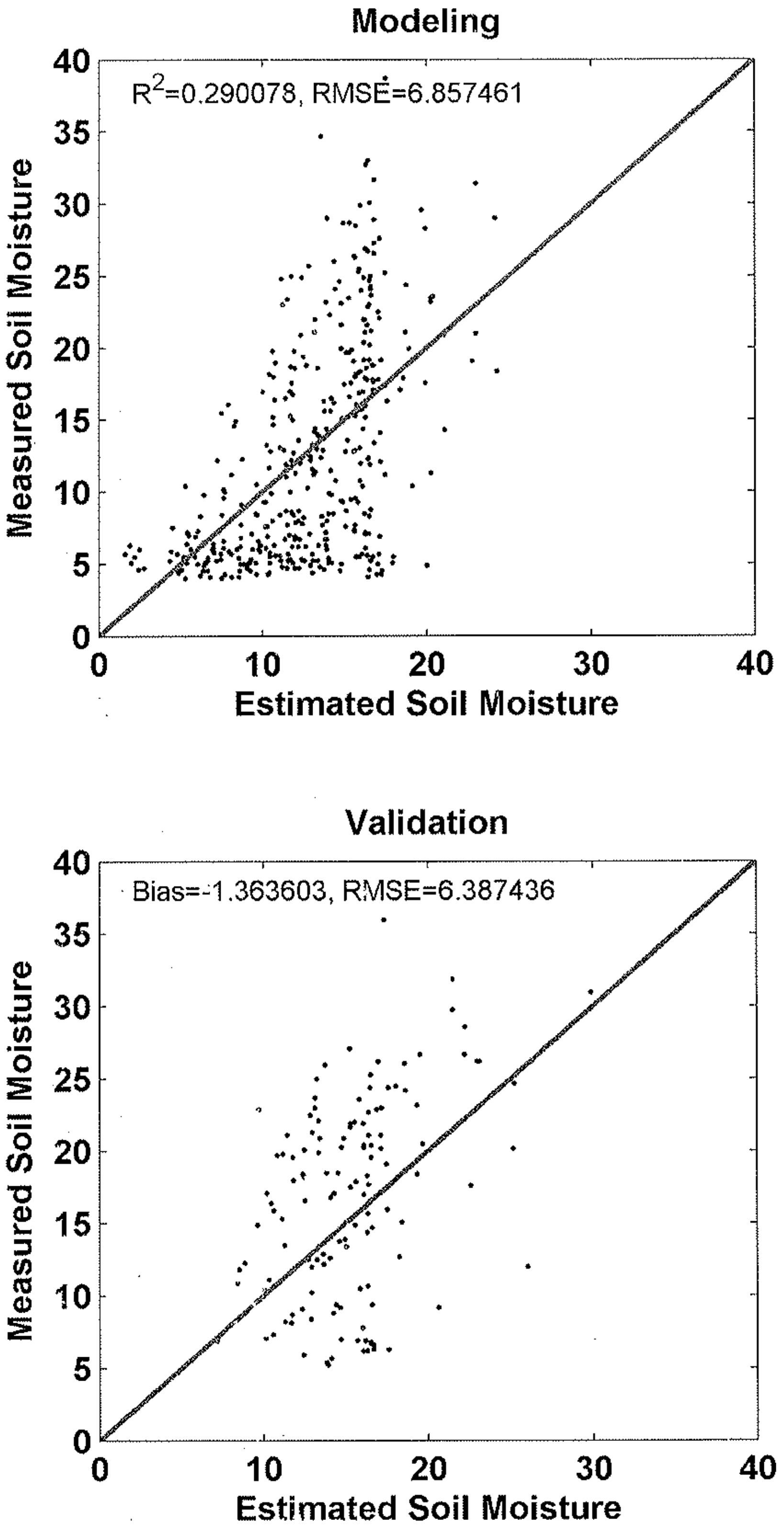

Figure 7: Modeling and validation results of SCAN site 2118.

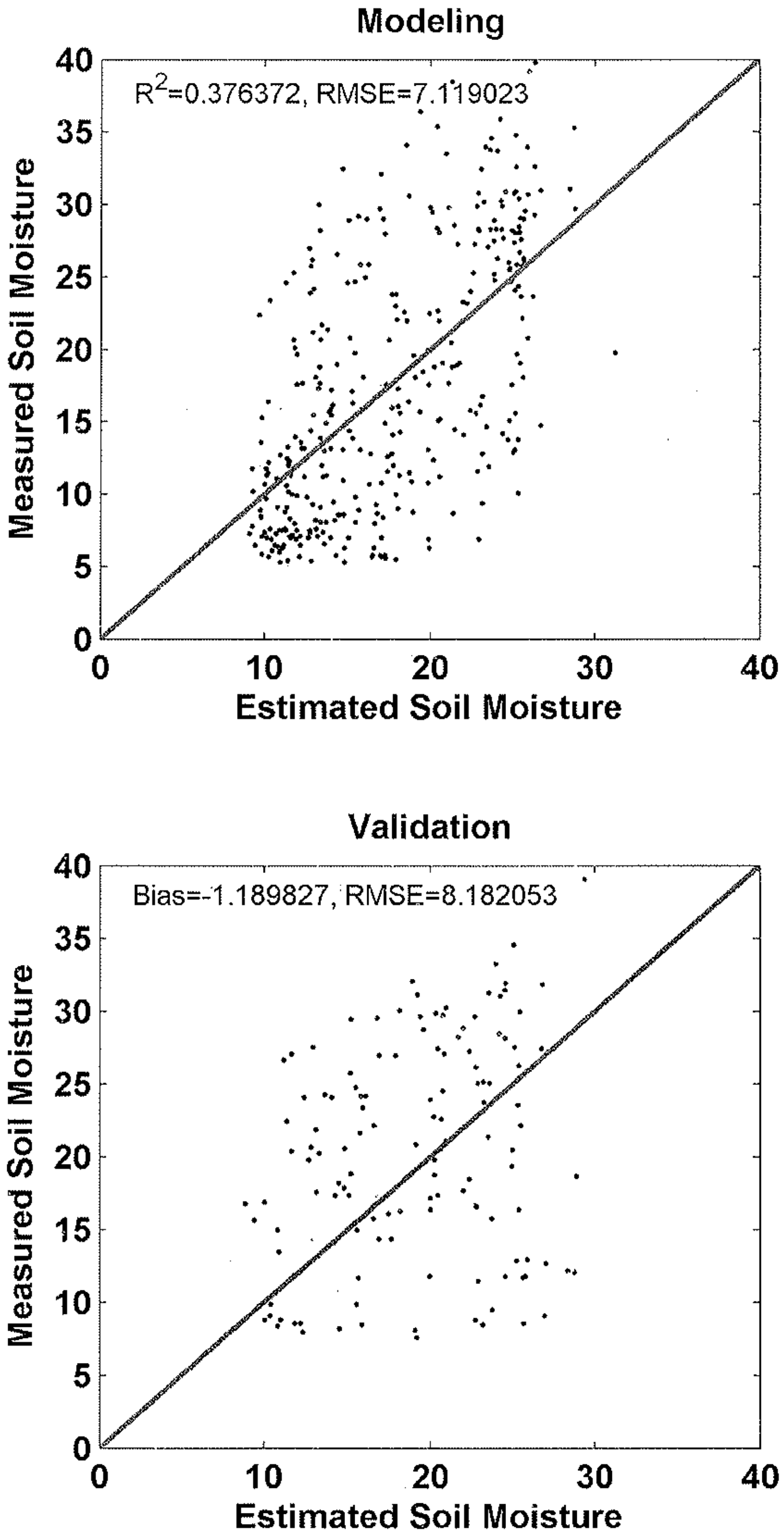

Figure 8: Modeling and validation results of SCAN site 2119.

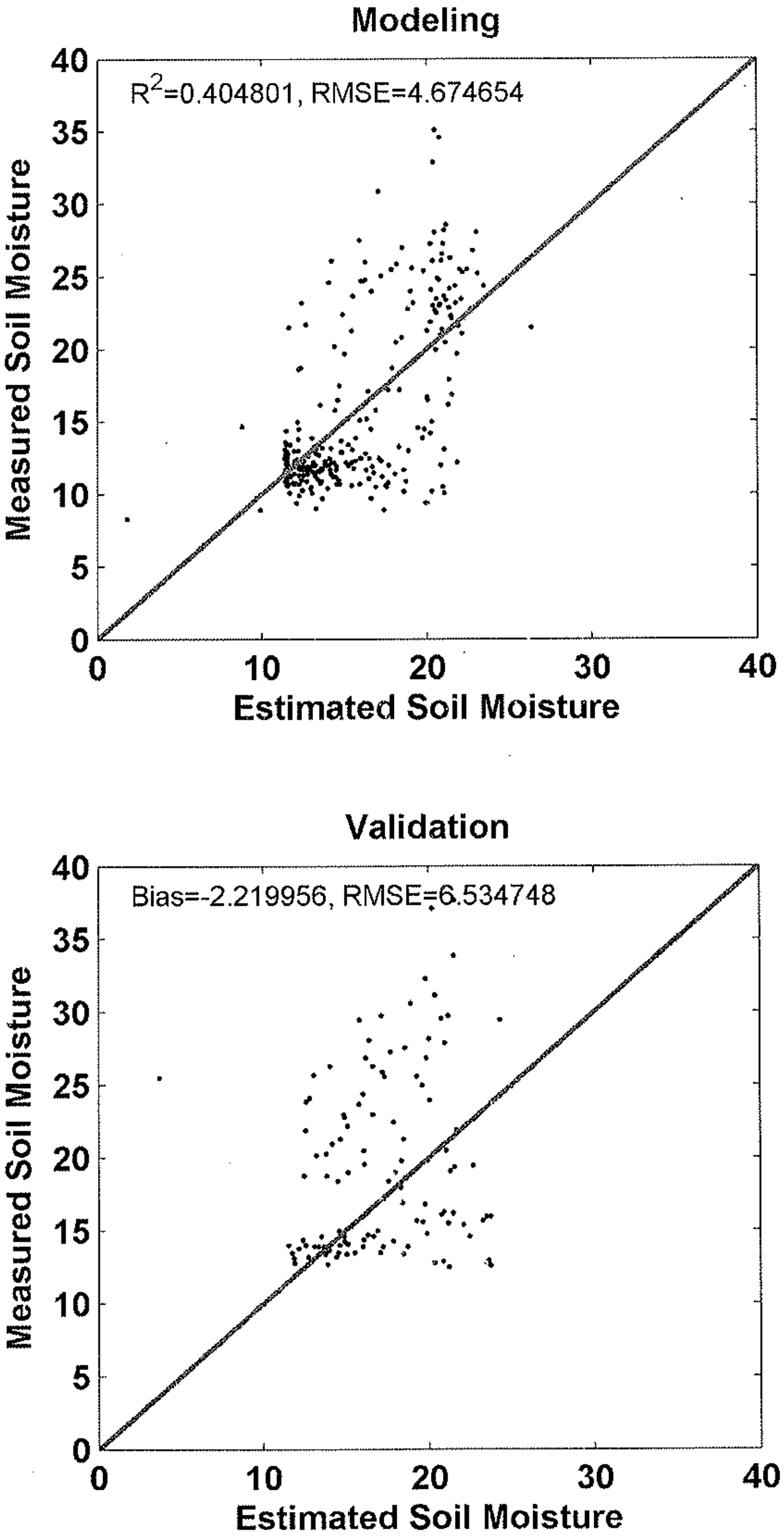

Figure 9: Modeling and validation results of SCAN site 2120.

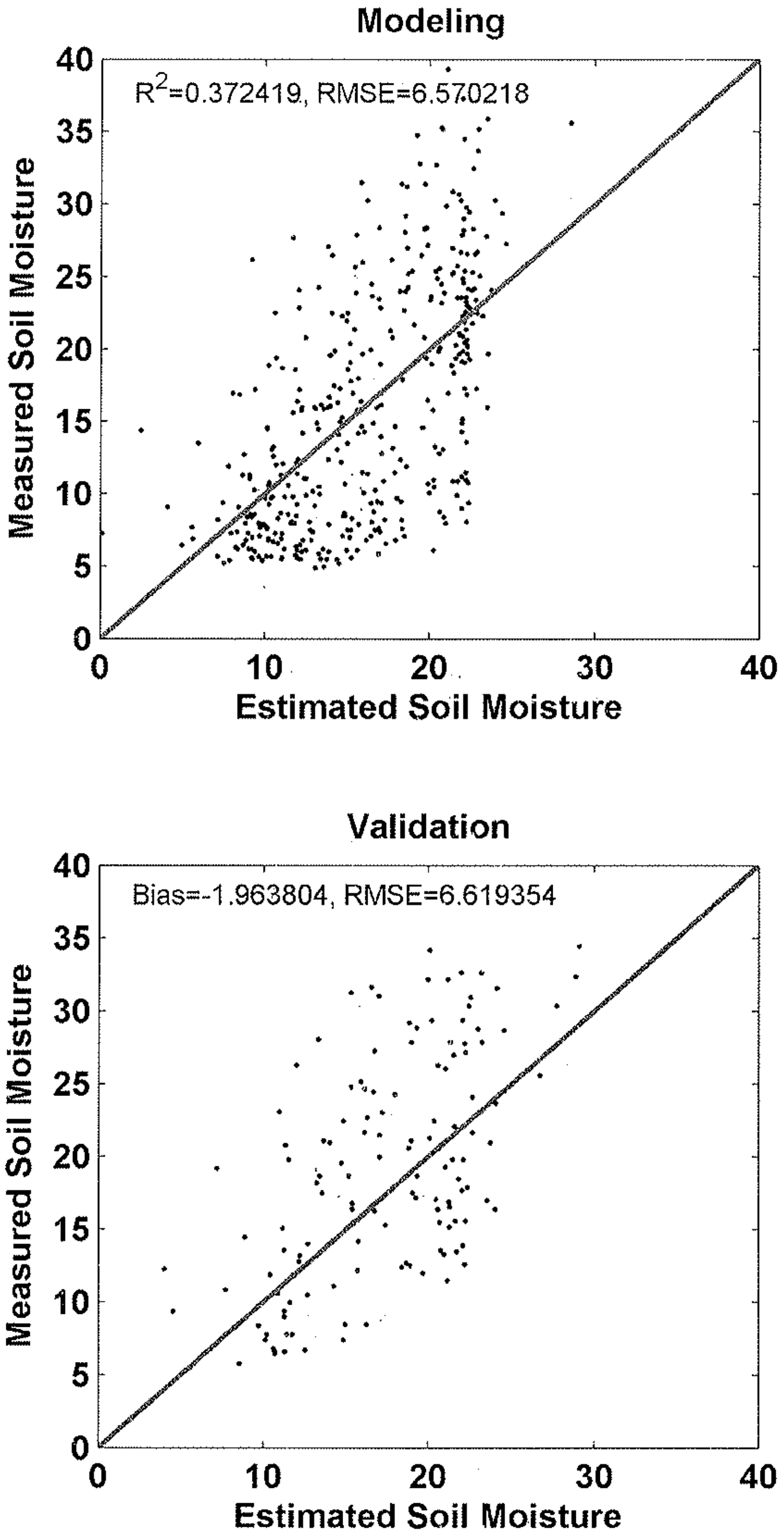

Figure 10: Modeling and validation results of SCAN site 2121.

Spectral indices using multiple MODIS RSB measurements

The spectral indices based on MODIS RSB measurements, including NDWI, NDII, NDMI, and NDVI, are very sensitive to vegetation. For pixels with vegetation cover, it is still a challenging problem to effectively separately signals from vegetation and soil. Although some indices, for example, NDMI, are sensitive to soil moisture, we couldn't find robust model to estimate soil moisture quantitatively with these indices. But, find some interesting patterns related to soil moisture.

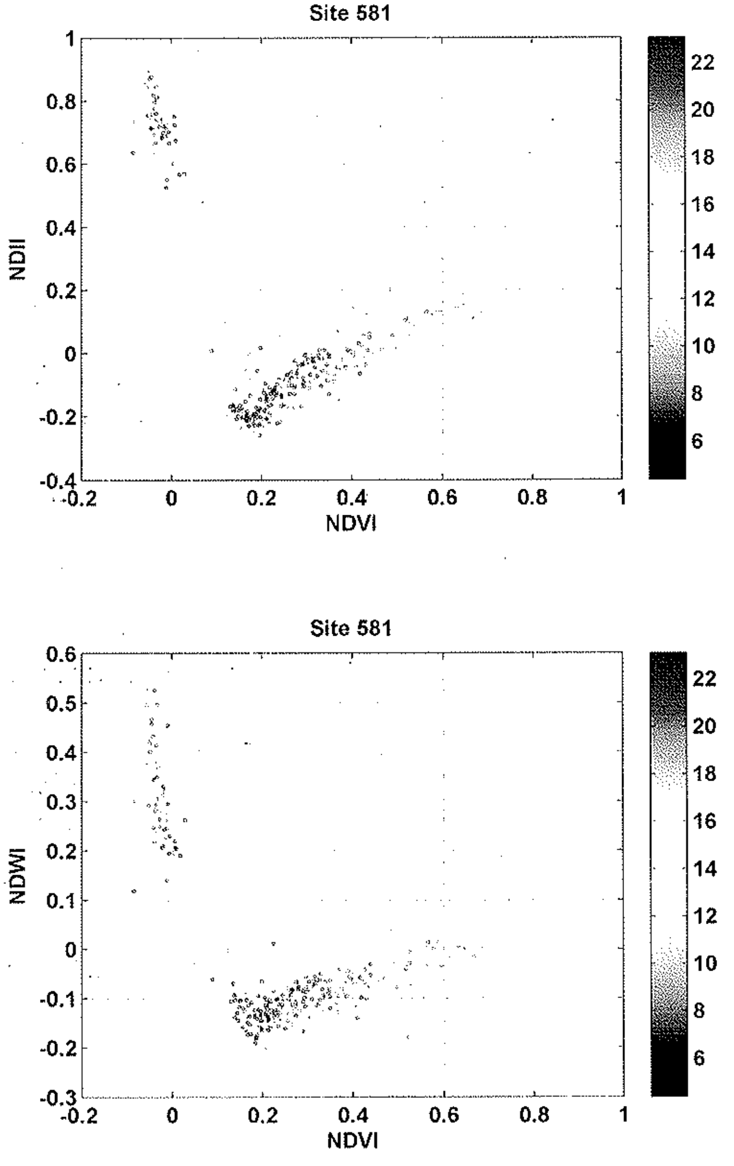

Figure 11: MODIS spectral indices and soil moisture (site 581)

Figure 11 illustrates the "V" shape relationship between NDVI and NDII, as well as NDVI and NDWI. Color of the points represents soil moisture (see color bar). From the figure 1, when NDVI is very low, soil moisture is usually low, and NDVI has a negative relationship with NDII or NDWI. When NDVI reaches certain value (around 0.2), there is a turning point, the relationship will be changed from negative to positive, but can't identify soil moisture in the NDVI-NDII space or NDVI-NDWI space. Results are similar for other SCAN sites, as shown in figure 12 for site 2019.

Based on our analysis, the "V" shape relationship and the turning point should be related to the fraction of vegetation cover. Identification of the turning point and "V" relationship should be helpful for further study towards quantitative estimation of soil moisture with MODIS SRB measurements.

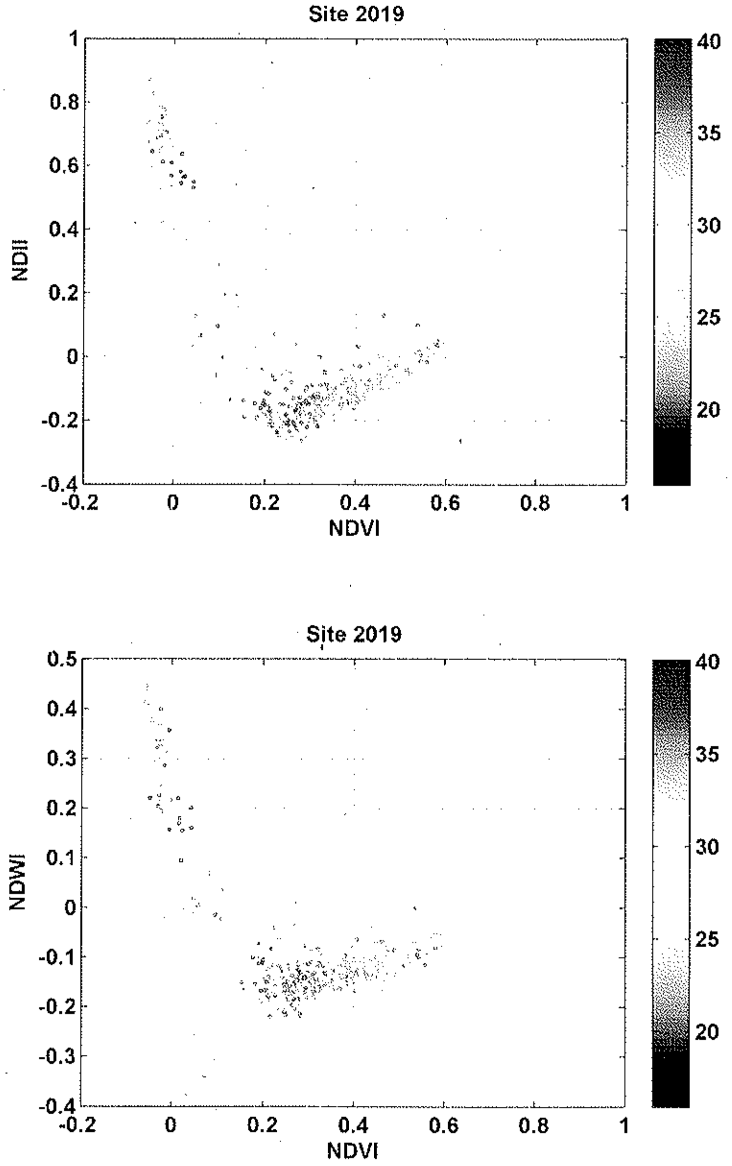

Figure 12: MODIS spectral indices and soil moisture (site 2019)

3. Benefits and Lessons Learned: Operational Partner Perspective

Operational soil moisture estimation with visible/infrared measurements from space is very important, but still quite challenging. Weather condition (cloud cover) may limit the availability of valid data, while lack of detailed information of fractional vegetation cover, and vegetation/soil response to water content change, may limit the accuracy of the universal triangle methods. Based on current study, it is feasible to get soil moisture at a reasonable accuracy at regional scale. Further improvements require investigation of vegetation and soil properties. For vegetation, there are very good models to link leaf and canopy properties with reflectance, but it is very complicated to link soil properties with surface reflectance because of the diversity of soil types. For operational use, it is necessary to conduct ground measurements of soil properties to create a database of soil reflectivity for various soil types with diverse moisture content.

4. Benefits and Lessons Learned: University Perspective

This project provides a good opportunity for researchers in university to investigate the feasibility to transfer research achievements for operational applications. While research achievements provide new insights for soil moisture study, it is challenging to transfer the results to operations at regional scale effectively. Learning the requirements of operations is very helpful for further improvements of research works.

5. Publications and Presentations

Wang, Lingli, 2008, Remote Sensing Techniques for Soil Moisture and Agricultural Drought Monitoring. George Mason University. Advisor: John J. Qu.

Lingli Wang, John J. Qu, and Xianjun Hao (2012). Advances in Remote Sensing of Soil and Vegetation Moisture from Space. Book chapter for *"Multi-Scale Hydrologic Remote Sensing: Prospects and Applications"* , edited by Ni-bin Chang, and Yang Hong. Taylor & Francis Group /CRC Press. Pages 507-536.

Lingli Wang and John Qu (2009). Multiband Drought Index Enhances Soil and Vegetation Moisture Monitoring, *SPIE Newsroom,* DOI: 10.1117/2.1200904.1623.

6. Summary of University/Operational Partner Interactions and Roles

The interaction between university and operation partner is critical in investigating research algorithms for operational use. Through interactions, both sides can understand the capabilities and limitations of research works more clearly.

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