SOIL MOISTURE ESTIMATION IN VEGETATED AREAS USING OPTICAL AND MICROWAVE REMOTE SENSING

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ABSTRACT

Soil moisture in the upper layer of the soil is an important variable in a wide range of applications. In recent years many different studies have employed remotely sensed data to quantitatively estimate soil moisture in areas with limited vegetative cover. In many areas of interest however, the soil is covered by vegetation canopy which highlights the need for a better method to accurately estimate soil water content beneath the vegetation canopy. During the plant growing season agricultural fields are covered with different heights and densities of vegetation canopy. Accurate information about the soil water content can be used for effective irrigation planning which will lead to optimized water consumption. In addition, information about oversaturation conditions will warn farmers to take a proper action to prevent root rot. Oversaturation of soil can also happen in man-made or natural structures where stability is important to the safety of people and their properties. Failure of the vegetation-covered levees is considered dangerous when it comes to control the flood; therefore their condition must be monitored continuously especially during flood season.

The Advanced Microwave Scanning Radiometer (AMSR-E) sensor onboard the Aqua satellite gathered global soil moisture data before the automatic shutdown in October 2011. Global soil moisture data were daily but had a coarse resolution of 25-km, which is not suitable for local-scale applications.

In this study, scatterplots of vegetation index (VI) and land surface temperature (LST) from MODIS are used to downscale AMSR-E data down to the moderate resolution of 1-km over an agricultural areas in Mississippi delta. Starting early in the growing season, soil moisture are estimated and continue as the crops begin to cover the soil. This data fusion technique has been completed using four sets of data collected from Jan 2010 to Feb 2011 to study the effectiveness of the results as plants start growing and reach to their highest stage of growing and then decay into the dead vegetation. In-situ soil moisture data measured at 15 stations of the National Resources Conservation Service (NRCS) in the delta are used to assess the accuracy of downscaled soil moisture information.

INTRODUCTION

The relationship between mean surface temperature and evaporation and their contribution to surface soil moisture was introduced by Price (1990) and combination of the thermal and reflective data to determine soil moisture was used by Moran et al. (1994), Carlson et al. (1994), Gillies et al. (1997) and Hossain and Easson (2006). The idea is that surface radiant temperature and vegetation cover has been demonstrated to be significantly dependent on the surface soil moisture content (Moran et al., 1994). As the range of surface radiant temperature decreases, the vegetation cover increases (Carlson, 2007). The scatterplots of vegetation cover versus surface temperature form a trapezoid or triangle shape (Hossain et. al, 2006) and these variables are used in so called “VI-LST triangle” model to back calculate soil moisture.

The microwave portion of the electromagnetic (EM) spectrum has the capability to quantitatively measure soil moisture under a variety of topography and vegetation (Notarnicola and Solorza, 2014). The AMSR-E sensor was a passive microwave radiometer operating at 6 frequencies ranging from 6.925 to 89.0GHz (JAXA, 2006). Prior to its shutdown in Oct 2011, AMSR-E provided daily soil moisture products at a spatial resolution of 25km. While these data were applicable for regional scale soil moisture investigations, local-scale applications, e.g. irrigation planning, crop monitoring and drought forecasting, higher resolution soil moisture maps are needed.

The retrieval of soil moisture in vegetated areas with microwave remote sensing is a challenging process because scattering from the vegetated area incorporates the volume scattering from the vegetation cover and surface scattering from the underlying soil (Prakash et al., 2012). Surface roughness including topographic perturbations and vegetation cover affect the signals that are received at the sensor. The effects of surface roughness distort the correlation between the signal and soil surface moisture and thevegetation canopy that covers the soil beneath makes the modeling more complicated.

OBJECTIVES

The main objective of this study is to estimate the volumetric soil moisture in an agricultural area at a 1 kilometer resolution. In order to quantify soil moisture, two different approaches are used to downscale soil moisture data to 1-km spatial resolution. First VI-LST triangle model is used to downscale the AMSR-E surface soil moisture data. Secondly, a nonlinear multivariate regression model is used to create 1-km soil moisture map from in-situ measured soil moisture at depth of 2 inches and the relationship of these data with land surface temperature and vegetation cover. Finally the accuracy of VI-LST triangle model over the vegetated area will be assessed by comparing results of two approaches.

DATASET USED AND STUDY AREA

Remote sensing data used in this study are AMSR-E soil moisture product and 8-day composites mod 09 and mod 11 products of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor which correspond with LST and VI respectively. The datasets were acquired in four time series Mar-22-2010, May-17-2010, June-10-2010 and Sep-06-2010. The in-situ measured soil moisture data are acquired from 13 stations of NRCS. These volumetric soil moisture data are measured at the depth of 2 inches below the surface.

Agricultural fields within the flood plains of the Mississippi river were selected as the study area for this project. Figure 1 illustrates the location of the study area in Mississippi delta along with the NRCS stations. The study area spans 256 km from west to east and 331km from south to north and expands over parts of Mississippi, Arkansas and Louisiana. There are several lakes and rivers in this region. Land cover is comprised mostly of agricultural fields within the delta and forest lands surrounding the delta.

Figure 1. The location of study area in Mississippi delta

METHODS

In this study the thematic map of volumetric soil moisture was created using VI-LST triangle model on the coarse-resolution AMSR-E products and then a multivariate regression model was used to model the in-situ measured soil moisture data to study the accuracy of AMSR-E in the vegetated area.

Triangle Model for Downscaling AMSR-E Soil Moisture Product

The triangle model relates surface soil moisture to land surface temperature and vegetation cover. Before using raw NDVI and LST values to determine their relationship with soil moisture, the NDVI and LST data must be normalized to extract warm and wet edge of the pixels (Carlson, 2007). For this purpose scatterplots of NDVI and LST are used to establish their contribution as individual physical parameters in surface soil moisture. The maximum and minimum temperature and NDVI values (T_{max} ,T_{min}, $NDVI_o$and $NDVI_s$) are acquired from the scatterplots to normalize the LST and NDVI values. Figures 2 to 5 illustrate the scatterplots of NDVI and LST for the four datasets.

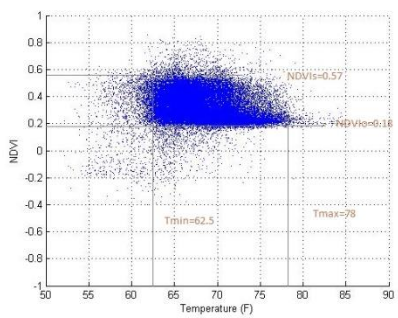

Figure 2. Scatterplot of NDVI and LST, Mar-22-2010

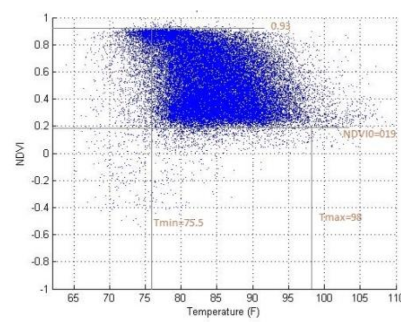

Figure 3. Scatterplot of NDVI and LST, May-17-2010

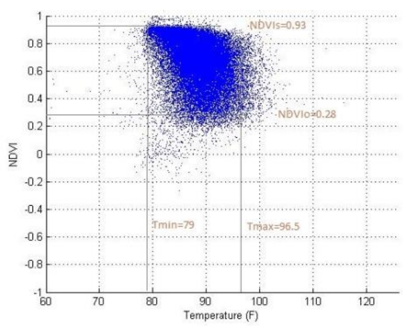

Figure 4. Scatterplot of NDVI and LST, June-10-2010

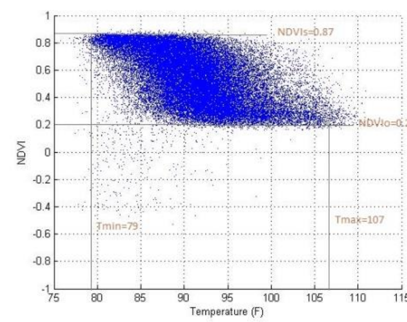

Figure 5. Scatterplot of NDVI and LST, Sep-06-2010

After estimating the max and min for LST and NDVI, the data are normalized using equations Eq. 1 and 2 to calculate fractional NDVI ($NDVI_{fr}$) and fractional LST (LST_{fr}).

$$NDVI_{fr} = \frac{NDVI - NDVI_o}{NDVI_s - NDVI_o} \quad \text{Eq. 1}$$

$$LST_{fr} = \frac{LST - LST_{min}}{LST_{max} - LST_{min}} \quad \text{Eq. 2}$$

Where $NDVI_o$ and $NDVI_s$stand for min and max NDVI values in the scatterplot and similarly LST_{max} and $LST_{min}$are minimum and maximum LST values.

The relationship for soil moisture (SM), NDVI and LST in triangle model is given by second order polynomial as Eq. 3 (Hossain, 2008).

$$\mathrm{SM}_{AMSRE} = \sum_{i=0}^{2} \sum_{j=0}^{2} a_{ij} {NDVI_{fr}}^{j} {LST_{fr}}^{i} \qquad \text{Eq. 3}$$

The expanded form of Eq. 3 is as follows.

$$\begin{aligned} \mathrm{SM}_{AMSRE} = \; & a_{00} + a_{10} NDVI_{fr} + a_{20} {NDVI_{fr}}^{2} + a_{01} LST_{fr} + a_{02} {LST_{fr}}^{2} \\ & + a_{11} NDVI_{fr} LST_{fr} + a_{22} {NDVI_{fr}}^{2} {LST_{fr}}^{2} \\ & + a_{12} NDVI_{fr} {LST_{fr}}^{2} + a_{12} {NDVI_{fr}}^{2} LST_{fr} \end{aligned} \qquad \text{Eq. 4}$$

This coefficients of a_{ij} are calculated using least square theory to fit the best model to SM, LST and NDVI values. The equation can be rewritten in matrix form of $L = A * \mathrm{X}$ as shown in Eq. 4.

$$\begin{bmatrix} SM_1 \\ SM_1 \\ \vdots \\ SM_n \end{bmatrix} = \begin{bmatrix} 1 & NDVI_{fr_1} & {NDVI_{fr_1}}^2 & LST_{fr_1} & {LST_{fr_1}}^2 & NDVI_{fr_1}.LST_{fr_1} & {NDVI_{fr_1}}^2.{LST_{fr_1}}^2 & NDVI_{fr_1}.{LST_{fr_1}}^2 & {NDVI_{fr_1}}^2.LST_{fr_1} \\ & \vdots & & & & \ddots & & \vdots & \\ 1 & NDVI_{fr_n} & {NDVI_{fr_n}}^2 & & & \cdots & & & \end{bmatrix} * \begin{bmatrix} a_{00} \\ a_{10} \\ \vdots \\ a_{22} \end{bmatrix} \qquad \text{Eq. 5}$$

In which he least square estimates for unknown matrix X is:

$$X = (A^T * \mathrm{A})^{-1} * A^T * \mathrm{L} \qquad \text{Eq. 6}$$

Eq. 5 is used to calculate coefficients of the triangle model and finally coefficients are applied in Eq. 3 to back-calculate soil moisture values for the 1-km SM and NDVI data to create a 1-km resolution soil moisture map.

Nonlinear Multivariate Regression of In-situ Measured Soil Moisture

The soil moisture values at the depth of 2 inches below the surface measured at NRCS stations were used in a multivariate regression analysis to fit a model to the normalized values of observed LST and NDVI data.

$$SM_{NRCS} = a_0 + a_1 NDVI_{fr} + a_2 LST_{fr} + a_3 {NDVI_{fr}}^2 + a_4 {LST_{fr}}^2 \ldots \qquad \text{Eq. 7}$$

In this study a polynomial regression of the second order was used to calculate the coefficients of the equation 6 and the equation was applied to LST and NDVI data to create a 1-km soil moisture map.

ANALYSES AND RESULTS

This investigation produced 1-km resolution soil moisture map of the four dates using both approaches. Figures 6 to 13 illustrate the soil moisture map created by different approaches. Generally, the in-situ measured soil moisture at the depth of 2 inches are greater than surface soil moisture values measured by AMSR-E sensor. This difference leads the results to have relatively significant scale difference. Both approaches show approximately the same high and low soil moisture values in the area for the April, June and September data. In the March dataset there is a good correlation between high and low estimated soil moisture in some areas, but in the Delta area in Mississippi there are some variations in the soil moisture values.

Triangle model

Multivariate Nonlinear Regression

March 22, 2010

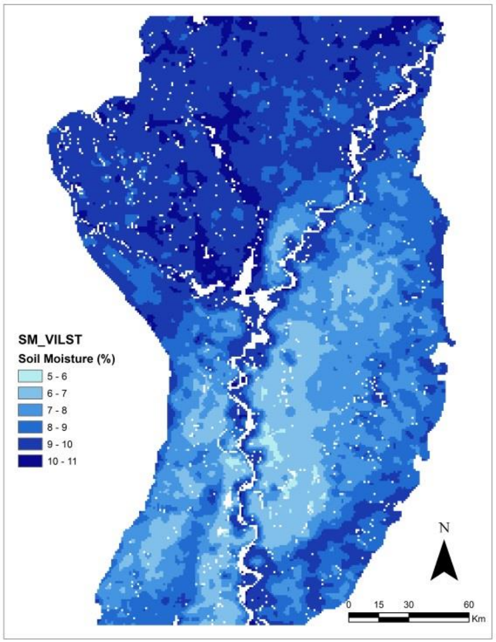

Figure 6. Soil moisture map created using triangle models, 03-22-2010

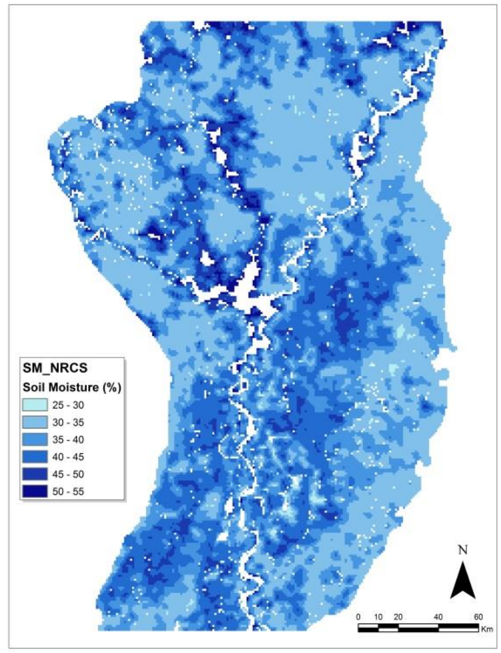

Figure 7. Soil moisture map created using in-situ data, 03-22-2010

May 17,2010

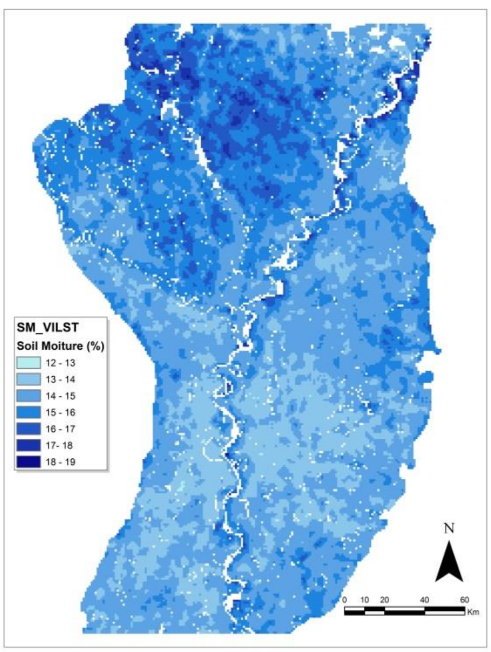

Figure 8. Soil moisture map created using triangle models, 05-17-2010

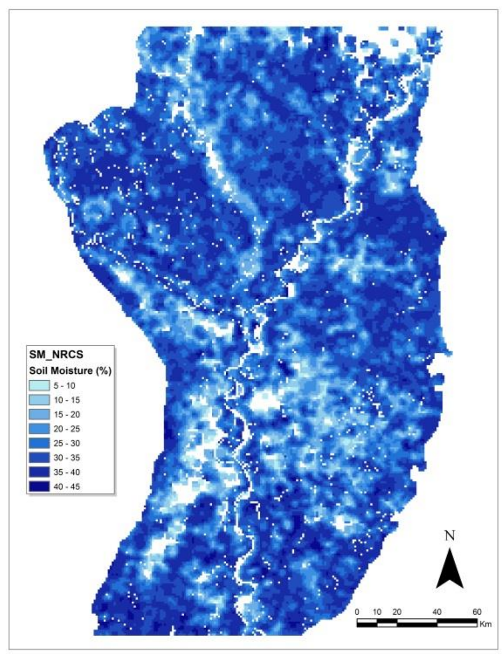

Figure 9. Soil moisture map created using in-situ data, 05-17-2010

June 10, 2010

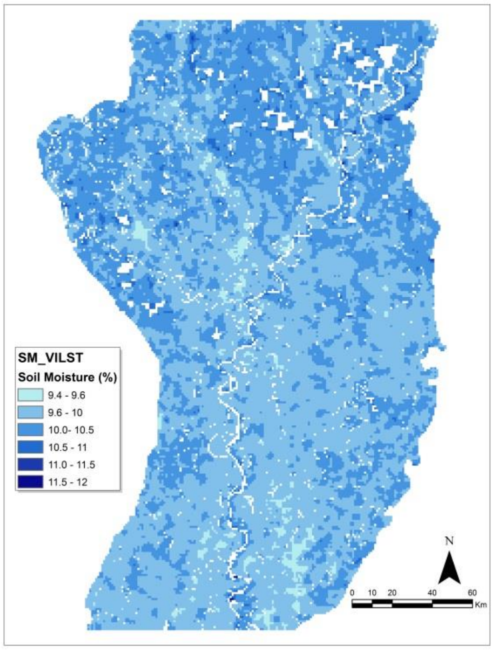

Figure 10. Soil moisture map created using triangle models, 06-10-2010

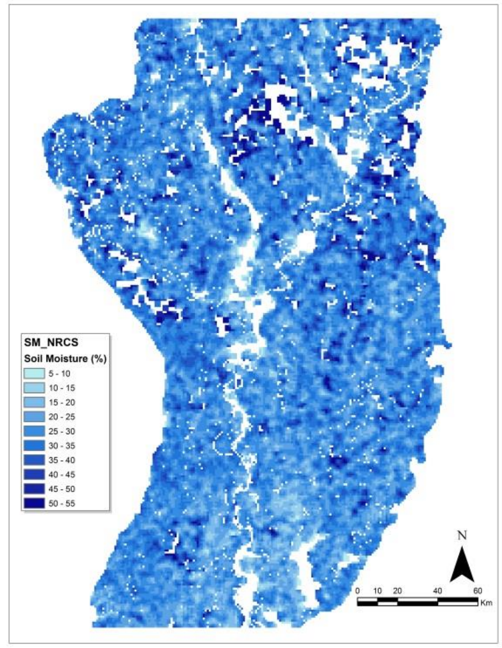

Figure 11. Soil moisture map created using in-situ data, 06-10-2010

September 06, 2010

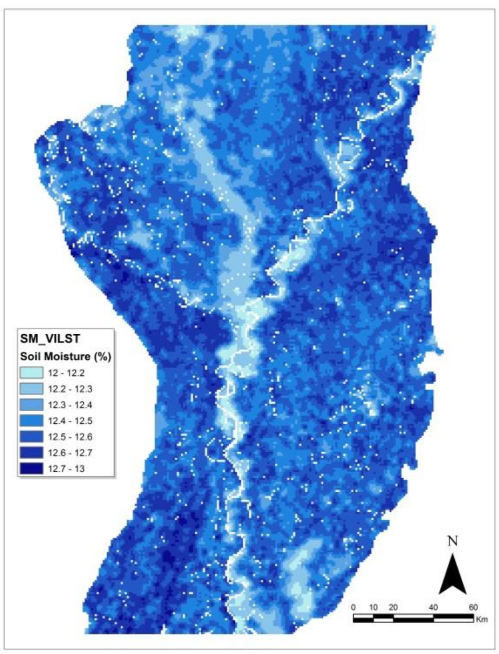

Figure 12. Soil moisture map created using triangle models, 09-06-2010

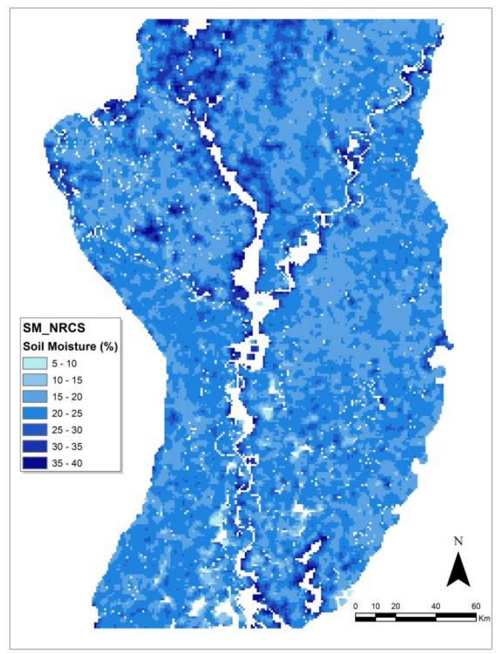

Figure 13. Soil moisture map created using in-situ data, 09-06-2010

In order to study the correlation between the two estimated soil moisture values a scatterplot of the values from AMSR-E and the NRCS soil moisture data was prepared to show the relationship. A limited set of points were randomly selected over the area to compare the soil moisture values. The Figures 14 shows the scatterplot of the in-situ measured soil moisture versus downscaled AMSR-E for one of the studied datasets. The scatterplot shows that the two types of the soil moisture data have a similar trend over the study area. Although the general pattern of the distribution of soil moisture map is similar in most of the area in different dates, the individual values are not well correlated.

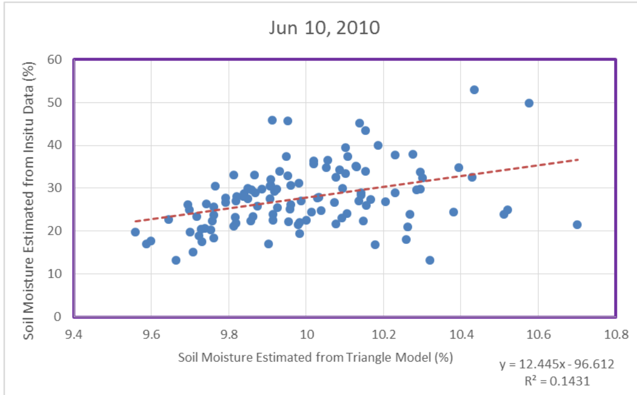

Figure 14. The correlation between in-situ measured soil moisture and downscaled AMSR-E data, Mar 22, 2010

CONCLUSION AND DISCUSSION

The general pattern existing in the soil moisture maps created by triangle model and multivariate regression model are similar for the majority of the study area, however, the soil moisture values do not agree. Soil moisture values estimated by the triangle model are generally less than those measured at the field. This may be explained by the fact that the in-situ soil moisture data are measured at the depth of 2 inches below the surface. The AMSR-E signal is affected by the vegetation cover and therefore penetration depth in soil varies depending on the amount of vegetation cover and penetration can range from 0 to a few inches in bare soil. Therefore the soil moisture values may be mapped at different depths. The vegetation cover plays an important role in the soil moisture values recorded by the AMSR-E by scattering the microwave data.

The soil in this area is generally organic and can hold water for a relatively longer period of time. In addition, the soils in the Delta region of Mississippi are generally heavier and more clay rich. This will likely impede the penetration of the microwave data into the soil. The result is that the AMSR-E data is likely detecting surface soil moisture and not the soil moisture at a depth of two inches.

FUTURE WORK

As part of an ongoing research there are important issues that still need to be addressed. After evaluating performance of triangle model over the vegetated area it may be necessary to develop a model that will include rainfall patterns that impact real time in-situ observations compared to 8-day remote sensing composites. Additionally, we will investigate synthetic aperture radar (SAR) data capabilities to map the soil moisture over the vegetated area in fine spatial resolution, using additional microwave satellite systems.

ACKNOWLEDGEMENTS

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