DOWNSCALING AND VALIDATION OF SMAP RADIOMETER SOIL MOISTURE IN CONUS

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ABSTRACT

The SMAP (Soil Moisture Active/Passive) satellite provides global soil moisture (SM) estimates that can be used for scientific research and applications (such as the hydrological cycle, agriculture, ecology, and land atmosphere interactions). Currently, SMAP provides the enhanced radiometer-only SM product (L2SMP) at 9 km grid resolution. However, this spatial resolution is still not enough to satisfy the needs of some studies that require a finer spatial resolution SM product, particularly in agricultural and watershed applications. This study applied a downscaling algorithm to the SMAP 9 km SM product to produce a 1 km resolution over the CONUS (Contiguous United States). The downscaling algorithm is based on the relationship between temperature change and SM modulated by Normalized Difference Vegetation Index (NDVI) of a given time period. This relationship was modeled using variables derived from NLDAS (North America Land Data Assimilation System) and NASA's LTDR (Land Long Term Data Record) between 1981 – 2018. The algorithm was implemented uses the 1 km MODIS Aqua LST (Land Surface Temperature) product. The downscaled SMAP 1 km SM was validated using *in situ* SM measurements from the ISMN (International Soil Moisture Network). The validation metrics show an improved overall accuracy of the downscaled SM.

***Index Terms*—** SMAP, NLDAS, soil moisture, downscaling.

1. INTRODUCTION

Over the last two decades, microwave remote sensing has been providing SM observations with higher spatial and temporal resolution from passive/active satellite sensors [1] - [4]. Soil moisture is a key factor in many applications in hydrology and agriculture. A series of satellites has carried active/passive microwave sensors that have supported this application. These have included AMSR-E (Advanced Microwave Scanning Radiometer for the Earth Observing System), AMSR2 (Advanced Microwave Scanning Radiometer 2), SMOS (Soil Moisture and Ocean Salinity), and SMAP satellite. There have been numerous studies dealing with the calibration, retrieval, and validation of the SM products [5] - [13] provided by these platforms. However, due to the limitation of antenna/aperture size of these passive microwave sensors, the spatial resolutions of the SM retrievals have been restricted to tens of kilometers, which does not support all potential uses of SM. Attempts have been made to extract higher spatial resolution information using disaggregation methods. In a recent paper [8], algorithms for downscaling SM products were classified by the input data type and modeling approaches as: (1) integration of multiple remote sensing data from different satellite platforms, (2) integration with other SM related geophysical variables, such as soil properties and topographic information, and (3) advanced numerical approaches. In this study, we implemented a methodology that falls into type 1 with SMAP observations. It integrates passive microwave SM with other variables (surface temperature and NDVI) derived from land surface model and visible/infrared sensors and uses the computed SM to downscale the original SMAP SM product over the CONUS area. The advantages of this methodology include the much higher spatial resolution as compared to microwave sensors, as well as the ability to readily provide SM estimates on a frequent temporal repeat at global scale.

2. METHODOLOGY

The SM downscaling model is based on the thermal inertia principle, which describes thermal resistance of an object to temperature change. The temperature of a dry object changes faster than a wet object [14-15]. Therefore, this principle can be applied to characterize the relationship between SM and temperature change during a period (SMAP morning/afternoon overpasses) by using a linear regression fit, as

$$\theta(i,j) = a_0 + a_1 \Delta T_s(i,j) \quad (1)$$

Where, θ and ΔT_s are the SM at the time of SMAP overpass and corresponding temperature change between morning and afternoon overpasses at i and j grid location, a_0 and a_1 are the best fit regression model coefficients. It is assumed that the $\theta - \Delta T_s$ relationship varies seasonally and each month is modeled separately. In addition, it is also assumed that the $\theta - \Delta T_s$ relationship is modulated by vegetation conditions. The relationship was modeled at the NLDAS grid scale from 1981 to 2018 for all the growing season months between April - September for fitting the $\theta - \Delta T_s$ correlations corresponding to different NDVI classes. The NDVI was resampled to NLDAS grid resolution in order to categorize the $\theta - \Delta T_s$ regression fitting lines with an interval of 0.1 from 0 - 0.8.

Since the SM downscaling algorithm is derived from model output variables and optical remote sensing observations, which are different from the microwave radiometer observations, the $\theta - \Delta T_s$ model 1 km SM θ output is required to be unbiased with respect to the SM estimated by microwave sensor. The 1 km SM values within each SMAP SM grid were corrected using the follow equation

$$\theta^c(i,j) = \theta(i,j) + [\Theta - \frac{1}{N}\sum_{i,j}\theta(i,j)] \quad (2)$$

Where, θ^c are the downscaled 1 km SM pixels included in one SMAP grid Θ while N is the number of θ. Previous studies with this approach are described in [16-18]. The equation (2) was applied on a 36 km domain of each 9 km SMAP SM point, which is the major improvement of the original algorithm and it can effectively solve sharp edges generated in the downscaled SM results. The downscaled SM results were validated by ISMN in situ measurements from four sites where have plenty of points within each 9 km SMAP grid.

3. RESULTS AND CONCLUSIONS

Figure 1 shows the NLDAS regression fitting lines for four selected sites; Walnut Gulch, Tonzi Ranch, Reynolds Creek and Stillwater of corresponding NLDAS grids in July. It can be summarized that the fitted lines are negatively correlated and that the lines corresponding to different NDVI classes are clearly separated. We also concluded that the sites with smaller NDVI (Walnut Gulch/Reynolds Creek) are generally better correlated. Additionally, for the lower vegetation sites, there is no clear decreasing trend of R^2 as the NDVI increases in 0-0.4 interval. However, the R^2 drops when NDVI > 0.4.

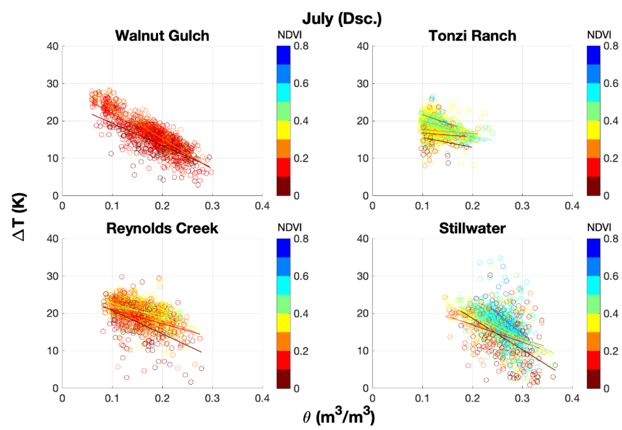

Figure 1. $\theta - \Delta T_s$ correlations of descending overpasses corresponding to NDVI classes between 0-0.8 in 4 study sites Walnut Gulch, Tonzi Ranch, Reynolds Creek and Stillwater in July. Colors represents different NDVI classes and the corresponding best fit lines.

The downscaling algorithm was implemented on the CONUS region, and the San Pedro watershed was mapped for comparing SM at 1 km / 9 km resolution. When comparing the downscaled 1 km and 9 km SMAP SM in June, 2018 (Figure 2), it can be summarized that the downscaled maps showed more SM spatial variabilities. Especially, wet areas along the San Pedro River channel in the central north of the watershed can be observed from 1 km SM. Such variabilities were not captured by the coarse resolution 9 km SM from SMAP.

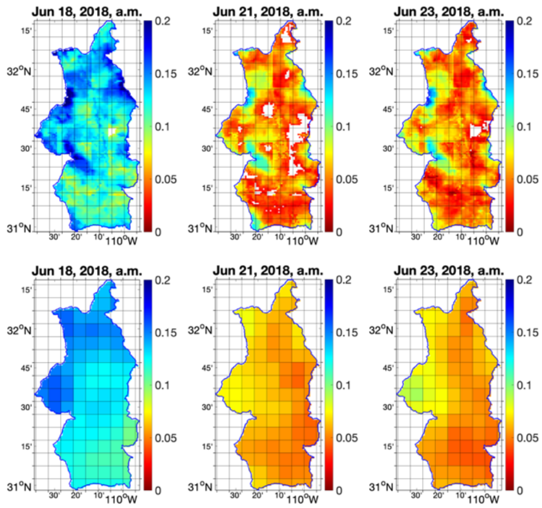

Figure 2. The downscaled 1 km SMAP θ compare with the original 9 km SMAP θ in San Pedro River watershed between June 18 - 23, 2018.

From the validation results using ISMN *in situ* data from 2018 [19] shown in Figure 3, it is observed that the 1 km SM validation data points are much more concentrated as compared to the scattered data points shown in 9 km SM validations. Additionally, both 1 km/9 km SM demonstrate underestimation trends.

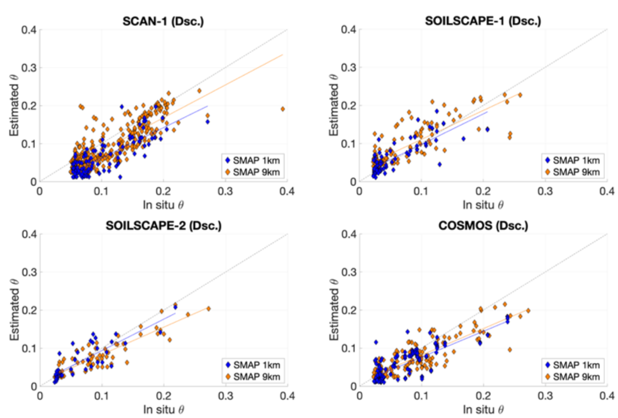

Figure 3. Scatter plots of 1 km/9 km SMAP θ validated using ISMN *in situ* measurements in 2018 from four grouped ground stations, including SCAN, SoilSCAPE and COSMOS validation result.

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