Downscaling of SMAP soil moisture using land surface temperature and vegetation data

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ABSTRACT

Remotely sensed soil moisture retrieved by the Soil Moisture Active and Passive (SMAP) sensor is currently provided at a 9 km grid resolution. Although valuable, some applications in weather, agriculture, ecology and watershed hydrology require soil moisture at a higher spatial resolution. In this study, a passive microwave soil moisture downscaling algorithm based on thermal inertia theory was improved for use with SMAP and applied to a data set collected at a field experiment. This algorithm utilizes a NDVI (Normalized Difference Vegetation Index) modulated relationship between daytime soil moisture and daily temperature change modeled using output variables from the Land Surface Model (LSM) of the NLDAS (North America Land Data Assimilation System), and remote sensing data from MODIS (Moderate-Resolution Imaging Spectroradiometer) and AVHRR (Advanced Very High Resolution Radiometer). The reference component of the algorithm was developed at the NLDAS grid size (12.5 km) to downscale the SMAP Level 3 radiometer-based 9 km soil moisture to 1 km. The downscaled results were validated using data acquired in SMAPVEX15 (Soil Moisture Active Passive Validation Experiment 2015) that included in situ soil moisture and PALS (Passive Active L-band System) airborne instrument observations. The resulting downscaled SMAP estimates better characterize soil moisture spatial and temporal variability and have better overall validation metrics than the original SMAP soil moisture estimates. Additionally, the overall accuracy of the downscaled SMAP soil moisture is comparable to the PALS high spatial resolution soil moisture retrievals. The method demonstrated in this manuscript downscales satellite soil moisture to produce a 1 km product, which is not site specific and could be applied to other regions of the world using the publicly available NLDAS/GLDAS (Global Land Data Assimilation System) data.
1.0 INTRODUCTION

Soil moisture is a key variable for studies that include land atmosphere interactions, hydrology, extreme weather prediction and water resource management. During recent decades, passive microwave satellite remote sensing has provided reliable soil moisture estimates over many regions of the world using space-borne sensors. These satellite observations began in the late 1970s with the Scanning Multichannel Microwave Radiometer (SMMR) - a C-band sensor (Guha and Lakshmi, 2004) and the Special Sensor Microwave Imager (SSM/I) at 19, 37 and 85 GHz (soil moisture was derived using 19 GHz) (Lakshmi et al., 1997a, b, c) and were followed by the Advanced Microwave Scanning Radiometer - EOS (AMSR-E) - a C-band sensor (Njoku et al., 2003) and the L band sensors - Soil Moisture and Ocean Salinity (SMOS) (Kerr et al., 2001) and Aquarius (Bindlish et al., 2015). The most recent observing system is the NASA 1.4 GHz Soil Moisture Active Passive Sensor (SMAP) launched in 2015, which provides soil moisture retrievals on a 9 km Earth grid with greater sensitivity to soil moisture as compared to the prior higher frequency sensors (Chan et al., 2018). Algorithms for soil moisture retrievals from the aforementioned passive microwave sensors are now well-established and validated (Schmugge et al., 1994; Narayan at al., 2004; Jackson et al., 2010, 2012; Kerr et al., 2016; Lakshmi et al., 2004, 2013; Bolten et al., 2003; Bindlish et al. 2015; and Chan et al., 2016, 2018).

Although reliable, these passive microwave radiometers have coarse resolutions (~25 – 40 km) (Njoku et al., 2003; Entekhabi et al., 2010; Jackson et al., 2012; Bindlish et al., 2015). Soil moisture at a spatial resolution of 10s of km derived from the space-borne sensors mentioned above cannot satisfy all of the science and application needs in the areas of ecology, agriculture, weather and watershed hydrology. There is a growing need for soil moisture observations at higher spatial resolutions (on the order of 1-10 km) and this has led to the development of a number of approaches.
that integrate coarse resolution microwave remote sensing data or retrievals with high-resolution
information. Peng et al. (2017) conducted an extensive review of different soil moisture
downscaling approaches and classified them into three groups –

(1) Satellite observations from various platforms (instruments).

(2) Physical relationships between soil moisture and other geophysical variables, such as
topography, soil and vegetation properties.

(3) Mathematical modeling approaches, such as statistical methods and data assimilation.

In this study, we focus on an approach that would fall into category 1, viz., – using soil moisture
retrievals from various satellite instruments. Category 1 is independent of modeling and is solely
based on observations, thereby providing an independent measure of soil moisture.

Within category 1, there is a group of downscaling methodologies that integrate passive
microwave soil moisture with remotely sensed land surface variables derived from visible/infrared
sensors. The general advantage of using visible/infrared sensors is a much higher spatial resolution
(order of 1-5 km) as compared to microwave sensors (order to 10s of km). In addition, the data are
readily available on a frequent global basis. Such approaches are based on the assumptions that
there are physical relationships between soil moisture and other land variables, which include land
surface temperature, vegetation, evapotranspiration (ET) and soil properties (Carlson et al., 2007;
Zhao et al., 2013).

The general approaches (for using the visible/infrared sensors) include the following
elements: The Disaggregation Based on Physical And Theoretical scale Change (DISPATCH)
method was developed based on the relationship between soil moisture and Soil Evaporation
Efficiency (SEE) to downscale SMOS soil moisture developed by Merlin et al. (2010), Merlin et
al. (2013) and Merlin et al. (2015). Merlin et al. (2008) used soil moisture indices, Evaporative
Fraction (EF) and Actual Evaporative Fraction (AEF). Fang et al. (2013), Fang and Lakshmi (2014b) compared different algorithms for computing SEE and applied them for downscaling AMSR-E soil moisture using NLDAS model data. Colliander et al. (2017) developed a model based on MODIS derived SEE for downscaling SMAP soil moisture. Another downscaling algorithm based on polynomial regression between MODIS NDVI, Land Surface Temperature (LST) and brightness temperature ($T_B$) has been applied to SMOS soil moisture (Song et al., 2014; Piles et al., 2009, 2011). Peng et al. (2016) developed a downscaling model based on a vegetation temperature index. Choi and Hur (2012) and Sánchez-Ruiz et al. (2014) used MODIS NDVI and LST to downscale AMSR-E and SMOS soil moisture. Kim et al. (2012) implemented an algorithm that uses a linear relationship between Soil Wetness Index (SWI) and soil moisture. Peng et al. (2015) developed an improved algorithm using a Vegetation Temperature Condition Index (VTCI) instead of the SWI. Other soil moisture downscaling approaches include: Narayan et al. (2006, 2008), Mascaro et al. (2010, 2011), Pablos et al. (2016), Montzka et al. (2016).

In the present work, we modified and applied an existing algorithm that exploits the vegetation – land surface temperature – soil moisture relationship (Fang et al., 2013; Fang and Lakshmi, 2014b, 2014c). This algorithm is attractive because (a) It employs a simple relationship that uses readily available satellite data and model outputs, (b) Does not require any parameters that need site or climate specific calibration, and (c) Has shown good results when applied to the C-band AMSR-E brightness temperatures over the state of Oklahoma as well as the smaller region Little Washita Watershed.

In this study, the soil moisture downscaling algorithm proposed by Fang et al. (2013) was applied to SMAP 9 km soil moisture retrievals obtained coincident to the time of the SMAPVEX15 campaign PALS airborne observations (Colliander et al., 2017). This study improved the
downscaling algorithm with modifications, as well as for the first time, implemented the algorithm over semi-arid region in Arizona.

The validation of downscaled soil moisture estimates can be challenging. The most robust evaluation requires high-density *in situ* soil moisture observations over the study area. In this investigation, we utilized a unique data set collected in SMAPVEX15. This data set includes concurrent high-resolution soil moisture obtained using an aircraft-based microwave radiometer Passive Active L-band System (PALS) that facilitated the direct comparison of the SMAP downscaled soil moisture.

2.0 STUDY AREA AND DATA

2.1 SMAPVEX15

The SMAPVEX15 field campaign was conducted in summer 2015 at the United States Department of Agriculture Agricultural Research Service’s (USDA-ARS) Walnut Gulch Experimental Watershed (WGEW) and nearby sites in Southeastern Arizona. The WGEW (center coordinates of 31.71°N, 110.68°W) covers approximately 150 km² within the Upper San Pedro River Basin. The major land cover of WGEW consists of brush and grass rangeland and has been the site of previous field experiments (Colliander et al., 2017) that have been conducted over this area. WGEW is located in a semi-arid climate zone where the majority of precipitation occurs during June – September as convective storms with highly variable spatial distributions. The entire SMAPVEX15 domain, WGEW and the other two study sites (Empire Ranch and Santa Rita) are shown in Figure 1.

A full description of SMAPVEX15 is provided in Colliander et al. (2017). Key data sets include the permanent *in situ* network, temporary stations added for the campaign, and aircraft
brightness temperature collected with the PALS. These data were used by Colliander et al. (2016) to produce soil moisture maps at a grid scale of 500 m. For the campaign, the aircraft-based measurements were performed concurrently with SMAP morning overpasses. Data were collected between August 2-18, 2015.

2.2 Data

2.2.1 NLDAS

The NLDAS contains land-surface model datasets which are temporally and spatially consistent and quality-controlled forcing data and model outputs. NLDAS provides land surface forcing data sets including surface fluxes, soil moisture and snow cover at 1/8° (12.5 km) resolution covering North America. Past studies have evaluated and discussed accuracy and uncertainties of NLDAS variables (Cosgrove et al., 2003; Mitchell et al., 2004; Robock et al., 2003; Schaake et al., 2004). The data was downloaded from http://ldas.gsfc.nasa.gov/nldas/. In this study, two NLDAS Phase-2 model variables: surface skin temperature and soil moisture at 0-10 cm soil layer at SMAP overpass times were extracted for building the downscaling model. These variables are computed from the National Oceanic and Atmospheric Administration Noah model, which is the land component of the National Centers for Environmental Prediction meso-scale Eta model (Chen et al., 1996; Koren et al., 1999; Ek et al., 2003; Mitchell et al., 2004; Xia et al., 2013).

2.2.2 MODIS/AVHRR

The MODIS sensors are onboard NASA satellites Terra and Aqua which were launched in 1999 and 2002, respectively, for monitoring and understanding global processes and dynamics of land, air and atmosphere, such as temperature, vegetation indices and land cover on a daily basis (Wan et al., 1997; Lakshmi et al., 2001). These sensors have a total of 36 visible/infrared bands
ranging from 0.4-14.4 µm at different spatial resolutions from 250 m - 1 km. In order to construct
the downscaling model, the 0.05° (5 km) spatial resolution Climate Modeling Grid daily NDVI
data was downloaded from NASA LTDR (Long Term Data Record) website
https://ltdr.nascom.nasa.gov/ and upscaled to match the NLDAS grid size 1/8° (12.5 km) by using
bilinear interpolation method. The LTDR Version 5 NDVI data consists of a collection from
AVHRR instruments on NOAA satellites N07–N19 (AVH13C1, 1981-present) (Tucker, 1979). In
addition, the 1 km daily Aqua and Terra MODIS LST (MYD11A1, MOD11A1) and 1 km
biweekly Aqua MODIS NDVI (MYD13A2) were downloaded from the online data pool Land
Processes Distributed Active Archive Center at https://lpdaac.usgs.gov/.

2.2.3 SMAP

The SMAP provides estimates of the moisture content of the 0 - 5 cm soil layer for
vegetation water content ≤ 5 kg/m². It is in a near polar and sun-synchronous orbit with a revisit
every 2-3 days. Both morning (6 a.m.) and afternoon (6 p.m.) products are available. The SMAP
soil moisture is derived from brightness temperature observations provided by an L-band
radiometer (1.41 GHz) and the native spatial resolution of the instrument is nominally 40 km
(Entekhabi et al., 2014). Data products are available beginning in March 31, 2015.

The standard SMAP soil moisture products are provided on a 36 km fixed Earth grid
(Chan et al., 2016) and the SMAP Enhanced soil moisture product is on a 9 km grid (Chan et al.,
2018). Enhanced Level-3 radiometer global daily 9 km soil moisture retrievals (Data set ID:
SPL3SMP_E) as well as 36 km retrievals (Data set ID: SPL3SMP) in EASE (Equal Area
Scalable Earth) - grid were acquired from National Snow and Ice Data Center website:
https://nsidc.org/data/SPL3SMP_E/versions/1. The Level-3 soil moisture retrievals are global
daily composites of the SMAP Level-2 data. In this study, the SMAP soil moisture retrievals of
morning overpasses were selected for implementing downscaling model, as they coincided with
the acquisition times of PALS airborne observations and field soil moisture sampled
measurements during SMAPVEX15.

In addition to the SMAPVEX15 study domain, in this study we also wanted to investigate
the downscaled soil moisture heterogeneity over a larger area. Therefore, the entire state of
Arizona was selected for downscaling and mapping. As an illustration of the spatial variability
that might be expected, Figure 2 shows the Level 3 10 km 3-day accumulated precipitation (mm)
derived from GPM (Global Precipitation Measurement) IMERG (Integrated Multi-satellitE
Retrievals for GPM) product acquired from https://pmm.nasa.gov/data-access/downloads/gpm,
between August 7 - 18, 2015 over Arizona and the SMAPVEX15 domain. Major rainfall
occurred in northwestern and southeastern Arizona followed by more scattered rainfall events.
The change of soil moisture heterogeneity at finer spatial scale after downscaling is expected to
be characterized in this study.

2.2.4 PALS

The PALS instrument provides L-band (1.413 GHz) radiometer T_B data at H (Horizontal)
and V (Vertical) polarizations and L-band (1.26GHz) radar backscatter coefficients at four
polarizations (Colliander et al., 2017). The PALS was to provide high spatial resolution T_B maps
that could be used to validate the original concept of SMAP that combined active passive sensing
for soil moisture retrieval. PALS data were acquired for 5 flight lines coincident with SMAP
morning overpasses on August 2 - 18, 2015. The PALS observations cover a domain of three
adjacent SMAP 36 km grids and the nominal spatial resolution is at 500 m. More details on these
products can be found in Colliander et al. (2017).
2.2.5 *In situ* observations

The ground observations consist of the existing network of precipitation gauges and soil moisture sensors, a temporary network of soil moisture stations, field sampled gravimetric soil moistures as well as other land surface parameter measurements such as vegetation and surface roughness. The *in situ* soil moisture measurements were recorded every 20 minutes at a depth of 5 cm using Stevens Water Hydra Probe from July to October 2015, while the field sampled soil moistures were collected using dielectric-based probes at three locations for each site from August 2 – 18. An overall root mean square error (RMSE) of 0.02 m$^3$/m$^3$ of the SMAPVEX15 ground measurements was achieved (Colliander et al., 2017; Cai et al., 2017). The *in situ* measurements were used to validate 1 km downscaled and 9 km SMAP soil moisture estimates in this study.

3.0 METHODOLOGY

3.1 Soil Moisture Downscaling Model

Thermal inertia theory as utilized here refers to the time-dependent response of an object to the variation of temperature. The volumetric heat capacity of soil increases when the soil layer becomes wetter, corresponding to a smaller diurnal temperature variation. During the soil moisture – temperature variation relationship modeling, it is assumed that the soil moisture at a particular time (e.g., morning) is inversely proportional to the daily temperature change. This soil moisture can be approximated by the temperature difference between the two overpasses of SMAP on the same day. In addition, the presence of vegetation in terms of NDVI will influence
the soil moisture-temperature relationship. Based on the studies by Carlson et al. (1995), Gillies et al. (1997) Wan et al. (1997) and Mallick et al. (2009), the remotely sensed variables NDVI-surface temperature ($T_s$) relationship has a triangular shape which changes into a polygonal when the vegetation is under water stress (Schmugge et al., 1974; Choudhury et al., 1979; Carlson et al., 1995; Gillies et al., 1997; Minacapilli et al., 2009; Hong et al., 2009; Merlin et al., 2010; Lakshmi et al., 2011). The triangular shape formed by three vertices, which corresponds to the vertex A of dry bare soil with low NDVI and high $T_s$, and the vertex B of moist bare soil with low NDVI and low $T_s$, as well as the vertex C of high NDVI and low $T_s$ on well-watered surface. The edge AB represents the dry edge corresponding to low ET, while the edge BC represents the wet edge of high ET.

Based upon previous studies, the soil moisture in the morning is negatively related to daily temperature difference (Fang and Lakshmi, 2014a). This fact was also used to estimate soil moisture by a triangle method (Schmugge et al., 1974; Carlson et al., 1995). For a single month, the relationship between soil moisture and temperature difference for a given NDVI range can be expressed by the following linear regression model

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

Where, for a NLDAS grid $(i, j)$, $\theta(i, j)$ is the NLDAS soil moisture in the morning at 6:00 a.m. and $\Delta T_s(i, j)$ is the NLDAS temperature difference between the two MODIS overpass times (1:30 a.m. / p.m.) of the same day. This relationship was built at the scale of the NLDAS grid using the NLDAS soil moisture and surface skin temperature variables from all August months between 1981 - 2016. The daily NDVI derived from AVHRR, MODIS data were combined,
upscaled and matched-up to the NLDAS grids by using a nearest neighbor method. The NDVI
were binned into 5 classes based on the range of NDVI values in Arizona, 4 classes with the
interval of 0.1 from 0 - 0.4, and 1 class from 0.4 - 1, which resulted in five regression fit lines in
the $\theta$ - $\Delta T_s$ scatterplots shown in Figure 3. The regression equations at the specific NLDAS
spatial resolution were applied on a daily basis to the 1 km MODIS grids within that NLDAS
grid. The 1 km soil moisture was then computed from the 1 km MODIS LST using the
regression equation corresponding to the proper NDVI class.

The SMAP soil moisture observations are retrieved from the microwave radiometer,
which is a different satellite platform from the optical imaging sensor MODIS. In order to solve
this issue, the 1 km soil moisture computed from the MODIS LST products should be corrected
by removing the difference between original SMAP soil moisture retrievals and MODIS LST
computed uncorrected soil moistures using the following equation

$$\theta(s, t) = \hat{\theta}(s, t) + [\theta - \frac{1}{N} \sum \hat{\theta}_N]$$  (2)

Where, $\theta(s, t)$ stands for a 1 km bias corrected SMAP soil moisture at the MODIS grid
$(s, t)$. $\theta$ is the 9 km SMAP soil moisture in the morning overpass. $\hat{\theta}_N$ are the $N$ of uncorrected 1
km SMAP soil moisture grids that fall in the 9 km SMAP grid $\theta$.

The downscaled soil moisture has the following characteristics: (a) the soil moisture at 1
km can be computed by the relationship between soil moisture and daily temperature variation,
(b) the bias between SMAP and MODIS derived soil moisture can be eliminated at the low
resolution, and (c) the $\theta$ - $\Delta T_s$ relationship varies in response to different vegetation conditions.

3.2 Data Processing
The Inverse Distance Weighting (IDW) method was applied for upscaling of LTDR and PALS data. It is a nonlinear interpolation technique using the weighted average of the values surrounding the predicted location. The IDW method assumes the influence of each measured point reduces as the distance increases, hence the weight becomes smaller. For any grid $Z^{lo}$ at low spatial resolution to be upcaled from high resolution grids $Z^{hi}$, it can be computed by using

$$Z^{lo} = \frac{\sum_{n} z_{hi}^{n}}{\sum_{n} d_{hi,lo}^{-1}}$$  \hspace{1cm} (3)

The $n$ of high spatial resolution neighbor grids $Z^{hi}$ were used to generate the new grid at low spatial resolution $Z^{lo}$. $n$ is determined by the number of $Z^{hi}$ grids that fall in the $Z^{lo}$. $d_{hi,lo}$ is the distance between the centroids of $Z^{hi}$ and $Z^{lo}$.

In a few occasions, the 1 km grid may overlap with more than one 12.5 km grid (2~4 adjacent grids at most) so multiple modeled $\theta - \Delta T_s$ relationship equations from the overlapped 12.5 km grids should be applied on the 1 km MODIS LST for calculating soil moisture. We applied an averaging method based on the proportion of each overlapped NLDAS grid to solve this issue.

$$\bar{\theta}' = \frac{1}{n} \sum_{n} P \times \bar{\theta}_n'$$  \hspace{1cm} (4)

Where, $\bar{\theta}'$ is the adjusted uncorrected 1 km soil moisture, $n$ is the number of 12.5 km grids overlapped the 1 km grid. $P$ is the proportion in percentage of each 12.5 km grid overlapped the 1 km grid, and $\bar{\theta}_n'$ is the soil moisture value calculated by each 12.5 km grid corresponded $\theta - \Delta T_s$ relationship equation.

### 3.3 Validation
The original and downscaled SMAP soil moisture data were evaluated using in situ soil moisture observations acquired from SMAPVEX15 campaign, which are point estimates at the permanent and temporary network stations, as well as the upscaled PALS soil moisture retrievals at 1 km and 9 km resolutions. The in situ soil moisture measurements that fall in each 1 km/9 km soil moisture grid were averaged for comparison. The statistical variables include $R^2$, slope, unbiased RMSE, bias and p-value from significance test of Pearson correlation coefficient. In order to compare the three estimated soil moisture products: 1 km / 9 km SMAP soil moisture and PALS soil moisture through the sampling days in SMAPVEX15, results were analyzed using the histogram plots showing distribution form, Empirical Cumulative Distribution Function (ECDF) plots as well as time series plots showing mean and standard deviation.

### 4.0 RESULTS AND DISCUSSION

#### 4.1 $\theta$ - $\Delta T_s$ relationship

NLDAS data from 1981-2016 were used to estimate the model function between $\theta$ and $\Delta T_s$ which is modulated by NDVI. Three NLDAS grids were selected to demonstrate the relationships for the three SMAPVEX15 study sites: Walnut Gulch, Empire Ranch and Santa Rita. From Table 1, the $\theta$ - $\Delta T_s$ regression fit lines are negatively correlated for all three sites. Walnut Gulch has better $R^2$ (0.5 - 0.809) than the other two sites. The $R^2$ do not vary much as NDVI increases. From the Figure 3, the ranges of slope for the three sites are -106.127 to -66.565, -66.239 to -47.302, -79.861 to -66.478, respectively. The ranges of slope for Walnut Gulch and Santa Rita are smaller than for Empire Ranch. The NDVI-based classes differentiate the data pairs and the five regression fit lines line up well from top to bottom which correspond to the NDVI classes from the highest to the lowest. From the scatterplot, given any $\Delta T_s$ value, the soil moisture corresponding to the
highest NDVI class (>0.4) are approximately 0.1 m$^3$/m$^3$ wetter than the lowest class (NDVI<0.1).

The results show that the NDVI - $T_s$ triangle principle is applicable in this study domain and can be used to downscale the SMAP soil moisture estimates. With regard to the significance of the correlations between $\theta$ and $\Delta T_s$, the results show that the p-values of the correlations of all NDVI classes from all three sites are much smaller than a significance level of 0.01.

4.2 1 km downscaled soil moisture

Figure 4 shows the soil moisture maps for the 1 km downscaled, the SMAP 9 km and the SMAP 36 km products $\theta_{1km}^{SMAP}$, $\theta_{9km}^{SMAP}$ and $\theta_{36km}^{SMAP}$, as well as difference between $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ respectively for the five sampling days (8th, 10th, 13th, 16th, 18th of August, 2015). It can be seen that the soil moisture distribution pattern was consistent between the downscaled $\theta_{1km}^{SMAP}$ and the original product $\theta_{9km}^{SMAP}$, while the $\theta_{1km}^{SMAP}$ displayed greater spatial variability. However, if we compare the difference between $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ through all five days, we find that the distribution patterns of the two products exhibited discrepancies, especially in central and southeast Arizona where the soil moisture pattern was more complex. In these regions, $\theta_{36km}^{SMAP}$ did not show any wetting or dry-down zones, which were found in the two finer resolution estimates.

The $\theta_{1km}^{SMAP}$ images demonstrated greater spatial heterogeneity of soil moisture over the SMAPVEX15 domain. The 500 m resolution PALS L-band radiometer soil moisture was retrieved using a version of the SMAP baseline algorithm (Single Channel Algorithm-Vertical Polarization) (Jackson et al., 1993, 2010) and upscaled to 1 km in order to compare directly with the 1km downscaled SMAP soil moisture. Figure 5 shows that the $\theta_{1km}^{SMAP}$ compares well with the upscaled 1 km PALS soil moisture $\theta_{1km}^{PALS}$ and SMAP 9 km soil moisture $\theta_{9km}^{SMAP}$ for the five sampling days. The black grids over each map outline the 9 km grid boundaries for easier visualization of the downscaled soil moisture heterogeneity within the coarser resolution grid. It can be summarized
that within each 9 km grid, the $\theta_{1km}^{SMAP}$ displayed soil moisture features in more detail than the
original $\theta_{9km}^{SMAP}$, as well as similar spatial distribution pattern with $\theta_{1km}^{PALS}$. For instance, the spatial
heterogeneity was more visible near the boundaries between the San Pedro River basin and Santa
Cruz River Basin and Whitewater Draw Basin. However, the overall range of soil moisture values
for the $\theta_{1km}^{SMAP}$ was generally lower than that of the $\theta_{1km}^{PALS}$. When compared for each day, the
discrepancies between the $\theta_{1km}^{SMAP}$ and $\theta_{1km}^{PALS}$ could be noted in Figure 5. Looking at the $\theta_{1km}^{PALS}$
product, two dry zones in middle west and east were apparent on August 8, as well as a wet zone
with a belt shape on August 16 which were not observed in $\theta_{1km}^{SMAP}$ maps. Some small and isolated
spots showed stronger drying or wetting trends than surrounding areas in $\theta_{1km}^{PALS}$, which were not
present in $\theta_{1km}^{SMAP}$. Additionally, the $\theta_{1km}^{PALS}$ showed greater contrast between the highest and lowest
soil moisture values than $\theta_{1km}^{SMAP}$. As opposed to this, the $\theta_{1km}^{SMAP}$ and $\theta_{1km}^{PALS}$ showed better
consistency on the other two days August 10 and 18.

The comparisons between uncorrected 1 km soil moisture $\theta_{1km}^{SMAP}$ calculated from
downscaling model and $\theta_{9km}^{SMAP}$ are shown in Figure 6. Better correlations were found in August
16 and 18, with unbiased RMSE ($\mu bRMSE$) = 0.026 and 0.019, bias = 0.03 and 0.025, respectively.
More scattered characteristic was noted especially on August 8, which had $\mu bRMSE$ of 0.043 and
bias of 0.048. Such inconsistency between $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ might have influences on the
downscaled soil moisture.

Figure 7 shows the frequency distribution histogram of the three soil moisture products. It
can be summarized that the $\theta_{1km}^{PALS}$ had more similar shape and data ranges as $\theta_{1km}^{SMAP}$ than $\theta_{9km}^{SMAP}$,
which had skewed or bimodal shapes on August 10, 13 and 16 and narrower ranges of the $\theta_{9km}^{SMAP}$
for corresponding days. Additionally, more similar data ranges and shapes of soil moisture values
between $\theta_{1km}^{SMAP}$ and $\theta_{1km}^{PALS}$ were observed in August 13 and 18, while $\theta_{1km}^{SMAP}$ had narrower ranges than $\theta_{1km}^{PALS}$ for the other three days.

The ECDF curves for the three soil moisture products $\theta_{1km}^{SMAP}$, $\theta_{1km}^{PALS}$ and $\theta_{9km}^{SMAP}$ for the five SMAPVEX15 sampling days of descending overpasses are displayed in Figure 8. It was found that the ECDF curves of $\theta_{1km}^{SMAP}$ had better agreement with $\theta_{1km}^{PALS}$ than $\theta_{9km}^{SMAP}$, which might indicate the improved accuracy of $\theta_{1km}^{SMAP}$. However, the inconsistency between PALS and SMAP was noted from three days: August 8, 10 and 16, of which $\theta_{1km}^{SMAP}$ had limited improvement of $\theta_{9km}^{SMAP}$.

The overall mean and standard deviation values of the three soil moisture products as well as the in situ measurements are shown as a time series in Figure 9. From the top graph, it can be observed that the mean values of in situ were always drier than the other three data sets, whereas the mean values of the $\theta_{1km}^{SMAP}$ were closer to either $\theta_{1km}^{PALS}$ or in situ than the $\theta_{9km}^{SMAP}$. In addition, August 13, 16, and 18 were found to have better agreement among the four data sets than August 8 and 10. Examining the bottom graph, the standard deviations of the $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ were approximately 0.02 m$^3$/m$^3$ lower than either the $\theta_{1km}^{PALS}$ or in situ. The $\theta_{1km}^{PALS}$ was more consistent with $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ on August 13 and 18, while it was more consistent with in situ observations for the other three days.

4.3 Validation

Table 2 and Figure 10 shows the results of the $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ validated using $\theta_{1km}^{PALS}$. The following observations can be made based on the validation results in Table 1: (1) the $R^2$ of the $\theta_{1km}^{SMAP}$ are higher and they range 0.189 – 0.697 for the $\theta_{1km}^{SMAP}$ and ranges 0.003 - 0.597 for the $\theta_{9km}^{SMAP}$, (2) the slopes for the $\theta_{1km}^{SMAP}$ are slightly higher for August 8, 10 and 18. They range 0.518 - 1.552 for the $\theta_{1km}^{SMAP}$ and range 0.07 - 1.915 for the $\theta_{9km}^{SMAP}$, (3) the $\mu$RMSEs and the biases are
improved on four days for the $\theta_{1km}^{SMAP}$ over the $\theta_{9km}^{SMAP}$, ranging 0.009 - 0.02 m$^3$/m$^3$ and -0.002 - 0.01 m$^3$/m$^3$, respectively. The range of $\mu_b$RMSEs for the $\theta_{1km}^{SMAP}$ meets the criteria that RMSE < 0.04 m$^3$/m$^3$ for validated SMAP soil moisture estimates. Additionally, the p-values of the Pearson’s correlation coefficient for the $\theta_{1km}^{SMAP}$ are all much smaller than the significance level $\alpha = 0.05$, indicating significant correlations between $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$. Examining the scatterplots in Figure 10, it appears that the locations of the highest density data points in the 1 km plots correspond to the locations of points in 9 km plots. From this figure, it is also seen that there is a relatively better consistency between $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{PALS}$. However, it should be noted that there is an obvious underestimation trend for either $\theta_{1km}^{SMAP}$ or $\theta_{9km}^{SMAP}$ when comparing to the $\theta_{1km}^{PALS}$. In addition, it is observed that the PALS soil moisture values cover a wider range (approximately 0.05 - 0.25 m$^3$/m$^3$) than either the $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ (approximately 0.1 - 0.2 m$^3$/m$^3$), which probably indicates greater soil moisture spatial variability. This fact corresponds to what is observed in Figure 5, 7 and 9.

Table 3 and Figure 11 illustrates the validation results for $\theta_{1km}^{SMAP}$ and $\theta_{9km}^{SMAP}$ using the in situ measurements. In this validation, only the 9 km $\theta$ grids having more than 8 in situ points within their boundaries were considered. For the $\theta_{1km}^{SMAP}$, the $R^2$ range 0.255 - 0.733 and $\mu_b$RMSEs range 0.006 - 0.044 m$^3$/m$^3$, comparing with the $R^2$ range of < 0.001 - 0.353 and $\mu_b$RMSEs range of 0.03 - 0.088 m$^3$/m$^3$ for validation results of $\theta_{9km}^{SMAP}$. It can be concluded that the validation metrics of the $\theta_{1km}^{SMAP}$ show an obvious improvement over $\theta_{9km}^{SMAP}$ and the RMSE range of $\theta_{1km}^{SMAP}$ meets the criteria < 0.04 m$^3$/m$^3$ for SMAP soil moisture. The improvement may also be observed in the slope values as well as the plots shown in Figure 11, where the scatter points for $\theta_{1km}^{SMAP}$ are closer to the 1-1 diagonal line. The p-values for the Pearson’s correlation coefficient for $\theta_{1km}^{SMAP}$ are significant at the $\alpha = 0.05$ significance level. Additionally, the bias range of -0.029 - < 0.001 m$^3$/m$^3$ for $\theta_{1km}^{SMAP}$ also indicates the underestimation tendency as compared to the in situ data.
The downscaling algorithm had varying performance on different days. One explanation could be that the precipitation during SMAPVEX15 may have an impact on the performance of the downscaling algorithm. As Figure 2 shows, it rained more between August 7 and 12 than after August 13, which corresponded to the relatively higher $\mu bRMSE$ for August 8, 10 and 13 and validation results using \textit{in situ} data in Figure 11. Additionally, the downscaled $\theta^{SMAP}_{1km}$ might not be sensitive to the wetting trends in the central and southern regions (August 8 and 10 in Figure 5). Similarly, another inconsistency was noted in the regions showing very dry condition in the eastern part of SMAPVEX15 for $\theta^{PALS}_{1km}$ in August 8, 10 and 16. However, these features were not fully captured in these regions for $\theta^{SMAP}_{1km}$. In addition, the spatial heterogeneity between $\theta^{SMAP}_{1km}$ and $\theta^{PALS}_{1km}$ observed for the day with less amount of rain (August 18) had better agreement than the other days. Secondly, the bias of $\theta^{SMAP}_{9km}$ might also influence the downscaling model performance, as the downscaled $\theta^{SMAP}_{1km}$ was corrected by $\theta^{SMAP}_{9km}$. So, if the original SMAP soil moisture is biased, the uncertainties will be passed down to the downscaled product.

There is a contradictory issue that the $\theta^{SMAP}_{1km}$ validation of August 18 had the worst $R^2$ but the best $\mu bRMSE$. One possible explanation could be $\theta^{SMAP}_{1km}$ validation of this day had narrower data range and lower variance than the other days. Additionally, better validation metrics: $R^2$ and $\mu bRMSE$ for $\theta^{SMAP}_{1km}$ using \textit{in situ} data were shown for August 18 than for other days in Figure 11 and Table 3 and therefore we are confident that the algorithm still performs well for August 18.

The PALS soil moisture was retrieved from the high spatial resolution L-band $T_B$ provided by the aircraft system using the SCA (Single Chanel Algorithm), which calculated soil moisture from single wavelength (L-Band) radiometer observations as well as other ancillary data such as soil properties, comparing with the 1 km downscaled SMAP soil moisture estimated from multiple
spaceborne observations (visible/infrared spectroradiometer derived LST and NDVI products as well as coarse resolution microwave radiometer derived soil moisture). The uncertainties in the soil moisture retrieval algorithm likely contributed to weaker results for the SMAP downscaled soil moisture estimates than the PALS retrievals.

This investigation introduced several improvements to the soil moisture downscaling algorithm proposed by Fang et al. (2013). First, the original algorithm used only three NDVI classes for building the NDVI corresponded $\theta - \Delta T_s$ model. The revised algorithm divides this into 5 classes with the increment of 0.1, which better characterizes the NDVI modulated $\theta - \Delta T_s$ relationship. Second, the original algorithm used the “drop-in-bucket” method for upscaling data to coarser resolution, while the revised algorithm applies an IDW interpolation technique that considers the distance between the new and fine resolution grid. And third, we applied an averaging method to improve the accuracy of the calculated 1 km soil moisture grids which overlap multiple 12.5 km (NLDAS) grids. Finally, we are now computing the downscaled soil moisture corresponding to the SMAP descending 6:00am overpass rather than calculating a daily averaged soil moisture.

Fang et al. (2013) point out that there were four limitations mentioned in the original downscaling algorithm. We have attempted to overcome these limitations in the current investigation. First, it is often very difficult to recover the cloud-contaminated pixels and the current cloud-remover algorithms may cause uncertainties. In this study, we selected MODIS data for the sampling days of SMAPVEX15 campaign site (it rarely rained during the latter part of the campaign) for testing the downscaling algorithm. Second, the downscaling model was built using 5 km AVHRR NDVI data, while the model was applied on 1 km MODIS NDVI data. The AVHRR NDVI and MODIS NDVI data of overlapping period (since 2001) are at different
spatial resolutions. Third, this article is a new application (our past application has been in Oklahoma) of the improved soil moisture downscaling algorithm by Fang et al. (2013). The validation results for downscaled soil moisture indicate the improvement of accuracy over the downscaled AMSR-E soil moisture in Fang et al. (2013) paper. Additionally, we also worked to improve the downscaling model performance, using IDW technique. Finally, as mentioned above, the other soil moisture related variables are often difficult to acquire. For example, the related variables, including soil properties, topography and land cover information can be acquired at very small scale of regions, which cannot fulfill the demands of providing soil moisture estimates of wider range. So, we need to use the simplified downscaling model based on the thermal inertia theory between temperature difference, soil moisture and vegetation.

Cosh et al. (2004) noted several inconsistency issues between the downscaled remotely sensed soil moisture and in situ observations. First, the remote sensing data sets provide the soil moisture data for an ellipsoidal region at a kilometer scale, as opposed to the in situ ground observations that record the soil moisture at the point scale. There are also potential mismatches in the sensing depth among all the soil moisture data sets. The brightness temperatures sensed by the passive microwave sensor (SMAP) and MODIS, soil moisture output from NLDAS, as well as the soil moisture measured by the SMAPVEX15 stations are all at different depths. The passive microwave sensors typically penetrate a few centimeters, while the MODIS penetrates only a few of millimeters, which are then compared with the NLDAS output soil moisture at 0-10 cm depth and the SMAPVEX15 ground measurements at 5 cm depth. Based on a previous study, the satellite-based soil moisture is expected to be noisier than LSM data (Fang et al., 2016). The actual contributing domain used to compute the SMAP L3 soil moisture product is at 33 km rather than 9 km. So, the discrepancy between assumed or grid resolution and actual
resolution could be a source of error, especially in the regions of strong heterogeneity. Due to a lack of a long-term monitoring of very high spatial resolution of land surface variables, the NLDAS outputs as well as AVHRR and MODIS products were upscaled to 12.5 km for downscaling the microwave soil moisture to 1 km. The spatial heterogeneity at 1 km within each 12.5 km grid during the model implementation was also ignored.

5.0 CONCLUSIONS

This study implemented a soil moisture downscaling algorithm with the SMAP Level 3 Radiometer Enhanced 9 km daily soil moisture product and validated the results using airborne PALS radiometer and in situ soil moisture measurements from the SMAPVEX15 field campaign in Arizona. This algorithm was developed based on a vegetation modulated daytime soil moisture - daily surface temperature change relationship. The algorithm uses only three variables: surface temperature, soil moisture and NDVI, as it is usually difficult to obtain high spatial resolution data for other soil moisture related variables, such as precipitation, soil properties and ET. The modeled relationship was applied on 1 km MODIS Aqua/Terra LST data to compute 1 km soil moisture, which was then bias corrected by SMAP 9 km soil moisture. Data from the five sampling days with aircraft coverage during the SMAPVEX15 campaign were used for soil moisture and validation along with in situ data sets. It was found that soil moisture spatial variability as well as dry-down and wetting trends were better characterized by the downscaled estimates than the original 9 km SMAP estimates. The 1 km downscaled and 9 km SMAP soil moisture estimates were validated using the SMAPVEX15 $\theta^{PALS}_{1km}$ retrievals and the in situ measurements. The validation metrics of $\theta^{SMAP}_{1km}$ showed overall better consistency with the $\theta^{PALS}_{1km}$ than the $\theta^{SMAP}_{9km}$, with $R^2$ increased by 0.169, $\mu$RMSE decreased by 0.002 m$^3$/m$^3$.
and bias decreased by 0.004 m$^3$/m$^3$. The downscaled soil moisture estimates also compared well with the *in situ* soil moisture over the SMAPVEX15 study domain. The validation metrics for $\theta_{1km}^{SMAP}$ has the following improvements on $\theta_{9km}^{SMAP}$: $R^2$ improved by 0.293, $\mu_b$RMSE decreased by 0.037 m$^3$/m$^3$ and bias decreased by 0.03 m$^3$/m$^3$. The p-values indicated significant correlations between the $\theta_{1km}^{SMAP}$ and $\theta_{1km}^{PALS}$ or $\theta_{1km}^{SMAP}$ and *in situ* measurements. Additionally, the overall RMSE ranges of the downscaled SMAP validated by either $\theta_{1km}^{PALS}$ or *in situ* data meet the criteria for retrieval accuracy that RMSE $< 0.04$ m$^3$/m$^3$. Based on these results, we believe the downscaling approach applied to SMAP soil moisture data is reliable and accurate for the conditions evaluated and expect to implement the algorithm for providing a daily high spatial resolution soil moisture product to the Contiguous United States.

With respect to these issues, future studies might include: (1) Other methodologies or data sets that could be used to improve the $\theta$ - $\Delta T_s$ correlation. Also, other land surface variables, such as evapotranspiration (ET) and soil evaporative efficiency could be considered. (2) Calibrated hydrological models could be helpful to provide correction for the SMAP soil moisture retrievals (Sridhar et al., 2013). (3) Confidence in the soil moisture validation results could be increased by having more *in situ* soil moisture stations within each soil moisture retrieval grid for better representation of the spatial heterogeneity of the soil moisture.
FIGURES AND TABLES

Table 1. $R^2$ of NLDAS soil moisture of top layer (m$^3$/m$^3$) at 6:00 a.m. versus daily surface skin temperature (K) difference (1:30 p.m. - 1:30 a.m.) corresponding to NDVI classes from 0-1 in August for the three SMAPVEX15 sampling sites: Walnut Gulch, Empire Ranch and Santa Rita.

<table>
<thead>
<tr>
<th>Site</th>
<th>NDVI Class</th>
<th>$R^2$</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walnut Gulch</td>
<td>0-0.1</td>
<td>0.528</td>
<td>-78.143</td>
</tr>
<tr>
<td></td>
<td>0.1-0.2</td>
<td>0.517</td>
<td>-77.023</td>
</tr>
<tr>
<td></td>
<td>0.2-0.3</td>
<td>0.5</td>
<td>-66.565</td>
</tr>
<tr>
<td></td>
<td>0.3-0.4</td>
<td>0.574</td>
<td>-78.334</td>
</tr>
<tr>
<td></td>
<td>&gt; 0.4</td>
<td>0.809</td>
<td>-106.127</td>
</tr>
<tr>
<td>Empire Ranch</td>
<td>0-0.1</td>
<td>0.348</td>
<td>-53.090</td>
</tr>
<tr>
<td></td>
<td>0.1-0.2</td>
<td>0.294</td>
<td>-47.302</td>
</tr>
<tr>
<td></td>
<td>0.2-0.3</td>
<td>0.62</td>
<td>-66.239</td>
</tr>
<tr>
<td></td>
<td>0.3-0.4</td>
<td>0.47</td>
<td>-54.967</td>
</tr>
<tr>
<td></td>
<td>&gt; 0.4</td>
<td>0.499</td>
<td>-61.209</td>
</tr>
<tr>
<td>Santa Rita</td>
<td>0-0.1</td>
<td>0.504</td>
<td>-79.861</td>
</tr>
<tr>
<td></td>
<td>0.1-0.2</td>
<td>0.366</td>
<td>-66.478</td>
</tr>
<tr>
<td></td>
<td>0.2-0.3</td>
<td>0.594</td>
<td>-75.577</td>
</tr>
<tr>
<td></td>
<td>0.3-0.4</td>
<td>0.638</td>
<td>-76.962</td>
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<tr>
<td></td>
<td>&gt; 0.4</td>
<td>0.572</td>
<td>-79.173</td>
</tr>
</tbody>
</table>
Table 2. Statistical variables of validating (with upscaled PALS soil moisture) downscaled 1 km and original 9 km SMAP soil moisture of descending overpass (6:00 a.m.) from five sampling days in August 2015 (The * symbol denotes p-value < 0.001).

<table>
<thead>
<tr>
<th>Date</th>
<th>SM Dataset</th>
<th>Number of Points</th>
<th>R²</th>
<th>Slope</th>
<th>µbRMSE (m³/m³)</th>
<th>Bias (m³/m³)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>08/08</td>
<td>1 km</td>
<td>4477</td>
<td>0.697</td>
<td>1.552</td>
<td>0.02</td>
<td>0.002</td>
<td>*</td>
</tr>
<tr>
<td>08/08</td>
<td>9 km</td>
<td>70</td>
<td>0.597</td>
<td>1.915</td>
<td>0.022</td>
<td>0.004</td>
<td>0.259</td>
</tr>
<tr>
<td>08/10</td>
<td>1 km</td>
<td>4514</td>
<td>0.544</td>
<td>1.279</td>
<td>0.009</td>
<td>0.004</td>
<td>*</td>
</tr>
<tr>
<td>08/10</td>
<td>9 km</td>
<td>70</td>
<td>0.538</td>
<td>1.514</td>
<td>0.011</td>
<td>0.001</td>
<td>0.933</td>
</tr>
<tr>
<td>08/13</td>
<td>1 km</td>
<td>4544</td>
<td>0.429</td>
<td>1.128</td>
<td>0.011</td>
<td>0.01</td>
<td>0.003</td>
</tr>
<tr>
<td>08/13</td>
<td>9 km</td>
<td>69</td>
<td>0.209</td>
<td>1.006</td>
<td>0.018</td>
<td>0.018</td>
<td>0.024</td>
</tr>
<tr>
<td>08/16</td>
<td>1 km</td>
<td>4586</td>
<td>0.438</td>
<td>1.517</td>
<td>0.01</td>
<td>-0.002</td>
<td>*</td>
</tr>
<tr>
<td>08/16</td>
<td>9 km</td>
<td>70</td>
<td>0.103</td>
<td>0.854</td>
<td>0.003</td>
<td>0.003</td>
<td>0.713</td>
</tr>
<tr>
<td>08/18</td>
<td>1 km</td>
<td>4523</td>
<td>0.189</td>
<td>0.518</td>
<td>0.009</td>
<td>-0.001</td>
<td>*</td>
</tr>
<tr>
<td>08/18</td>
<td>9 km</td>
<td>70</td>
<td>0.003</td>
<td>0.07</td>
<td>0.013</td>
<td>0.007</td>
<td>0.106</td>
</tr>
</tbody>
</table>
Table 3. Statistical variables of validating (with *in situ* data) downscaled 1 km and original 9 km SMAP soil moisture of descending overpass (6:00 a.m.) from five sampling days in August 2015. The validation soil moisture data set is acquired from SMAPVEX15 *in situ* soil moisture sites (The * symbol denotes < |0.001|).

<table>
<thead>
<tr>
<th>Date</th>
<th>SM Dataset</th>
<th>Number of Points</th>
<th>$R^2$</th>
<th>Slope</th>
<th>$\mu$RMSE (m$^3$/m$^3$)</th>
<th>Bias (m$^3$/m$^3$)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>08/08</td>
<td>1 km</td>
<td>48</td>
<td>0.409</td>
<td>0.236</td>
<td>0.044</td>
<td>-0.029</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>9 km</td>
<td>11</td>
<td>0.088</td>
<td>-0.126</td>
<td>0.088</td>
<td>-0.079</td>
<td>0.375</td>
</tr>
<tr>
<td>08/10</td>
<td>1 km</td>
<td>39</td>
<td>0.255</td>
<td>0.27</td>
<td>0.032</td>
<td>-0.023</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>9 km</td>
<td>11</td>
<td>*</td>
<td>0.004</td>
<td>0.081</td>
<td>-0.068</td>
<td>0.979</td>
</tr>
<tr>
<td>08/13</td>
<td>1 km</td>
<td>42</td>
<td>0.454</td>
<td>0.419</td>
<td>0.013</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>9 km</td>
<td>11</td>
<td>0.353</td>
<td>-0.217</td>
<td>0.06</td>
<td>-0.035</td>
<td>0.054</td>
</tr>
<tr>
<td>08/16</td>
<td>1 km</td>
<td>44</td>
<td>0.443</td>
<td>0.352</td>
<td>0.02</td>
<td>-0.009</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>9 km</td>
<td>11</td>
<td>0.091</td>
<td>0.044</td>
<td>0.04</td>
<td>-0.024</td>
<td>0.368</td>
</tr>
<tr>
<td>08/18</td>
<td>1 km</td>
<td>39</td>
<td>0.733</td>
<td>0.705</td>
<td>0.006</td>
<td>-0.002</td>
<td>*</td>
</tr>
<tr>
<td></td>
<td>9 km</td>
<td>11</td>
<td>0.131</td>
<td>0.132</td>
<td>0.03</td>
<td>-0.023</td>
<td>0.274</td>
</tr>
</tbody>
</table>
Figure 1. Location of the study sites: (1) Walnut Gulch; (2) Empire Ranch and Santa Rita. Permanent *in situ* soil moisture stations from the three study sites are denoted in red dots.
Figure 2. 10 km GPM (IMERG) 3-day accumulated Level 3 precipitation (unit: mm) from August 7-18, 2015 at Arizona (top row) and SMAPVEX15 (bottom row).
Figure 3. NLDAS surface soil moisture (m$^3$/m$^3$) at 6:00 a.m. versus daily surface skin temperature (K) difference (1:30 p.m. - 1:30 a.m.) in August for the three SMAPVEX15 sampling sites: Walnut Gulch, Empire Ranch and Santa Rita. The $\theta - \Delta T_s$ point pairs are classified into 5 classes, based on the MODIS NDVI value corresponding to each NLDAS grid.
Figure 4. SMAP Level 3 radiometer soil moisture (m$^3$/m$^3$) retrievals of 1 km downscaled, 9 km, 36 km, and difference between 1 km and 9 km of descending overpasses (6:00 a.m.) in Arizona of the five SMAPVEX15 sampling days.
Figure 5. 1 km downscaled SMAP soil moisture vs. 1 km upscaled PALS soil moisture and 9 km original SMAP soil moisture retrievals of descending overpasses (6:00 a.m.) at SMAPVEX15 field (center coordinates: 31.71°N, 110.68°W), from the five SMAPVEX15 sampling days. Boundaries of the Upper San Pedro River Basin and San Pedro River are depicted in black and blue lines. The black grids outline the 9 km grid boundaries.
Figure 6. Uncorrected 1 km soil moisture calculated from downscaling model comparing with 9 km SMAP soil moisture of descending overpasses (6:00 a.m.) from the five SMAPVEX15 sampling days.
Figure 7. Soil moistures for 1 km downscaled SMAP, 1 km upscaled PALS and 9 km original SMAP soil moistures of descending overpasses (6:00 a.m.) in SMAPVEX15 field from the five sampling days.
Figure 8. The empirical cumulative distribution function $f(\theta)$ of the 1 km downscaled SMAP, 1 km upscaled PALS and 9 km original SMAP of descending overpasses (6:00 a.m.) for the five SMAPVEX15 sampling days.
Figure 9. Time series of the overall mean and standard deviation values of the 4 soil moisture data sets: 1 km downscaled SMAP, 1 km upscaled PALS and 9 km original SMAP of descending overpasses (6:00 a.m.) as well as *in situ* soil moisture measurements.
Figure 10. Validation scatterplots of 1 km downscaled and 9 km original SMAP soil moisture (m³/m³) comparing with upscaled 1 km / 9 km PALS soil moisture (m³/m³). Warmer color in 1 km comparison plots indicates higher density of scatter points.
Figure 11. Validation scatterplots of 1 km downscaled and 9 km SMAP soil moisture estimates (m$^3$/m$^3$) at 6:00 a.m. overpasses comparing with \textit{in situ} soil moisture measurements for the five SMAPVEX15 sampling days. Comparison was made when there was a minimum of 8 \textit{in situ} observations in each 1 km / 9 km SMAP soil moisture grid.
References


