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# Validation of SMAP soil moisture for the SMAPVEX15 field campaign using a hyper-resolution model

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## Abstract

Accurate global mapping of soil moisture is the goal of the Soil Moisture Active Passive (SMAP) mission, which is expected to improve the estimation of water, energy, and carbon exchanges between the land and the atmosphere. Like other satellite products, the SMAP soil moisture retrievals need to be validated, with the validation relying heavily on in situ measurements. However, a one-to-one comparison is ill advised due to the spatial mismatch of the large SMAP footprint ( $\sim 40$  km) and the point scale in situ measurements. This study uses a recently developed hyper-resolution land surface model—HydroBlocks—as a tool to upscale in situ soil moisture measurements for the SMAPVEX15 (SMAP Validation Experiment 2015) field campaign during 2–18 August 2015. Calibrated against in situ observation, HydroBlocks shows a

satisfactory Kling-Gupta efficiency (KGE) of 0.817 and RMSE of 0.019 m<sup>3</sup>/m<sup>3</sup> for the calibration period. These results indicate that HydroBlocks can be used to upscale in situ measurements for this site. Different from previous studies, here in situ measurements are upscaled using a land surface model without bias correction. The upscaled soil moisture is then used to evaluate SMAP (passive) soil moisture products. The comparison of the upscaled network to SMAP shows that the retrievals are generally able to capture the areal-averaged soil moisture temporal variations. However, SMAP appears to be oversensitive to summer precipitation. We expect these findings can be used to improve the SMAP soil moisture product and thus facilitate its usage in studying the water, energy, and carbon cycles.

## 1 Introduction

As a critical component of the terrestrial water cycle, soil moisture reflects the moisture status of the land surface and is vital to different forms of life (including human) that rely on it. Recognizing this importance, soil moisture has been an important focus in hydrology, meteorology, ecology, and environmental sciences [Koster *et al.*, 2004; Niyogi and Xue, 2006; Seneviratne *et al.*, 2010; Liu *et al.*, 2011; Wanders *et al.*, 2012; Xia *et al.*, 2014]. Given the relevance of soil moisture in the Earth system, several satellite missions have been launched to map soil moisture over the globe. These missions include the European Remote Sensing Scatterometer (ERS SCAT) [Wagner *et al.*, 1999], the Meteorological Operational Advanced Scatterometer (METOP ASCAT) [Bartalis *et al.*, 2007], the Advanced Microwave Scanning Radiometer-Earth Observing System (AMSR-E) [Njoku *et al.*, 2003], and the Soil Moisture and Ocean Salinity (SMOS) [Kerr *et al.*, 2001]. The recently launched Soil Moisture Active Passive (SMAP) mission [Entekhabi *et al.*, 2010], which received the highest ranking in terms of mission priority from the U.S. National Research Council [U.S. National Research Council, 2007], adds to this critical effort to more adequately measure surface soil moisture over the globe. SMAP measurements have the potential to provide invaluable data for many science and application areas including hydrology, climate, carbon cycle, agriculture, environmental, and ecology [Entekhabi *et al.*, 2010].

Prior to the launch of SMAP (31 January 2015), there was an extensive effort to both develop the retrieval algorithms and implement robust testing through calibration and validation (Cal/Val) activities [Entekhabi *et al.*, 2014]. Postlaunch Cal/Val activities are now critical to assess the performance of the satellite's hardware, and to further verify and improve the performance of the retrieval algorithms. As described in the SMAP Cal/Val Plan [Jackson *et al.*, 2014], the project uses five methodologies; in situ core sites, sparse networks, satellite intercomparisons, model intercomparisons, and field experiments. Ground-based measurements are typically taken at a point scale and are difficult to compare to SMAP grid-scale data due to the spatial mismatch

[Crow *et al.*, [2012](#)] unless there is intensive ground sampling such as that employed at core sites [Jackson *et al.*, [2014](#)]. Like other satellite soil moisture products, SMAP's footprint is large, specifically 39 km by 47 km for the passive radiometer and 29 km by 35 km for the active radar (real-aperture); while in situ soil moisture networks sample the footprint with the expectation that they accurately reflect the fine-scale spatial heterogeneity of soil, vegetation, topography, and precipitation [Famiglietti *et al.*, [2008](#)].

To overcome this spatial mismatch, sparse in situ measurements are commonly upscaled to the satellite footprint using the approaches discussed in Crow *et al.* [[2012](#)]: simple averaging of station data using time stability concepts [Cosh *et al.*, [2008](#)], upscaling using block kriging [Wang *et al.*, [2015](#)], upscaling using field campaign data [de Rosnay *et al.*, [2009](#)], upscaling using land surface modeling [Crow *et al.*, [2005](#)], and statistical upscaling by estimating the magnitude of upscaling errors [Chen *et al.*, [2016](#)].

Qin *et al.* [[2013](#)] proposed an approach based on MODIS-derived apparent thermal inertia, which later was claimed to be the best upscaling approach in a particular study [Qin *et al.*, [2015](#)]. They further argued that upscaling using a land surface model was an unstable approach because the model failed to accurately represent the observed spatial variability of soil moisture for the model they used [Qin *et al.*, [2015](#)]. It is true that a model based upscaling approach depends heavily on the quality of atmospheric forcing, static information (e.g., soil, land use, and topography), and model structure and parameters. In particular, earlier macroscale land surface models (LSMs) had very coarse spatial resolutions, such as the 0.25° resolution of the Global Land Data Assimilation System Noah LSM soil moisture product used in Qin *et al.* [[2015](#)].

However, recent advances in land surface modeling suggest that they might now be a suitable approach for upscaling. One of the most important areas of progress is the emergence of hyper-resolution LSMs [Wood *et al.*, [2011](#); Bierkens *et al.*, [2015](#)], due primarily to the increasing resolution of global environmental data sets that can be used in LSMs [Shangguan *et al.*, [2014](#)] and the advancement in high-performance computing. A new model called HydroBlocks [Chaney *et al.*, [2016a](#)] was designed to exploit this concept by taking advantage of these new resources. It allows for the water, energy, and biogeochemical cycles to be modeled at the field scale (sub-100 meters) over continental extents while maintaining the computational efficiency of existing macroscale land surface models.

Progress has also been made in the enhanced physical parameterization of LSMs. For example, compared to its predecessor Noah LSM, the community Noah LSM with multiparameterization options (Noah-MP, one of the two constituent submodels of HydroBlocks) [Niu *et*

*al.*, [2011](#); *Yang et al.*, [2011](#)] has been substantially improved in terms of better model physics and a more complete representation of land surface processes. Unlike the models mentioned in *Koster et al.* [[2009](#)] where model-simulated soil moisture is highly model dependent, Noah-MP can produce soil moisture that is generally consistent with observation in terms of both temporal variability and time series mean [*Cai et al.*, [2014a](#), [2014b](#)].

In this study, we use HydroBlocks as a tool to upscale field-scale soil moisture measurements. The upscaled soil moisture is then used to validate SMAP soil moisture retrievals. Our objectives are to (1) examine the feasibility of the HydroBlocks based upscaling approach and (2) validate the SMAP soil moisture product and provide possible recommendations for improvements to the retrieval algorithm. Here we focus on the data from the SMAP Validation Experiment 2015 (SMAPVEX15), during which intensive soil moisture sampling and aircraft-based measurements were conducted between 2–18 August 2015 in the USDA-ARS Walnut Gulch Experimental Watershed (WGEW) and its surrounding area. Due to the irrecoverable hardware failure of SMAP's active radar on 7 July 2015, our primary focus is using the passive soil moisture product. The remainder of this paper is structured as follows: section [2](#) describes the methodology including model, data sets, and upscaling approach; section [3](#) details how the model was calibrated to match in situ measurements; section [4](#) presents the main results for the validation of SMAP soil moisture products for both “in situ sites” and the temporary SMAPVEX15 field campaign measurements; section [5](#) discusses the uncertainties in upscaling using hyper-resolution modeling; and the final section summarizes the main findings of the paper.

## 2 Methodology

### 2.1 Land Surface Modeling

HydroBlocks is a recently developed hyper-resolution model that is designed to represent the spatial heterogeneity of land surface processes at the field scale by clustering the grid cells of a catchment into hydrologic response units (HRUs) [*Chaney et al.*, [2016a](#)]. HydroBlocks couples Noah-MP [*Niu et al.*, [2011](#); *Yang et al.*, [2011](#); *Cai et al.*, [2016](#)], a vertical one-dimensional land surface model that acts independently on each response unit, to Dynamic TOPMODEL [*Beven and Freer*, [2001](#)], a hydrologic model that links the hydrologic response units via a subsurface kinematic wave (for further details, see *Chaney et al.* [[2016a](#)]). HydroBlocks's novelty is its ability to simulate water and energy fluxes at the field scale (10–100 m) using existing available environmental data sets while only requiring an increase of 1–2 orders of magnitude for computational resources when compared to existing macroscale land surface models. It is

designed to handle global high-resolution data sets effectively by capitalizing on the concepts of hydrologic similarity and high-performance computing.

HydroBlocks simulates the water movement in the top 2 m soil depth. The soil column is evenly divided into 20 soil layers with 10 cm of depth for each layer. Water movement in the unsaturated soil is calculated using the diffusive form of Richards equation [*Chen and Dudhia, 2001*],

$$\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial z} \left( D \frac{\partial \theta}{\partial z} \right) + \frac{\partial K}{\partial z} + F_{\theta}, \quad (1)$$

where  $\theta$  is volumetric soil moisture content,  $D$  is soil water diffusivity ( $\text{m}^2 \text{s}^{-1}$ ),  $K$  is hydraulic conductivity ( $\text{m s}^{-1}$ ),  $t$  is time (s), and  $z$  is the vertical coordinate (downward positive) (m).

The primary step in running HydroBlocks is to delineate the HRUs for a given catchment (or macroscale grid cell). Following *Newman et al. [2014]*, the HRUs are defined by using the  $k$ -means algorithm to cluster topography, land cover, soil properties, and meteorology—proxies of the drivers of spatial heterogeneity of land surface states and processes. The algorithm divides the  $n$  dimensional proxy space into  $k$  clusters (HRUs);  $n$  is the number of proxies of spatial heterogeneity. The objective of the algorithm is to minimize the sum of squared differences between the constituent data points and their mean, within each cluster. To ensure that all proxies are equally weighted, prior to clustering they are normalized to be from 0 to 1.

Currently, HydroBlocks is set up for the contiguous United States, based on the USGS 10-digit hydrologic code (HUC10) watersheds. The average size of the HUC10 watersheds is  $568 \text{ km}^2$ , each consisting of approximately 631,000 grid cells ( $30 \text{ m} \times 30 \text{ m}$ ). For a watershed of this size, 1000 HRUs are recommended to robustly approximate the spatial information of a corresponding fully distributed simulation [*Chaney et al., 2016a*]. This approach minimizes the computational expense while maintaining the accuracy and the representation of the observed field-scale spatial heterogeneity.

## 2.2 Study Domain

The SMAPVEX15 domain was centered around the USDA Walnut Gulch Experimental Watershed (WGEW) and its surrounding region in southeastern Arizona in the United States—near the historical western town of Tombstone, AZ ( $31^{\circ}43'N$   $110^{\circ}04'W$ ). The WGEW encompasses  $150 \text{ km}^2$  and is within the Upper San Pedro River Basin, which covers  $7600 \text{ km}^2$  in Sonora (Mexico) and Arizona (USA). The elevation of the watershed ranges from 1250 to 1585 m above sea level. The mean annual temperature at Tombstone is  $17.7^{\circ}\text{C}$  and mean annual precipitation is 350 mm. Dominated by the North American Monsoon, slightly more than 60% of

the annual total precipitation comes in July–September, with about 25% in August alone (the SMAPVEX campaign period). With this amount of precipitation and uneven distribution throughout the year, the watershed is dry most of the year. Summer rainfall is dominated by convective systems with high spatial variability of both rainfall and soil moisture. Such variability makes it a challenging site for SMAP soil moisture validation, which is the reason the field campaign was conducted here and at this time of the year.

## 2.3 Data

### 2.3.1 Static Data

The static input data (i.e., land cover, soil properties, and topography) for HydroBlocks is acquired from various available high-resolution environmental data sets. The land cover data comes from the National Land Cover Database (NLCD) 2006 [Fry *et al.*, 2011], which includes 16 land cover types at a spatial resolution of 30 m (~1 arc sec) for CONUS. The parameters associated with the land cover data are then assigned based on the lookup table of the model. Topography data are from the 1 arc sec U.S. Geological Survey (USGS) National Elevation Data Set (NED). For this study, we use its elevation data (digital elevation model) and associated products including flow accumulation area, slope, topographic index, and eight directional (d8) flow direction.

The soil property data are from the new POLARIS soil database developed by Chaney *et al.* [2016b], which was created by spatially disaggregating and harmonizing SSURGO [Soil Survey Staff, 2013] to create a consistent 30 m gridded soil product. Compared to SSURGO, POLARIS has the following improvements: (1) gap-filling of the unmapped areas by using survey data from the surrounding areas, (2) removal of the disconnected political boundaries, and (3) disaggregation of the coarse polygons using high-resolution environmental covariate data. The parameters derived from POLARIS soil database are listed in Table 1. Most soil hydraulic properties used in the model are available through POLARIS; however, for the Brooks-Corey parameters, the set of pedotransfer functions described in Maidment [1993] are used.

**Table 1.** The Parameters Derived From the POLARIS Soil Database

Parameter	Description
BB	The Brooks-Corey “b” parameter in hydraulic functions

Parameter	Description
DRYSMC	Top layer soil moisture threshold at which direct evaporation from soil ceases
MAXSMC	Maximum volumetric soil moisture (porosity)
REFSMC	Soil moisture threshold for maximum transpiration
SATPSI	Saturated soil matric potential
SATDK	Saturated soil hydraulic conductivity
WLTSMC	Soil moisture wilting point at which transpiration ceases

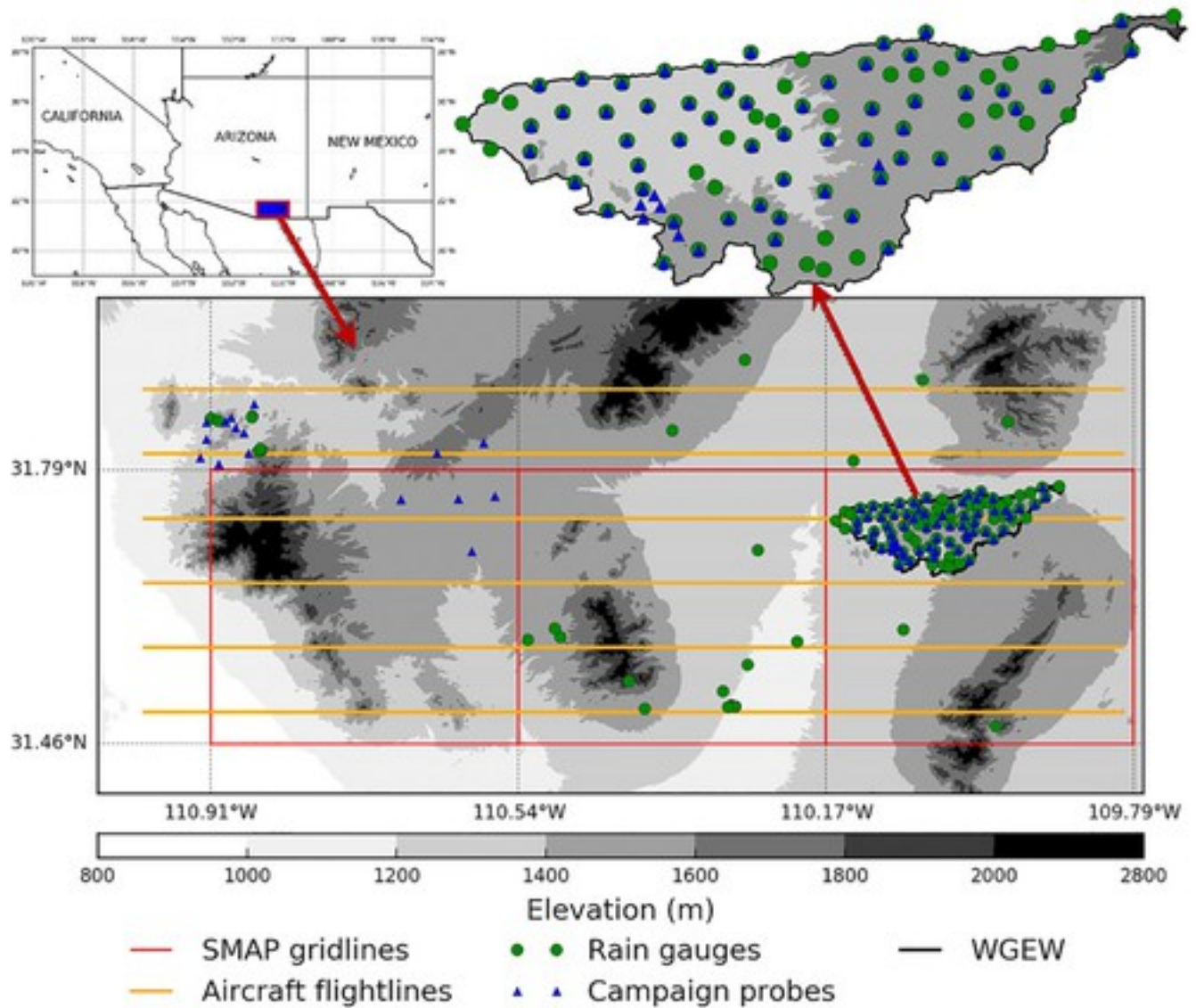
### 2.3.2 Forcing Data

For this study, the model is set up in a way that can directly use atmospheric forcing data from the NLDAS-2 [Xia *et al.*, [2012](#)] and the NCEP's Stage IV radar product [Lin and Mitchell, [2005](#)]. NLDAS-2 provides precipitation, air temperature, wind speed, specific humidity, surface pressure, surface downward shortwave radiation, and surface downward longwave radiation, at 0.125° spatial resolution and hourly temporal resolution.

For precipitation, we first tried the data combined from NLDAS-2 and Stage IV radar product (~4 km and hourly). We found that the simulated soil moisture was constantly higher than field measurements. This is due to the overestimation of precipitation by the two products in this region; particularly the long-term, Stage IV accumulations are about twice that of the gauged rainfall. Because precipitation comes from Stage IV whenever it is available, it dominates the variation of the simulated soil moisture. Precipitation from NLDAS is about one third higher than that from rain gauges. The final precipitation data for modeling are from the dense local rain gauges [Goodrich *et al.*, [2008](#)]. In total, there are 121 rain gauges across the study domain, with



88 of them located within WGEW (Figure 1). The gauge-based precipitation is spatially interpolated using the inverse distance weighting.



**Figure 1**  
[Open in figure viewer](#) [PowerPoint](#)

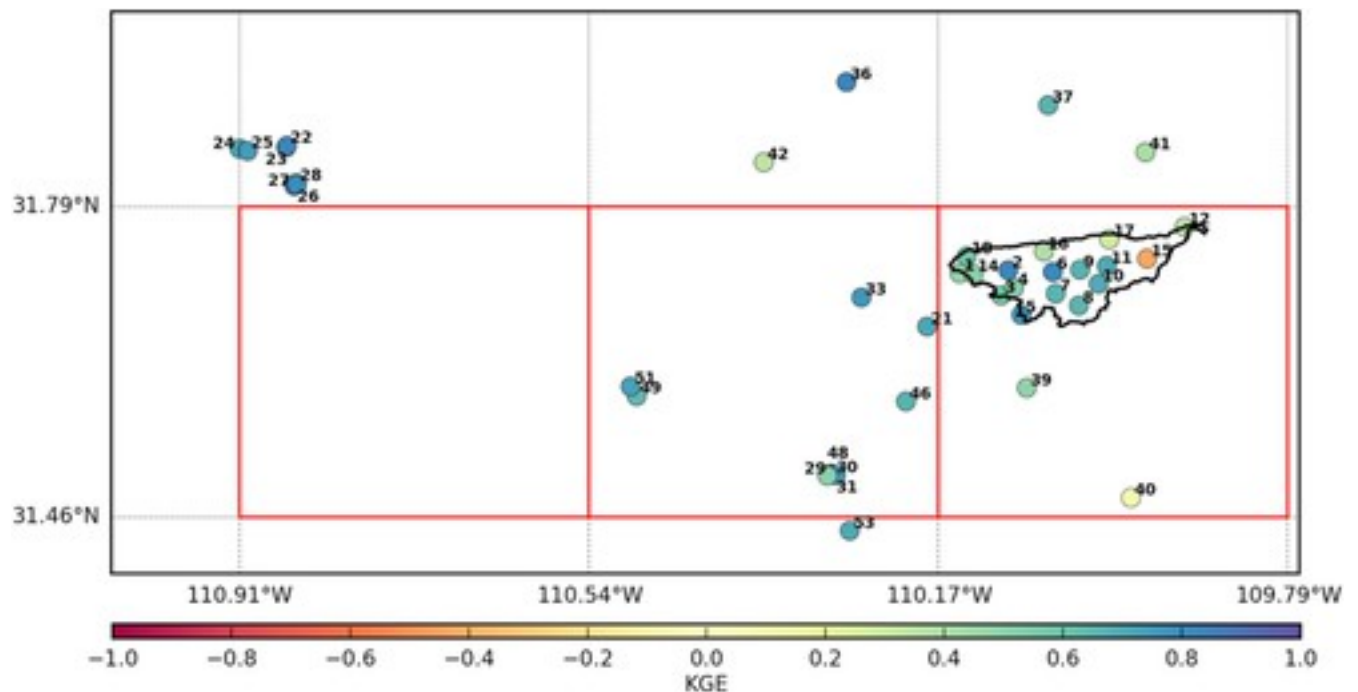
Maps showing the SMAPVEX15 field campaign, the modeling domain, rain gauges, SMAPVEX15 sampling in situ sites, and aircraft flight lines. WGEW: Walnut Gulch Experimental Watershed.

### 2.3.3 Soil Moisture Data

We use soil moisture data from three sources: SMAP, in situ sites, and the intensive SMAPVEX15 field campaign. For SMAP, we use three Level 3 soil moisture products obtained from the National Snow and Ice Data Center (NSIDC): 36 km passive radiometer product

(SMAP L3\_SM\_P), the 9 km active/passive (radar/radiometer) combined product (SMAP L3\_SM\_AP), and the 3 km active (radar) product (SMAP L3\_SM\_A). Due to the permanent failure of the SMAP radar on 7 July 2015, we focus on the passive product SMAP L3\_SM\_P, which is retrieved using the *tau-omega* model by using the constant-incidence-angle brightness temperature data produced by the SMAP conically scanning radiometer [O'Neill et al., 2016]. We assess the public release version of SMAP L3\_SM\_P only, which uses both H and V polarization channels, i.e., the Dual Channel Algorithm (DCA). See Chan et al. [2016] for the discussions on the retrieval methods.

The in situ soil moisture measurements consist of 52 permanent Vitel soil moisture probe sensors distributed across the study domain, with 19 in situ sites within WGEW, 7 in the Santa Rita Experimental Range, and 26 in the Upper San Pedro River basin surrounding WGEW. A select few of these stations have multiple soil depths, but to be comparable with SMAP soil moisture, only the top layer (at 5 cm soil depth) is used in this study. Removing those with very little data availability (less than 25%) during the period from 13 April 2012 to 12 April 2016, we selected the 40 in situ sites shown in Figure 2 (section 3).



**Figure 2**

[Open in figure viewer](#) [PowerPoint](#)

Map showing Kling-Gupta efficiency (KGE) for the 40 in situ sites on the study domain for the calibration period (13 April 2013 to 12 April 2015). The three red boxes in panel are SMAP (passive) grids.

The SMAPVEX15 field campaign was conducted between 2 and 18 August 2015 (<http://smap.jpl.nasa.gov/science/validation/fieldcampaigns/SMAPVEX15/>). In addition to ground measurements using both handheld probes and gravimetric sampling (at 5 cm depth), we used aircraft-based radiometer measurements from the Passive Active L-band System (PALS) instrument.

The PALS instrument collects coincident (in time and place) radar and radiometer measurements with SMAP morning overpasses [Wilson *et al.*, 2001]. Both measurements are obtained through the same antenna similarly to SMAP architecture. PALS has been used in several soil moisture studies in the past [e.g., Njoku *et al.*, 2002; Bindlish *et al.*, 2009; Colliander *et al.*, 2012, 2016]. During SMAPVEX15 PALS was installed on a DC-3 aircraft. In its 2015 configuration PALS employed a lightweight antenna with a 21° beam width [Yueh *et al.*, 2008]. It was attached to a scan head under the fuselage of the aircraft allowing a full 360° conical scan at 40° incidence angle. Same as SMAP L3\_SM\_P, the PALS aircraft data were retrieved using the DCA method. Although the PALS aircraft data were gridded onto 500 m grids, the actual resolution is about 1 km. The locations of the sampling in situ sites and flight lines are shown in Figure 1. It should be noted that within the experimental watershed, most soil moisture in situ sites are collocated with rain gauges.

## 2.4 Upscaling Approach

The hyper-resolution HydroBlocks model operates at a 30 m resolution and is used to upscale observed soil moisture from the in situ sites to the SMAP footprint. The model is first set up and calibrated for the hydrologic response units (HRUs) that are collocated with in situ sites. Soil moisture is upscaled from the in situ sites to the SMAP footprint by aggregating all of the grid cells within each SMAP grid. This can be expressed in equation 2,

$$\theta_t^u = \frac{1}{M} \sum_{i=1}^M \theta_{t,i}^m \quad (2)$$

where  $\theta_t^u$  is the upscaled soil moisture at time step  $t$ ,  $\theta_{t,i}^m$  is the modeled soil moisture in grid cell  $i$  at time step  $t$ , and  $M$  is the total number of model grid cells within one SMAP grid. Different from traditional upscaling using LSMs with bias correction by in situ measurements, here probe-based measurements are only used in the model calibration stage and therefore not included in equation 2. Instead, upscaling is implemented through aggregating the distributed model simulations.

## 2.5 Kling-Gupta Efficiency

The Kling-Gupta efficiency [Gupta et al., 2009] metric is used to measure the goodness of fit between simulations and observations. It can be expressed in equation 3,

$$KGE = \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (3)$$

$$\alpha = \sigma_{sim} / \sigma_{obs} \quad (4)$$

$$\beta = \mu_{sim} / \mu_{obs} \quad (5)$$

where  $r$  is the correlation coefficient,  $\alpha$  is the ratio of standard deviation between simulations ( $\sigma_{sim}$ ) and observations ( $\sigma_{obs}$ ), and  $\beta$  is the ratio of the simulated mean ( $\mu_{sim}$ ) to the observed mean ( $\mu_{obs}$ ).  $KGE$  ranges from minus infinity (poor fit) to 1 (perfect fit).

## 2.6 Latin Hypercube Sampling

To assess the role of model parameter uncertainty in the modeling results, we use Latin Hypercube Sampling (LHS). LHS is statistical method introduced by McKay et al. [1979] to generate a random sample of model parameter values from a multidimensional distribution. LHS splits the distribution of each parameter (uniform in this study) into  $n_L$  regions of equal probability;  $n_L$  parameter values are then drawn by sampling once from each region of equal probability. The parameter values for each parameter are then used to assemble  $n_L$  parameter sets by drawing without replacement from the drawn values of each parameter. These unique parameter sets are then used in HydroBlocks. This approach allows users to obtain a stable output from a much smaller number of samples than other statistical methods such as Monte Carlo simulation.

## 3 Model Calibration

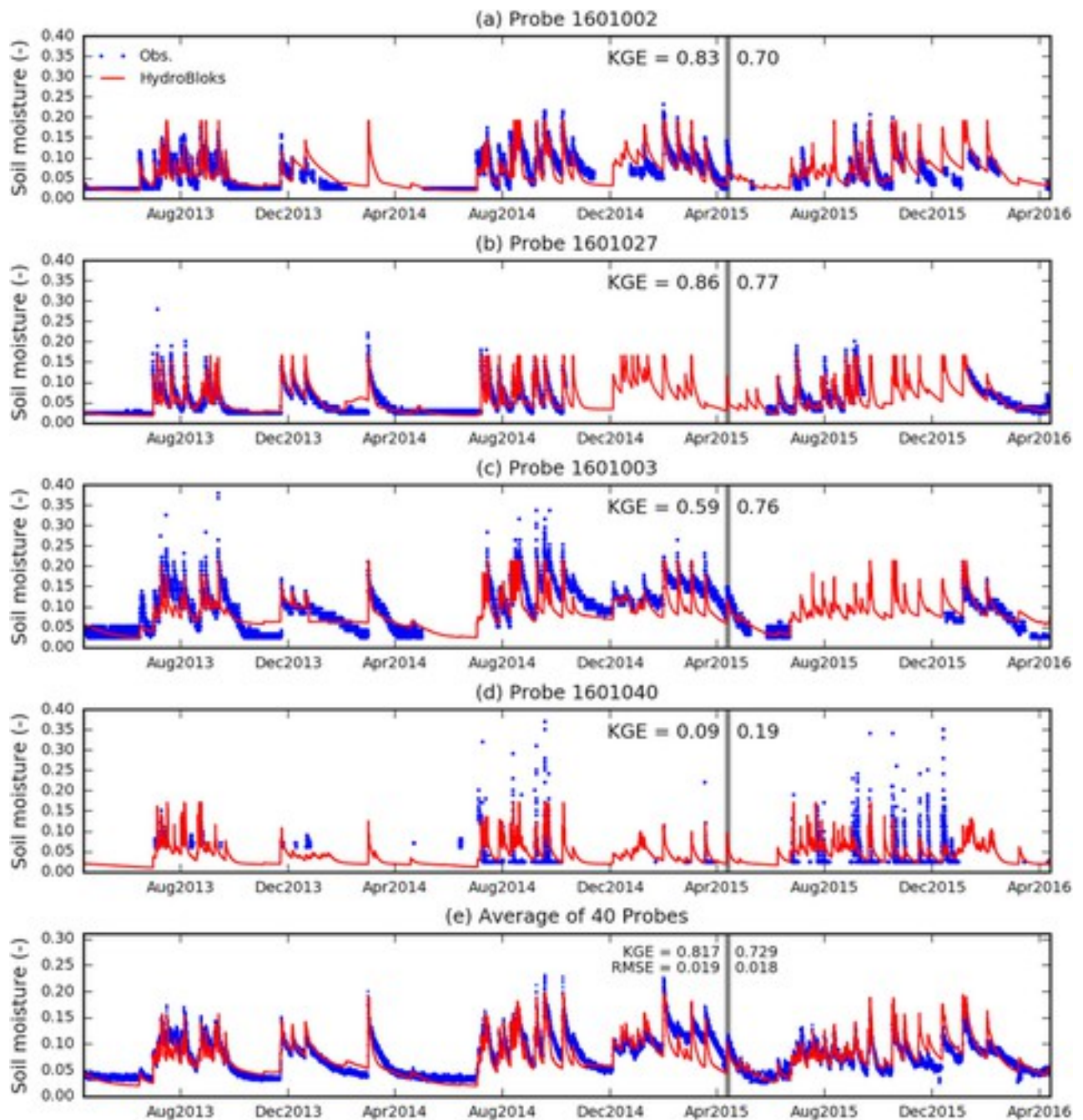
Before using the model for SMAP validation, we ensure that HydroBlocks's performance is reliable. The model is calibrated and validated against observations taken at 40 permanent in situ sites. Soil moisture simulations are from 1 January 2012 to 12 April 2016, with the last date (12 April 2016) being the most recently available rain gauge data at the time of the study (there is about a 2 month delay before the data are available online by the Southwest Watershed Research Center, Agricultural Research Service, United States Department of Agriculture). This provides a 1 year overlap period with the SMAP data. The simulation period is further divided into a model spin-up period (1 January 2012 to 12 April 2013; ~15.5 months), a model calibration period (13 April 2013 to 12 April 2015; 2 years), and a model validation period (13 April 2015 to 12 April 2016; 1 year). The model calibration effort is performed by first conducting sensitivity tests to identify the most sensitive parameters. We found that soil moisture is highly sensitive to soil related parameters, particularly the wilting point soil moisture, the saturated soil moisture content (soil porosity), and the saturated hydraulic conductivity. We calibrate these parameters for each

in situ site's collocated model HRU. However, the majority of the model HRUs do not have collocated in situ sites and thus their associated parameters cannot be directly calibrated. Land surface and hydrologic models (e.g., Noah-MP) commonly read soil parameter values from lookup tables at the time of running, which are assigned based on the soil texture type for each computing unit (grid cell, HRU, or catchment). Following this concept, we assigned each HRU the soil parameter values calibrated HRU that has the same soil texture type. The uncertainty from soil parameters is discussed in section [5.3](#).

Figure [2](#) shows the spatial distribution of KGE of the calibrated soil moisture simulation against field measurement at 40 in situ sites over the study domain for the calibration period. There is only one probe (1601015) that shows negative KGE, five in situ sites between 0 and 0.4, six in situ sites between 0.4 and 0.6, and the remainder, 23 in situ sites, had higher than 0.6 with the highest being 0.86. The averaged KGE of the 40 in situ sites is 0.59. For the validation period (not shown), the averaged KGE is 0.56, which is slightly degraded from the calibration period, while the highest KGE is 0.94, which is even higher than the calibration period.

Figure [3](#) shows the time series of four selected in situ sites and their associated KGE. The first two panels represent the high KGE in situ sites, from which we can see the simulated soil moisture is consistent with in situ observations. The third panel represents the in situ sites with intermediate KGE values. For this site, the HydroBlocks simulation is generally comparable to the in situ values; however, the model has difficulty in capturing some of the dry-downs, particularly in the last part of the calibration period. The fourth panel represents the low KGE in situ sites. We can see some special characteristics in the in situ measurement (Figure [3d](#)): during the first year of simulation (April 2013 to April 2014), although there are only a few observed values, they are close to the model simulation. However, after that, the observed values are either constantly low or jump to very high values. These events are the response to rainfall. We can see that they coincide with the model simulations; however, in the in situ observations, we cannot see the wetting-up or dry-down processes as shown in model simulation. This is possibly due to the probe at a site becoming detached from the soil (perhaps more precisely rock) and can only detect soil moisture content when the soil is close to saturation. Given this behavior, the data from the site should probably be rejected from the network until confirmation that it is operating properly. It is also possible that simply due to the high rock content of the soil, the dry-down process is very rapid after rainfall events.





**Figure 3**  
[Open in figure viewer](#) [PowerPoint](#)

Observed daily soil moisture at individual probe and simulation from HydroBlocks for the corresponding collocated grid cell. (a–d) Time series of selected in situ sites and (e) time series of the 40 in situ sites average. The gray lines separate the calibration period and validation period.

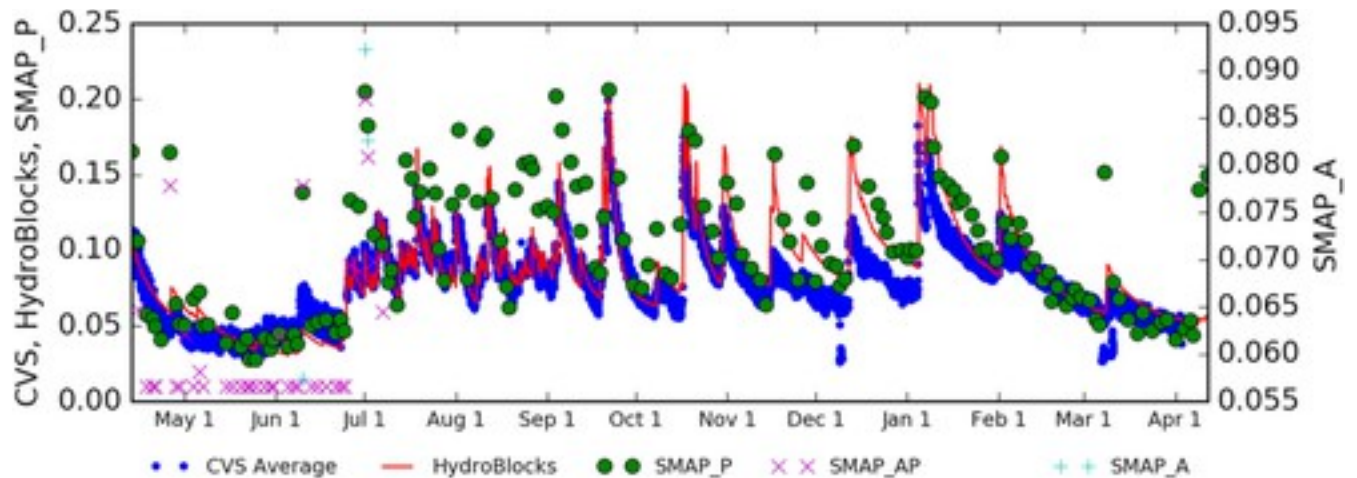
Figure 3e shows the soil moisture comparison of the 40 in situ sites average and their collocated grid cells from the HydroBlocks simulations, which demonstrates how well HydroBlocks can

reproduce the in situ sites average. As indicated on the figure, KGE is 0.82 for the calibration period and 0.73 for the validation period. RMSE is  $0.019 \text{ m}^3/\text{m}^3$  for the calibration period and  $0.018 \text{ m}^3/\text{m}^3$  for the validation period, which is much better than the SMAP soil moisture retrieval accuracy target of  $0.040 \text{ m}^3/\text{m}^3$  [Chan *et al.*, 2016]. HydroBlocks simulated the wet-ups and dry-downs extremely well for most of the time—there were particularly good matches during the dry-downs in Spring 2014 and good performance during summers (July–August). Differences between model and observation are found from February to March 2015, during which model simulated dry-downs are much faster than the observation. This may be due to the larger bias in the atmospheric forcing data in some in situ sites (e.g., site 1601003 of Figure 3c). From the time series, we see the very steady dry-down in Spring periods of other years. However, during Spring 2015, the frequent wet-ups and dry-downs are as strong as those in Summers. Overall, the aggregated result of the HydroBlocks simulation is considered to be very good.

## 4 Results

### 4.1 SMAP Validation Using In Situ Sites

In this section, we focus the long-term validation in the 36 km SMAP grid containing the Walnut Gulch Experimental Watershed due to the very dense in situ sites in and around the watershed. The mean values of SMAP retrieved (passive), field measured, and HydroBlocks simulated soil moisture (13 April 2015 to 12 April 2016) are 0.102, 0.078, and  $0.086 \text{ m}^3/\text{m}^3$ , respectively (Figure 4). The RMSE of SMAP L3\_SM\_P is  $0.035 \text{ m}^3/\text{m}^3$  in reference to the HydroBlocks upscaled values and  $0.039 \text{ m}^3/\text{m}^3$  in reference to the average of in situ sites measurements. This means that SMAP L3\_SM\_P meets the SMAP soil moisture retrieval accuracy target of  $0.040 \text{ m}^3/\text{m}^3$ . SMAP L3\_SM\_A and SMAP L3\_SM\_AP, which are also shown in the figure, are not in agreement with either the probe observation or the upscaled HydroBlocks simulation. This is possibly due to the permanent hardware failure of the active radar sensor after less than 3 months of observations, which provides too short a data set for careful sensor calibration and assessment.



**Figure 4**

[Open in figure viewer](#) [PowerPoint](#)

Validation of SMAP soil moisture against HydroBlocks simulation and in situ observations over the permanent sites over the SMAP grid containing the Walnut Gulch Experimental Watershed. Time period is from 13 April 2015 to 12 April 2016. Blue dots are the simple average of probe observations in this core validation site (CVS); red line is the HydroBlocks upscaled soil moisture which aggregates all model grid cells within the SMAP grid.

From Figure 4, we can see that SMAP L3\_SM\_P shows a similar wet-up and dry-down pattern as the HydroBlocks upscaled and probe observations. There is a particularly strong consistency among the three products for the low values. However, SMAP L3\_SM\_P exhibits less frequent intermediate values and more frequent and pronounced peaks in response to rain events. The stronger temporal variation can be confirmed from their standard deviations. The standard deviations of field-measured and HydroBlocks-simulated soil moisture are 0.025 and 0.032  $\text{m}^3/\text{m}^3$ , respectively. However, the standard deviation of SMAP L3\_SM\_P is 0.044  $\text{m}^3/\text{m}^3$ , which is about 50% higher than the average of the former two products. This difference is most obvious for the first half period (13 April 2015 to 10 October 2015). When there are small rises in the ground measurements and HydroBlocks simulations, we can see the very high values in SMAP. This can be due to the high rain rates associated with the summertime convective rainfall that can lead to excess infiltration (temporary waterlogging) and a SMAP measurement that suggests a wetter 5 cm soil profile. In the second half period when the rainfall characteristics change, SMAP soil moisture agrees relatively well with HydroBlocks and field measurements in terms of fewer peaks/valleys.

There are three possible explanations for the different behavior in these two periods. First, the SMAP sensor or retrieval algorithm may respond differently to different rainfall types. For the first half period, it is dominated by summer convective rainfall (we can see the localized



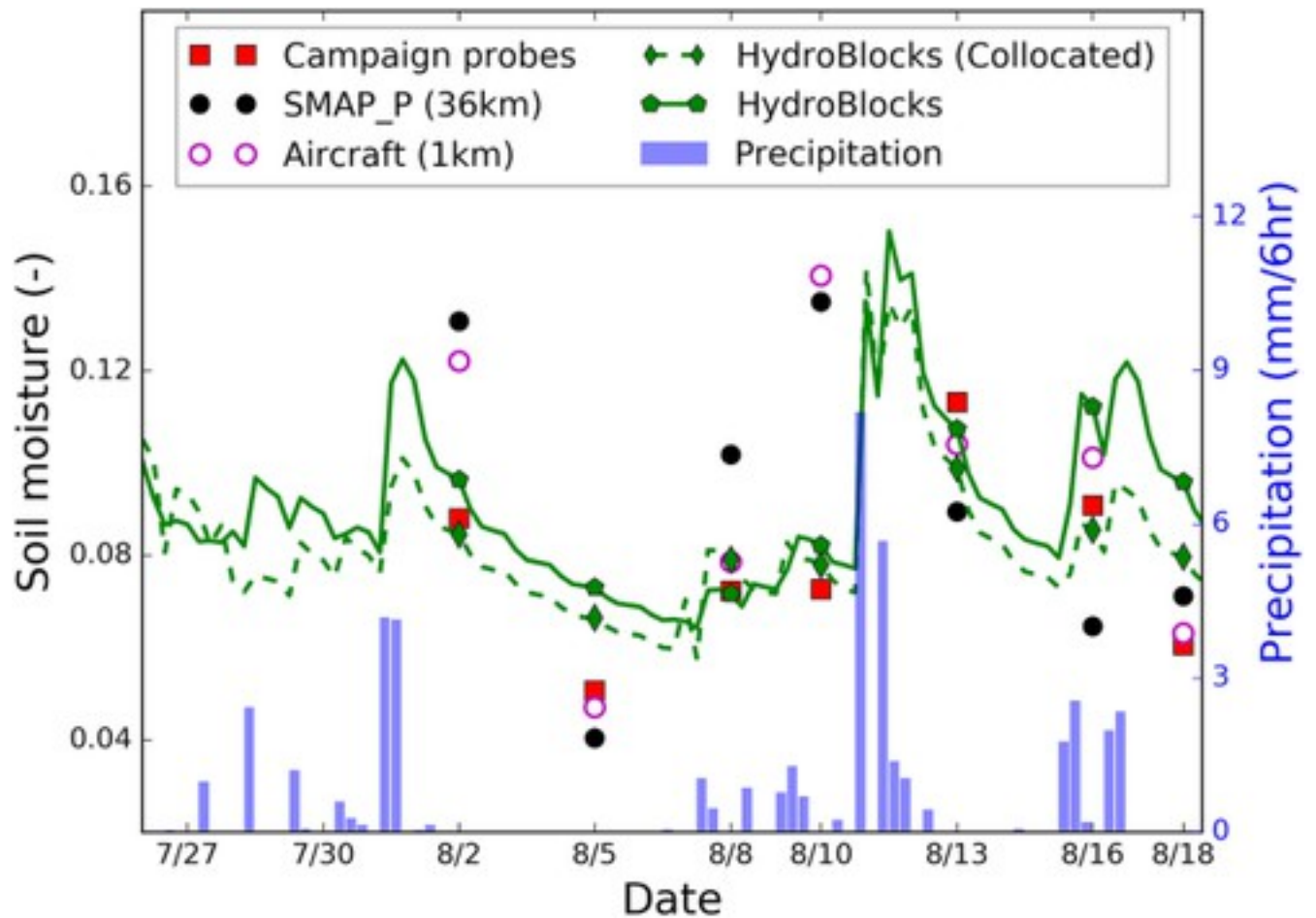
convective system in 8 and 16 August of the aircraft panels of Figure 6); while for the second half, there are more frontal precipitation events. The different response of the retrieval algorithm is due to the assumption that SMAP sensors can only and always penetrate the top 5 cm of the soil profile. Second, there are differences in the soil depths that are represented in each product. In situ measurement for the top layer is the measurement taken at 5 cm depth; HydroBlocks simulation for the first layer is from surface to 10 cm depth; even though it represents the top 5 cm soil moisture, what SMAP observes is mostly the signal from near-surface soil layer [Jackson *et al.*, 2012]. As we know, generally upper soil has stronger variations than lower soil. Therefore, this difference can explain the stronger variations in SMAP. Third, it may be due to increased vegetation coverage during summer, which holds some intercepted water on leaf surfaces and thus give SMAP sensor wrong signals that the soil moisture is saturated.

## 4.2 SMAP Validation Based on the SMAPVEX15

During the SMAPVEX15 field campaign, soil moisture was measured using handheld probes, gravimetric sampling, and aircraft-based radiometer (PALS) concurrently with the SMAP's overpasses in this area. We validate SMAP data from both temporal and spatial aspects. Since the aircraft data provides very rich spatial information of soil moisture distribution, we focus more on the spatial pattern aspect.

### 4.2.1 Temporal Pattern

Soil moisture is compared among SMAP retrieved, in situ sites measured, and HydroBlocks upscaled for the seven dates of aircraft coverage (2, 5, 8, 10, 13, 16, and 18 August 2015) of the field campaign (Figure 5). In order to show the antecedent soil moisture, gauged precipitation and HydroBlocks upscaled soil moisture are also shown for the full validation experiment period. We can see that HydroBlocks simulated soil moisture averaged over model grids containing in situ sites (green dashed line with diamonds) matches the in situ measured soil moisture (red squares) very well. Except for the two dry dates (5 and 18 August) when there is a slight underestimation, HydroBlocks values are almost identical with the in situ measurements. Therefore, we should have high confidence in the upscaled soil moisture by HydroBlocks (green solid line with pentagon) for the SMAP grid. The difference between the upscaled and collocated soil moisture from HydroBlocks indicates the bias of the in situ site locations in approximating the SMAP footprint average.



**Figure 5**  
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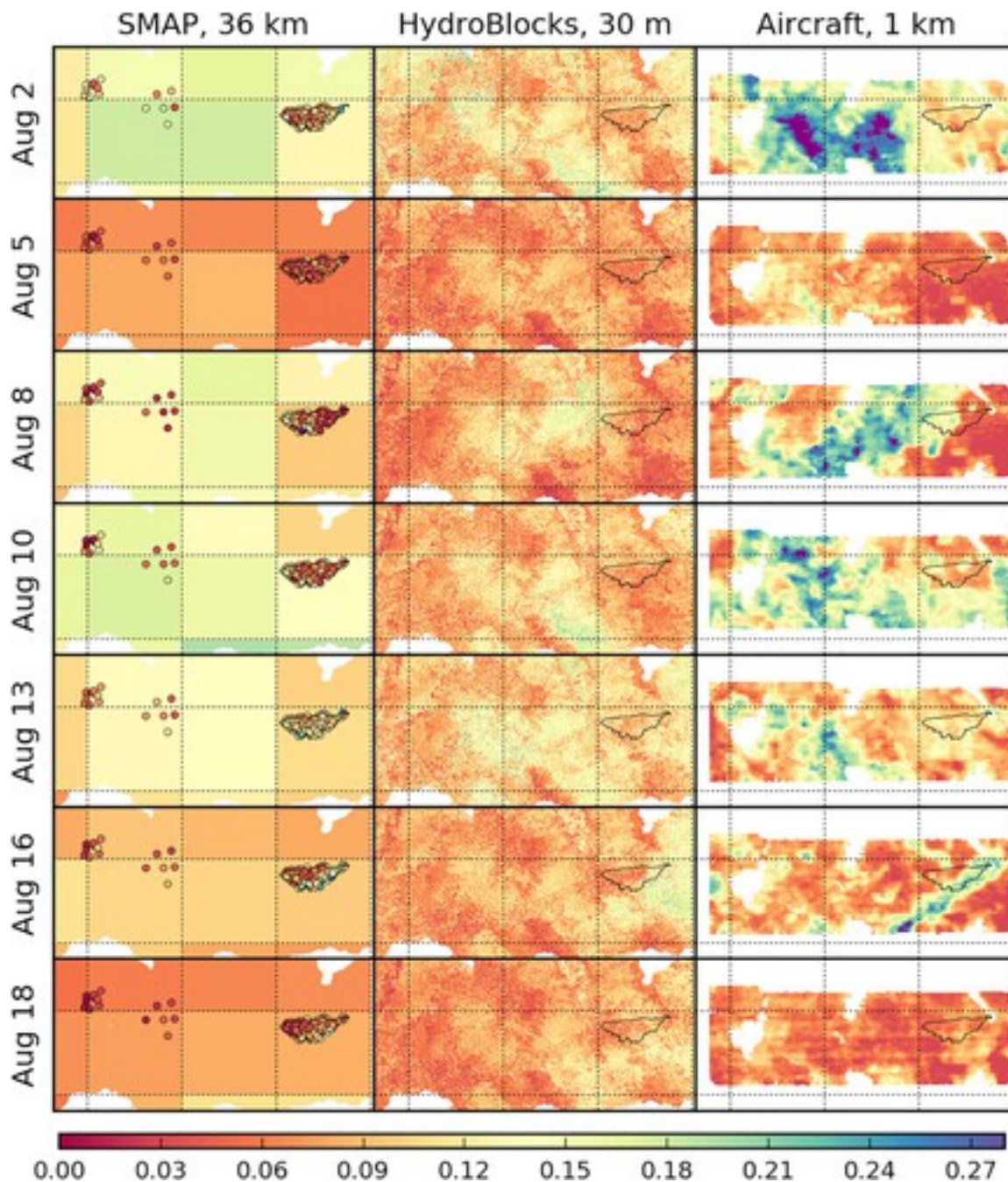
Time series of SMAP observed, in situ network average, and HydroBlocks simulated soil moisture for the SMAPVEX15 field campaign (2–18 August 2015) for the one extensively sampled SMAP grid. The blue bars show 6 hourly precipitation. Field campaign measurements were conducted on the following dates: 2, 5, 8, 10, 13, 16, and 18 August 2015, around the same time that SMAP satellite overpassed this region.

In addition, the temporal pattern of PALS aircraft-measured soil moisture is similar to SMAP L3\_SM\_P. There is only 1 day (16 August) when the aircraft-measured soil moisture shows a big difference to SMAP L3\_SM\_P. Although we can see that some precipitation occurred before 16 August, SMAP L3\_SM\_P soil moisture continued to drop while the aircraft data showed the correct response to the localized convective precipitation event. For the other days, the differences are very small between the aircraft and SMAP L3\_SM\_P retrieved soil moisture.

#### 4.2.2 Spatial Pattern

Assuming that the aircraft data are the best remote sensing product and HydroBlocks simulation as the upscaled ground-based measurement, we can use the HydroBlocks simulation to evaluate the aircraft data. From Figure 5, we can see that HydroBlocks simulation and aircraft data have similar pattern of drying down and wetting up. Due to the limited overpass time, aircraft (and SMAP) missed some major peaks during the campaign period. For example, if there were aircraft measurements available on 1 or 11 August, we would expect much higher peaks from aircraft data. As in the validation on the permanent in situ sites, when aircraft data were observed during or after rainfall events, aircraft soil moisture was much higher than HydroBlocks simulation, particularly on 2 and 10 August. This is most likely due to the aircraft estimates having a greater response to surface soil moisture. As opposed to the in situ validation, we see more intermediate values in the aircraft data (see, e.g., 8, 13, and 16 August). In contrast, we still do not see as many intermediate values from the SMAP L3\_SM\_P. Only the 13 August value can be considered as intermediate value.

Figure 6 shows the spatial patterns of soil moisture for each campaign date. We can see that aircraft and SMAP L3\_SM\_P soil moisture is usually wetter than HydroBlocks and in situ soil moisture, except for 5 and 18 August when they are slightly drier. Although on average, it is very close to in situ measurement, HydroBlocks soil moisture tends to have smaller spatial variation. As shown in Figure 6, there are some in situ sites that have very high soil moisture (blue) while very low (red or dark red) for almost every day. We cannot observe this in HydroBlocks, which is quite uniform, ranging from red to very small portion of light blue. This indicates that HydroBlocks has smaller spatial variability than the in situ sites, which may be due to the small spatial variability in the soil data that inherited from the limited survey locations of the SSURGO (and thus POLARIS) data.



**Figure 6**

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Spatial patterns of soil moisture from SMAP, HydroBlocks, in situ network, and aircraft for the entire SMAPVEX15 field campaign domain.

If we only focus on the three complete SMAP L3\_SM\_P grids, the relative dry/wet patterns among the three grids are very consistent between SMAP L3\_SM\_P and aircraft data. For example, for 8 August, the right SMAP L3\_SM\_P grid is the driest, followed by the left grid,

with the middle grid the wettest. This dry/wet pattern is generally consistent with HydroBlocks predictions.

There are some areas showing very wet conditions in the aircraft data for most of the campaign dates. This wet pattern is similar to convective rainfall patterns, such as those seen in radar maps for weather forecasts. This pattern can sometimes be found in the in situ observations. For example, on 16 August, there is only a very narrow band around the southeastern region of the Walnut Gulch Experimental Watershed that appears to be very wet that may be due to convective rainfall. This is confirmed by the in situ measurements. We can see this more clearly in Figure 7, where there are several in situ sites that show very wet (blue or light blue) for 16 August. Although HydroBlocks showed this pattern as well, any indication of wet conditions is quite weak, compared to aircraft and in situ sites.



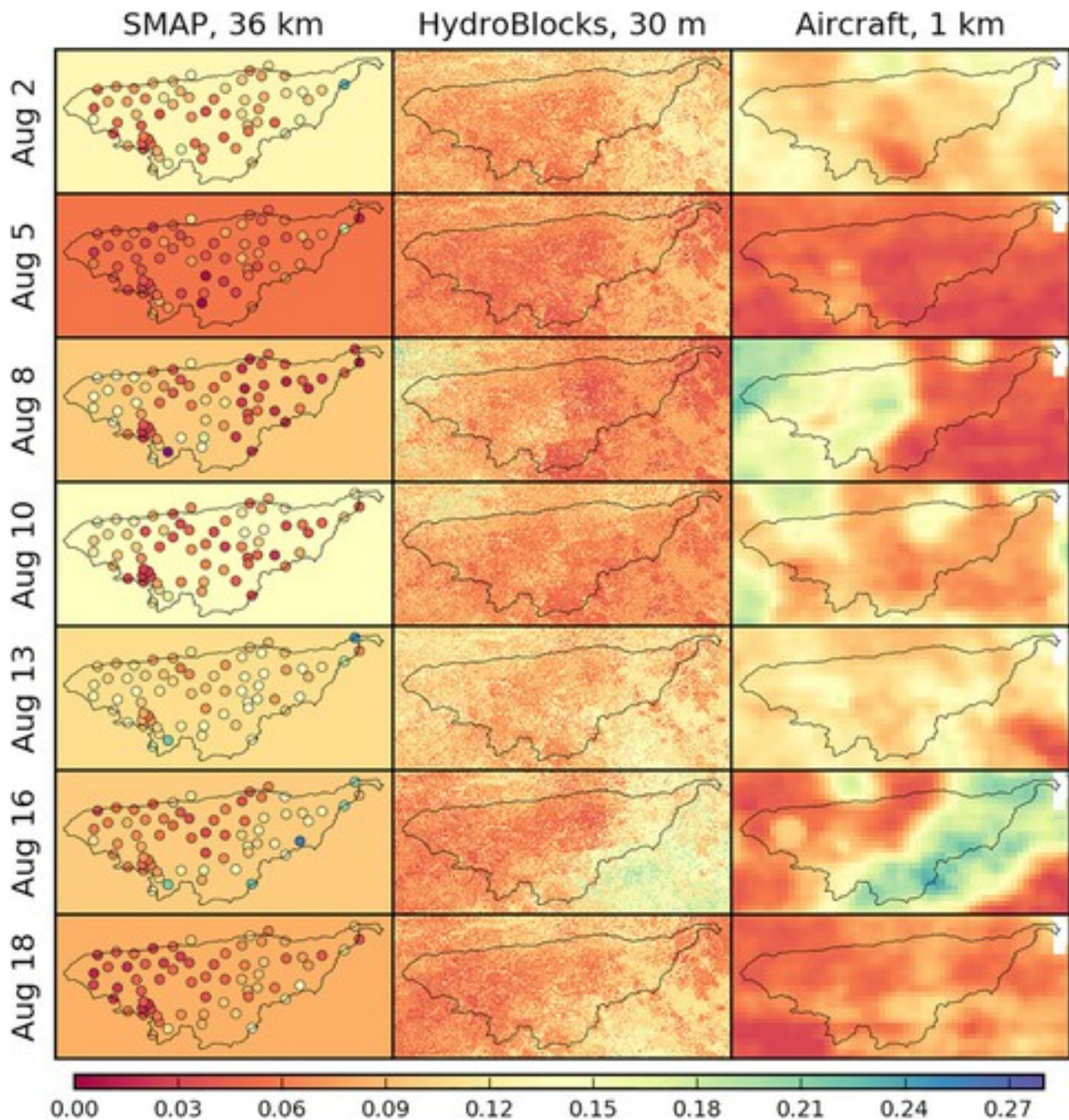


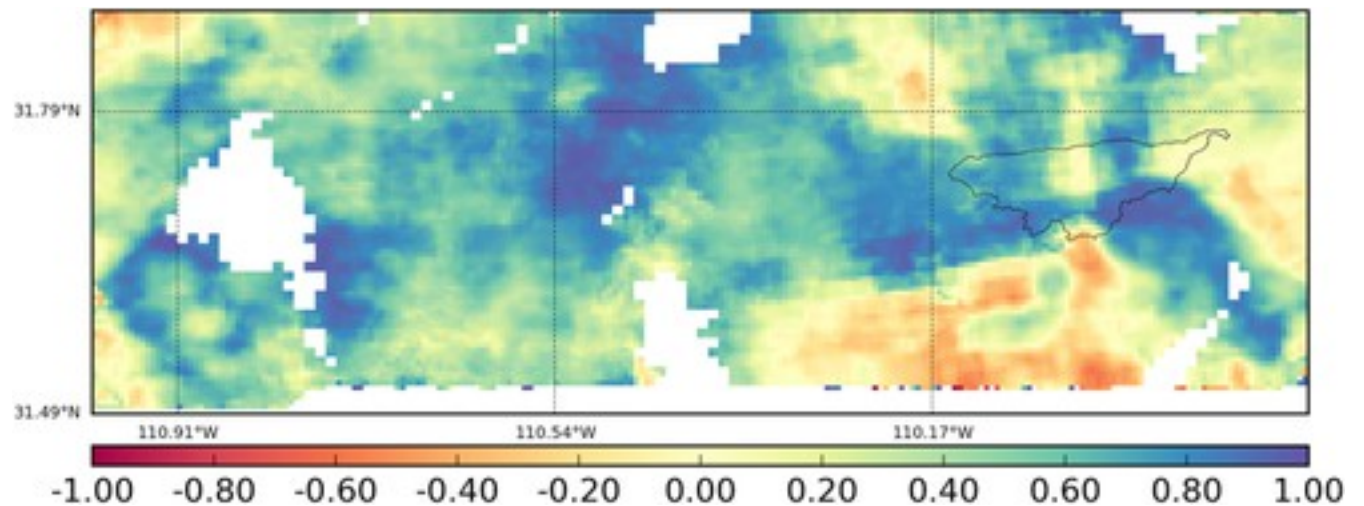
Figure 7

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Spatial patterns of from SMAP, HydroBlocks, in situ network, and aircraft for the Walnut Gulch Experimental Watershed (a zoom in from Figure 6).

The temporal correlation between the HydroBlocks simulation and the aircraft data at each grid is shown in Figure 8. This is computed by upscaling the 30 m resolution HydroBlocks grids to the 500 m aircraft grids. Aircraft and HydroBlocks data generally show positive correlation for most grids. Some low/negative correlation grids are also found. From Figure 6, we can see that

these low/negative correlation grids are collocated with areas with strong convective precipitation.



**Figure 8**

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Map showing the temporal (7 days of field campaign) correlation between aircraft observed and HydroBlocks simulated soil moisture for each aircraft grid cell. 30 m resolution of HydroBlocks simulation is resampled to match the 1 km resolution aircraft grid cells. White shaded area indicates missing values.

Overall, the dry/wet signal captured by the aircraft is confirmed by in situ data but with a stronger amplitude. This stronger amplitude is very likely due to the dominant signal from the wetter near surface layer rather than the signal from the surface to 5 cm soil depth. Such depth representation issues can be addressed in Level 4 products through model based data assimilation and/or postprocessing (e.g., bias correction, CDF-matching). On the positive side, if we can increase its spatial resolution in the future, it is expected that SMAP L3\_SM\_P data can capture the convective rainfall events. This can be used to improve precipitation products in regions that have strong convective rainfall with sparse gauges.

## 5 Discussion

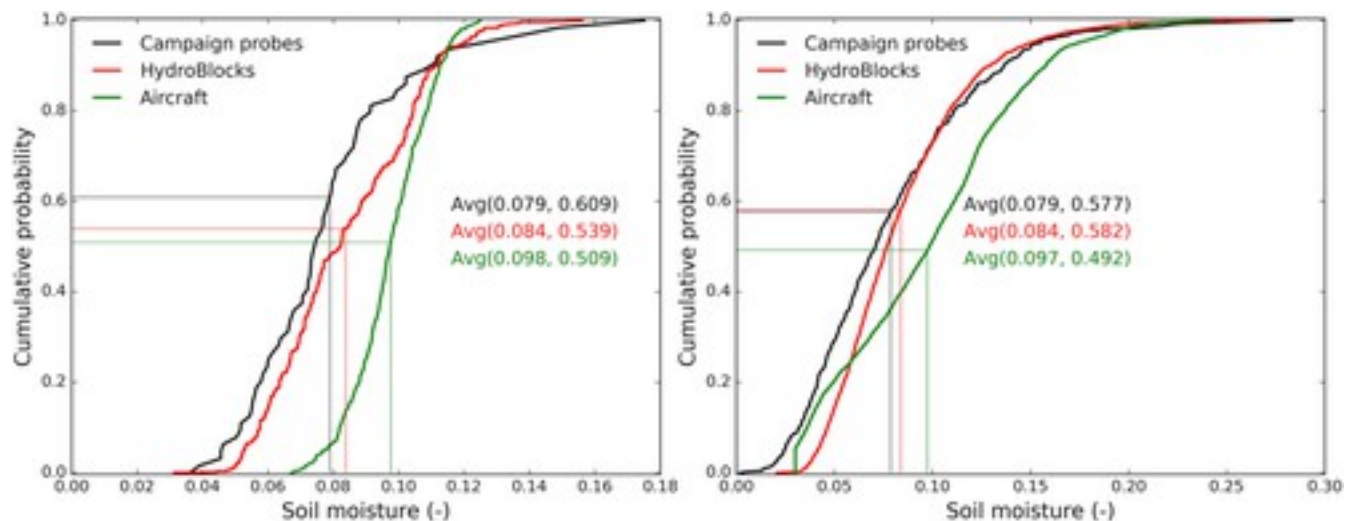
In this investigation we demonstrated for the first time that soil moisture upscaling from field measurement using hyper-resolution land surface modeling with a preprocessing calibration approach (rather than postprocessing bias correction). In other words, soil moisture simulation by hyper-resolution LSMs can be directly compared with in situ measurements after calibration on collocated in situ sites. However, several uncertainties will undermine the usefulness of this

framework such as the representative of the in situ sites, precipitation bias, and uncertainties due to soil parameters.

## 5.1 Biases in In Situ Measurements

The quality of in situ data used to calibrate model is very important, especially in situ sites need to be temporarily stable and spatially representative of model characterization of the satellite footprint. For example, we found that the soil parameters that were calibrated in this study are highly associated with soil texture types. Therefore, a good distribution of in situ sites is needed so as to include all the soil texture types within the footprint. In addition, in situ sites also need to cover a variety of topographic conditions and land use/land cover types.

The cumulative probability function is compared among in situ measurements, aircraft data, and HydroBlocks simulations (Figure 9). In general, we can see that the in situ measurements are drier than the model results, and the aircraft observations are wetter than the modeled soil moisture. Since HydroBlocks was calibrated against the in situ sites (most of them collocated with the field campaign in situ stations), HydroBlocks simulation is probably biased dry, compared to SMAP-derived soil moisture.



**Figure 9**

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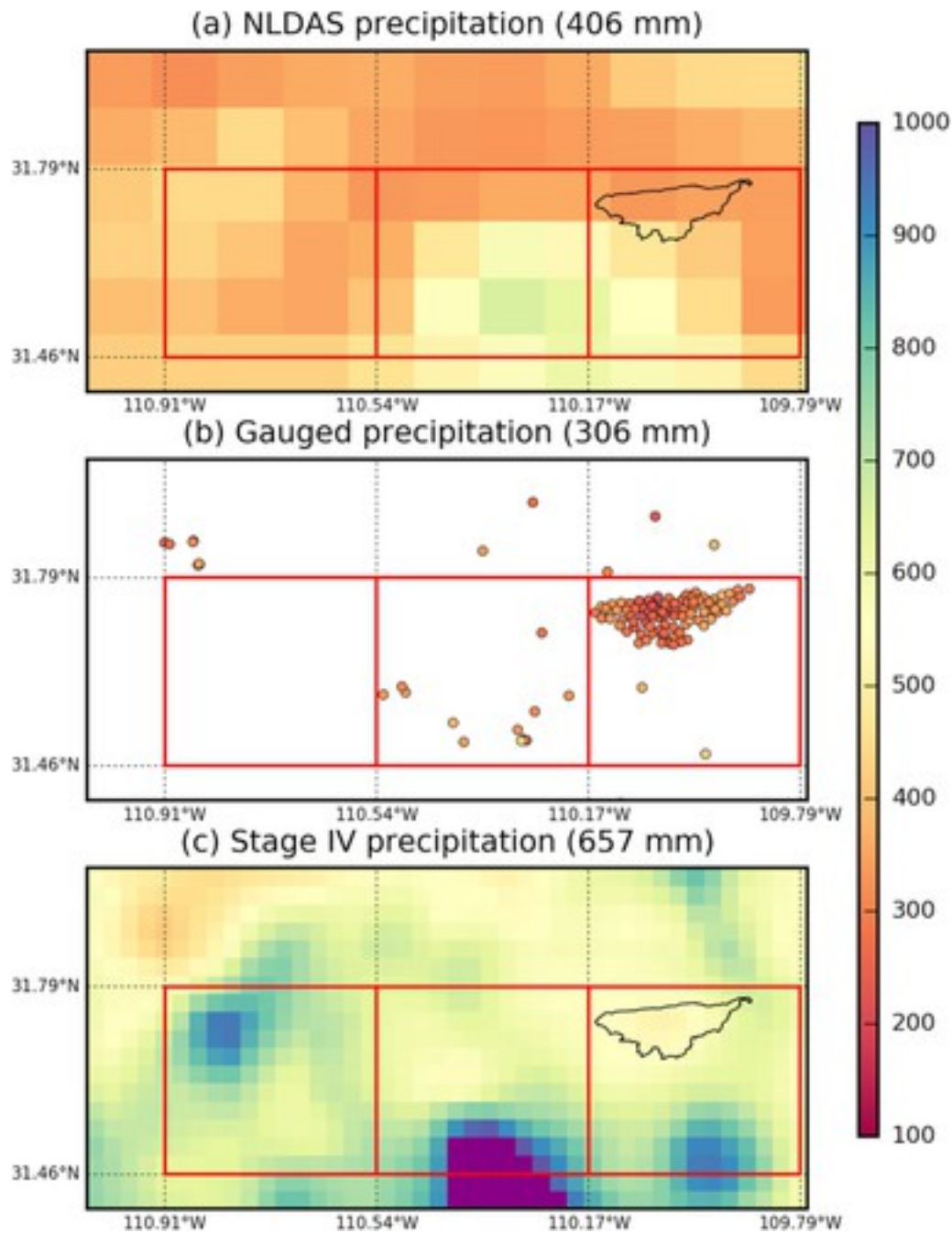
Cumulative probability function distribution (CDF) of ground sampled, model simulated, and aircraft observed soil moisture during the SMAPVEX15 field campaign. (left) Spatial CDF with each grid/probe being averaged over all campaign dates and (right) spatial/temporal CDF with values on an individual date at each grid/probe being a separate sample.



In addition, in situ measurements are also affected by the accuracy of the utilized probes. In this semiarid region with large amount of rock and gravel at the soil surface [*Cosh et al.*, [2008](#)], it is difficult to insert probes down until a designated soil depth and with the appropriate contact to the soil. Some in situ sites may be detached from soil during its operation and thus cannot capture the soil moisture dynamics in that location. For example, in Figure [3d](#), the probe was likely detached from soil so that it reported constant low values during dry days and very high values on rainy days.

## 5.2 Bias From the Precipitation Data

Atmospheric forcing, especially precipitation, needs to be as high quality as possible. We need to address any potential bias before we can calibrate the model. In this study, since the study domain is located in a mountainous region (the experimental watershed is surrounded by mountains). The radars used in the Stage IV product are placed on top of mountains. Therefore, Stage IV measured precipitation in this region is affected by beam blockage and beam overshoot [*Smalley et al.*, [2014](#)]. In this specific case, precipitation is highly overestimated by Stage IV, about twice that of the gauged precipitation (Figure [10](#)), which suggests the radar is observing precipitation aloft that is affected by virga. NLDAS precipitation is also a bit higher than gauged precipitation. Therefore, in this study, Stage IV and NLDAS precipitation was replaced by gauged precipitation data. Gauge locations are shown in Figure [1](#), which features the very dense gauges within the WGEW and very sparse gauges in some other areas. Gauged precipitation was interpolated for the SMAPVEX15 domain by using an inverse distance weighting approach. For those areas with very sparse rainfall gauge coverage, the model accuracy is degraded to some extent.



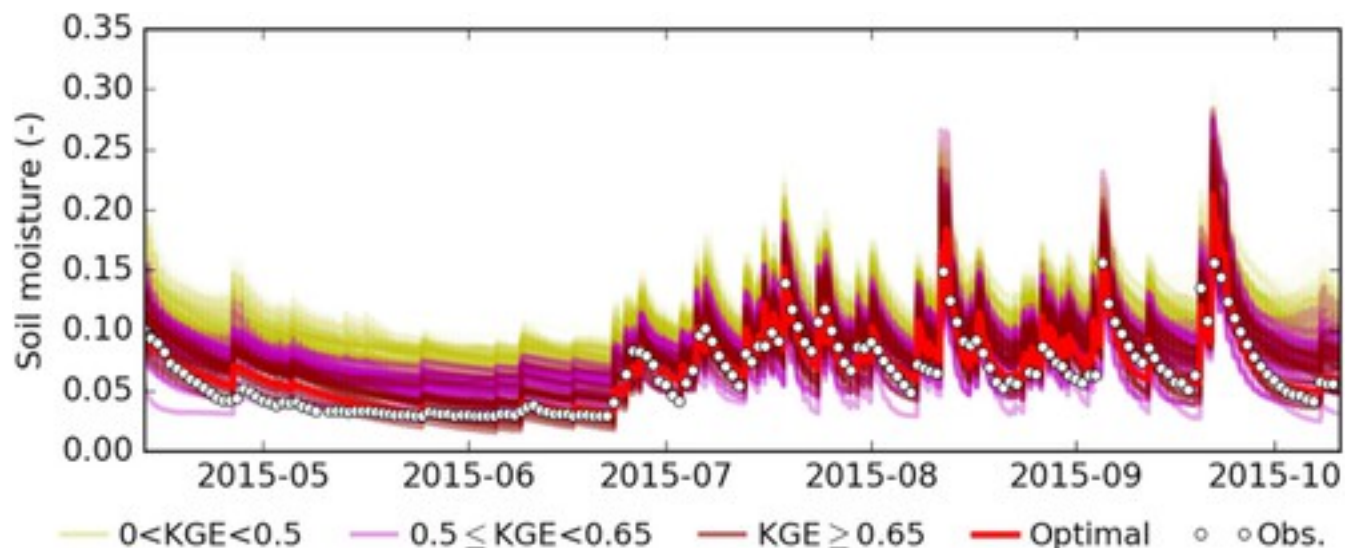
**Figure 10**  
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Precipitation for 1 January to 10 October 2015 from (a) NLDAS 2; (b) rain gauges; and (c) Stage IV.

### 5.3 Uncertainty Due to Soil Parameters

In section 3, it was noted that model simulation is very sensitive to soil parameters. Even though we used a high-resolution soil database—POLARIS [Chaney et al., 2016b], the soil parameters still do not match well for each 30 m resolution grid cell.

To assess the model uncertainties from soil parameters, the Latin hypercube sampling (LHS) technique is used to generate 160 parameter sets from the model parameter space defined by the soil parameters listed in Table 1. Figure 11 shows the spread of uncertainty among the equally plausible (possible) parameter sets. We can see that the lower KGE values, the larger spread of the model simulations is expected. Out of the 160 parameter sets, 64 have KGE values higher than 0.5—a model skill that is usually considered acceptable. Most of the parameter sets result in large overestimation of the in situ network observed soil moisture. This is most likely due to the default wilting point soil moisture values are much higher than the real world and thus they need to be reduced significantly.



**Figure 11**

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The HydroBlocks simulated and in situ observed soil moisture for the Walnut Gulch Experimental Watershed. The black circles are the mean values from the in situ network. The single red line is the optimal model simulation out of the 160 combinations of soil parameters. The dark red, purple, and yellow lines are the model simulations for  $KGE \geq 0.65$  (23 lines),  $0.5 \leq KGE < 0.65$  (41 lines), and  $0 < KGE < 0.5$  (51 lines), respectively.

## 6 Conclusions

To overcome the spatial mismatch between SMAP and in situ soil moisture, we used the HydroBlocks hyper-resolution model for upscaling. After a simple calibration, the model

upscaled soil moisture compared well with in situ measurements, both at the site level and the watershed level. At the watershed level, KGE reached 0.82 for the calibration period. This demonstrated that HydroBlocks can be used for upscaling in situ soil moisture measurements to the satellite footprint with confidence. Despite recent progress, challenges remain for representing the spatial heterogeneity of soil moisture in LSMs. These include obtaining gridded high-resolution atmospheric forcing (mainly precipitation) data of high accuracy, improving the soil related parameters, and further reducing computational costs.

SMAP retrievals generally captured the soil moisture variations. It can meet the SMAP soil moisture retrieval accuracy target of  $0.040 \text{ m}^3/\text{m}^3$ . However, SMAP was overly sensitive to rainfall events. Particularly during convective rainfall events in summer, SMAP-derived soil moisture is much higher than ground-based measurements. This is most likely because the signal detected by SMAP radiometer is dominated by the wetter near surface layer. Such depth representation issue can be addressed in the Level 4 soil moisture products through data assimilation using a land surface model.

## Acknowledgments

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