REMOTE SENSING

High-Resolution SMAP Satellite Soil Moisture Product

Exploring the Opportunities

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The amount (soil moisture) and state (freeze–thaw) of the water in soil plays a pivotal role in global water, energy, and carbon cycles. The water content of the top few centimeters (~5 cm) of soil is typically referred to as surface soil moisture (SSM), which defines how wet or dry the soil is in its top layer. SSM is a key component of the microclimate that governs the interaction of water and heat fluxes between the ground and the atmosphere, regulating air temperature and humidity, and thus, affecting climatic conditions and weather changes. Knowledge of the temporal dynamics and spatial variability of soil moisture is crucial in understanding many environmental processes and their impacts on plant fertility, crop yields, droughts, or exposure to flood hazards.

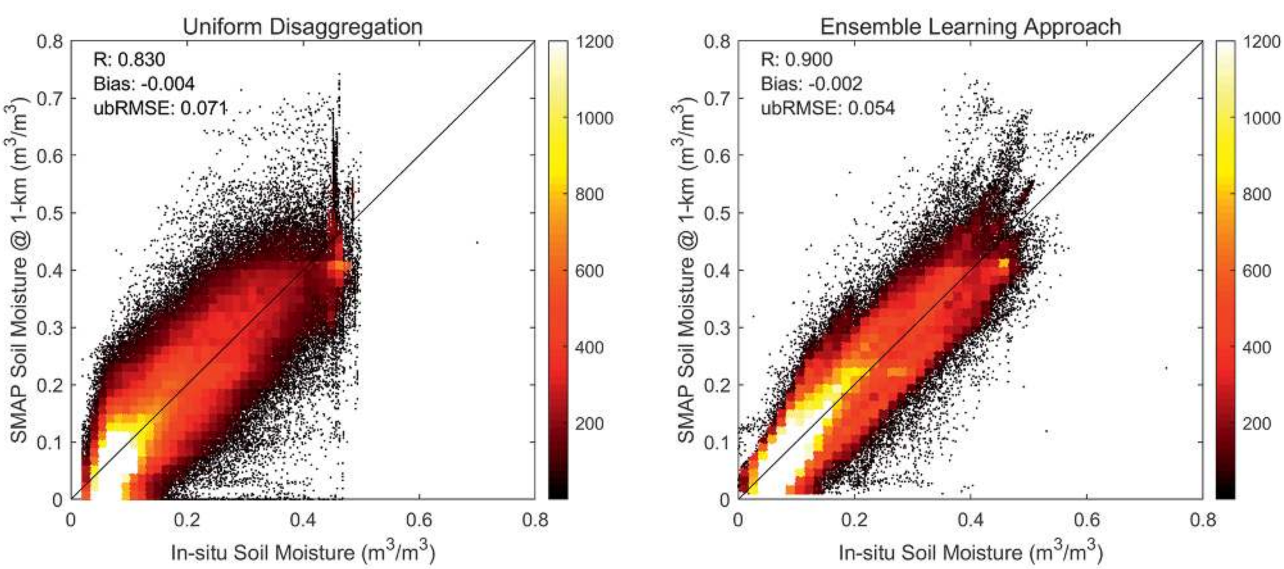

Fig. 1. Comparison of downscaling accuracy between the proposed ensemble learning approach and the uniform disaggregation approach for the period of April 2015–April 2020. Both SCAN and USCRN in situ networks were used in this analysis. Abbreviations are as follows: ubRMSE = unbiased root-mean-square error; *R* = Pearson correlation coefficient; SMAP = Soil Moisture Active Passive.

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DOI:10.1175/BAMS-D-21-0016.1

In final form 22 February 2021

Recent advances in satellite remote sensing technologies have provided unprecedented information on soil moisture across spatiotemporal scales, which is logistically unachievable from in situ observation networks. The Soil Moisture Active Passive (SMAP) satellite was launched on 31 January 2015 by the National Aeronautics and Space Administration (NASA) to provide SSM using brightness temperature through its active (radar, 3 km) and passive (radiometer, 36 km) sensors at an intermediate resolution of 9 km. Although the active sensors (such as synthetic aperture radar) provide data relatively at a higher spatial resolution compared to the radiometer sensors, they are prone to higher error/uncertainties due to their swath width and sensitivity to sparse vegetation cover. Unfortunately, due to the failure of the SMAP radar instrument 3 months after the satellite's launch, the radiometer instrument has been the only operational instrument since then, providing the soil moisture product at the 36-km grid cell from both ascending (1800 LT) and descending (0600 LT) passes. In December 2016, NASA released a data product, the so-called enhanced SMAP radiometer. In this dataset, the standard SMAP data gridded at 36 km are interpolated into 9-km grid spac-

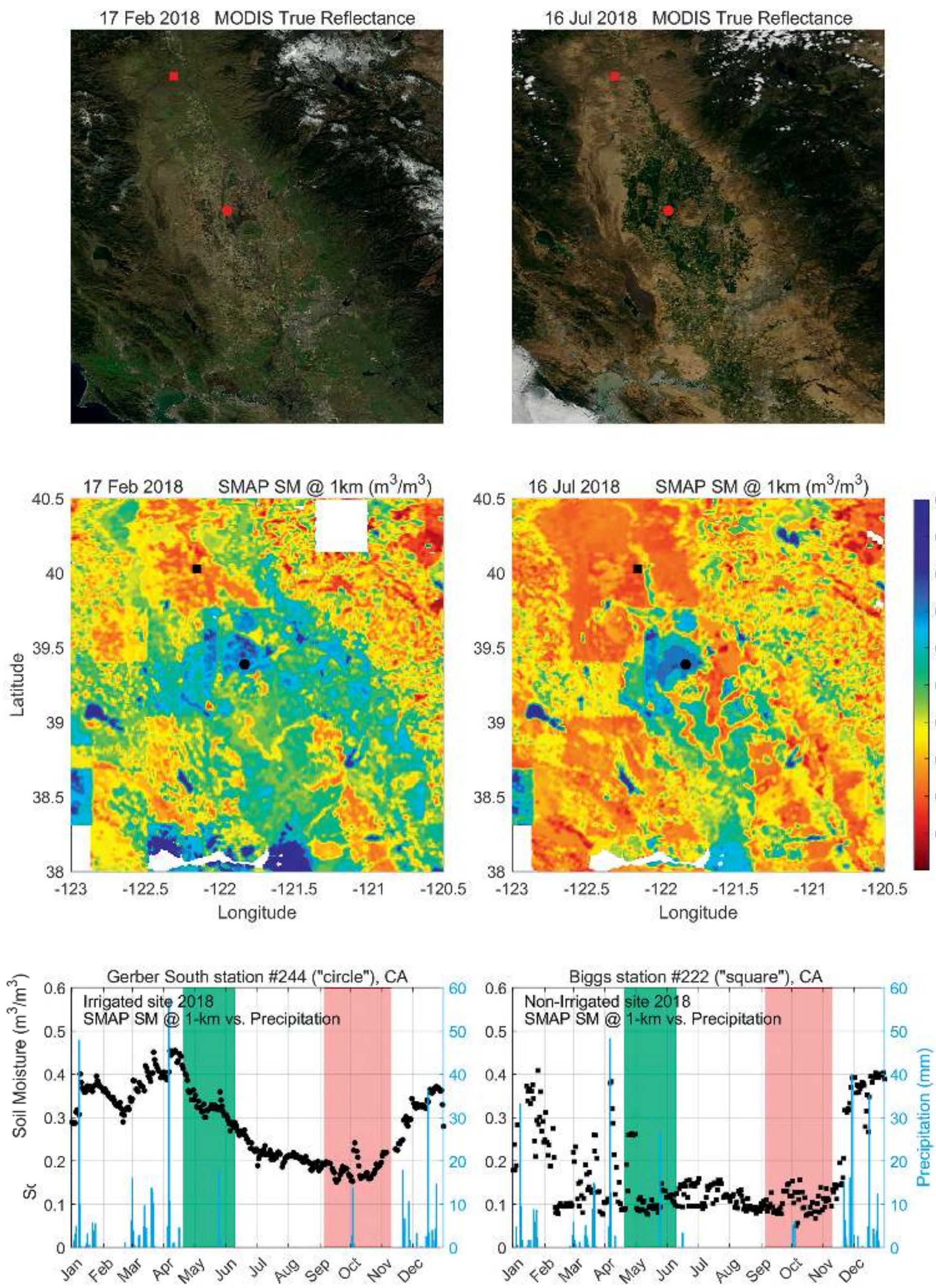

Fig. 2. (top) MODIS *Terra* true color reflectance for 17 Feb and 16 Jul 2018. (middle) SMAP soil moisture data at 1-km spatial resolution on the same days. The dark square (Biggs station 222) and circle (Gerber South station 244) markers display the nonirrigated and irrigated sites, respectively. (bottom) The 1-km SMAP SM at the irrigated and nonirrigated sites. Planting and harvest windows are in green and red colors, respectively, and were acquired from USDA NASS reports.

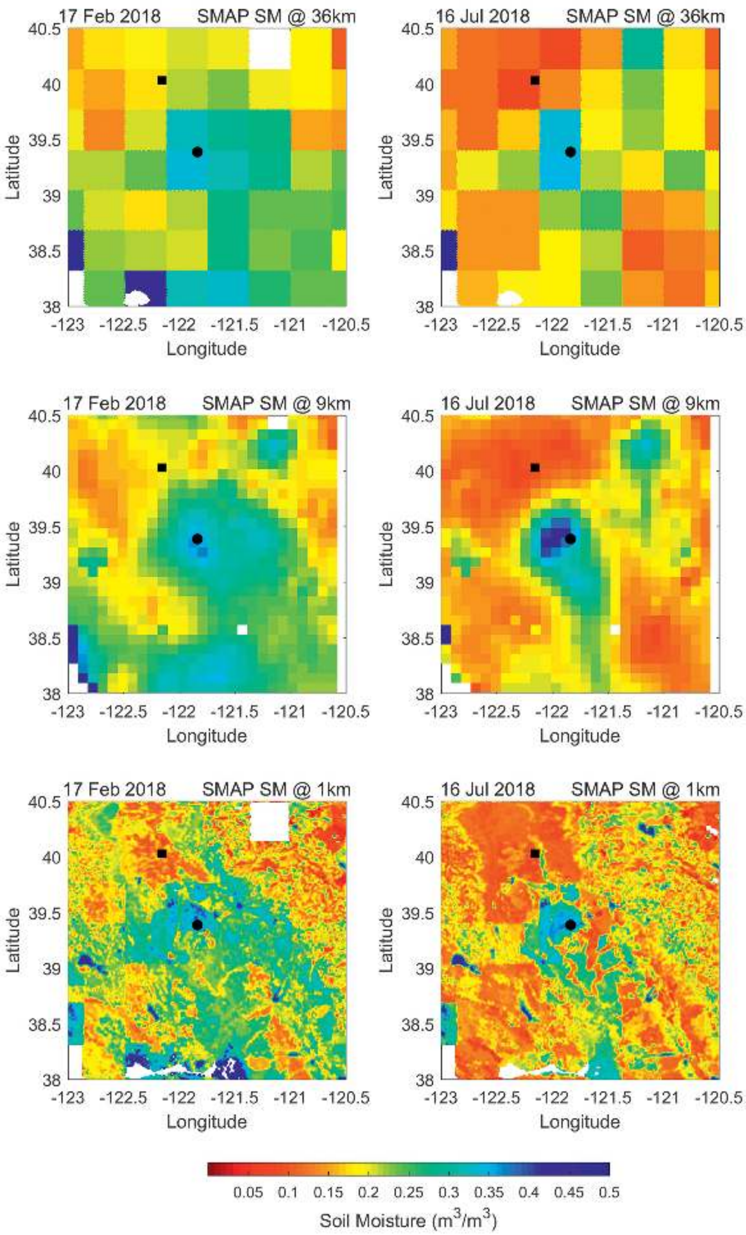

Fig. 3. (top) Original SMAP soil moisture at ~36-km spatial resolution. (middle) Enhanced SMAP soil moisture at 9-km spatial resolution. (bottom) Downscaled SMAP soil moisture at 1-km spatial resolution. The dark square and circle markers display the nonirrigated and irrigated sites, respectively. Please note that the images in this figure are from the same dates as Fig. 2.

ing using the Backus–Gilbert optimal interpolation algorithm. Later in October 2018, Das and colleagues used Sentinel-1A and *Sentinel-1B* data in the SMAP active–passive algorithm to generate disaggregated brightness temperature and soil moisture at a finer resolution of 3 km. The assessment of this product has been performed using the soil moisture calibration and validation sites and the results showed reasonable accuracy of ~0.05 $m^3\ m^{-3}$.

Although this $1 billion NASA satellite provides valuable information for global- and continental-scale applications, the coarse spatial resolution is inadequate for regional or local studies, such as agricultural drought monitoring, irrigation management and planning, flood forecasting, crop production, and water resources management. To address this need, we have developed a machine learning (ML) framework based on an ensemble learning approach to rescale SMAP soil moisture from its native resolution (36 km) to a finer resolution (1 km) while using atmospheric and geophysical information acquired from high-resolution remote sensing data and ground-based observations. For more information about the proposed downscaling algorithm and its validation, we refer readers to the 2019 research of Abbaszadeh et al. (see For Further Reading). The downscaled SMAP soil moisture product was generated and released in May 2018 when the SMAP soil moisture data were only accessible on descending overpass. Recently, the original SMAP data have not only become available on both ascending and descending overpasses, but their interpolated version at 9-km spatial resolution has been developed and released to the public. Hence, we utilized these advancements to further postprocess the downscaled soil moisture dataset at 1-km spatial resolution and provide a more accurate and reliable product. In this excerpt, we show the usefulness of the postprocessed high-resolution soil moisture data through a comprehensive validation analysis based on in situ soil moisture networks operating across the conterminous United States (CONUS) and list the benefits of the product in several hydrometeorological applications.

Figure 1 illustrates the original SMAP soil moisture data and our downscaled product against Soil Climate Analysis Network (SCAN) and U.S. Climate Reference Network (USCRN) datasets. USCRN instruments are scattered uniformly across the United States mainly to represent the annual temperature and precipitation variance, while SCAN stations are installed in agricultural areas to accommodate specific research needs. When remotely sensed soil moisture estimates are compared against in situ observations, it is recommended that the disparity of spatial scale along with the sensing depths are accounted for. Although in some studies it is seen that the bias is removed between the remotely sensed and in situ soil moisture observations due to scale differences, it is usually common to compare in situ observations without scale adjustment even when only one observation is available per pixel. In this study, the postprocessed downscaled soil moisture estimates are compared against in situ observations without bias correction or upscaling. More than 300 SCAN and USCRN stations were active during the period of study (April 2015–April 2019) providing daily soil moisture at different soil depths and other meteorological observations such as precipitation and soil temperature. Figure 1 shows the soil moisture observations that were collected at ≤2-in. (~5-cm) depth consistent with the sensing depth of the SMAP satellite. Also, Fig. 1 displays the overall statistics of the disaggregated remotely sensed surface soil moisture compared with the SCAN and USCRN observations over the CONUS. Compared to the standard disaggregation method, the proposed ensemble learning approach can provide more accurate soil moisture data at a spatial resolution of 1 km. This newly developed product offers useful data to not only the academic community for further research but also the variety of sectors that are beneficiaries of these data.

Figure 2 shows that the SMAP soil moisture at 1-km spatial resolution is capable of detecting the irrigation signal in the Northern California Central Valley (CCV) that encompasses rice fields. This figure demonstrates how the landscape from Moderate Resolution Imaging Spectroradiometer (MODIS) *Terra* imagery has been changed from the wet season (17 February 2018) to the dry season (16 July 2018). The green areas turn brown by July except the regions where irrigated rice and forests cover the lands. These contrasts are distinguishable from the fine resolution SMAP soil moisture maps. Our dataset shows the region in February uniformly wet (on average >0.3 $m^3\ m^{-3}$). However, according to our produced soil moisture map, the entire area is almost dry in July, except the regions covered by irrigated rice and forest that generally indicate much higher soil moisture levels. According to the U.S. Department of Agriculture National Agricultural Statistical Service (USDA NASS), the rice farmlands are flooded and seeded each year from late April through May. Harvest begins in September and ends in November. While the soil moisture at both irrigated and nonirrigated sites follows the temporal variation of precipitation closely, it behaves differently in irrigated sites where the field is flooded for planting in mid-April. The timing is corroborated with the 2018 crop report of the USDA NASS. In the growing season, the irrigated site is kept wet through early September when the harvesting begins. This pattern is discernible by the fine-resolution soil moisture data. Note that a similar set of comparisons for these dates presented by Lawston and

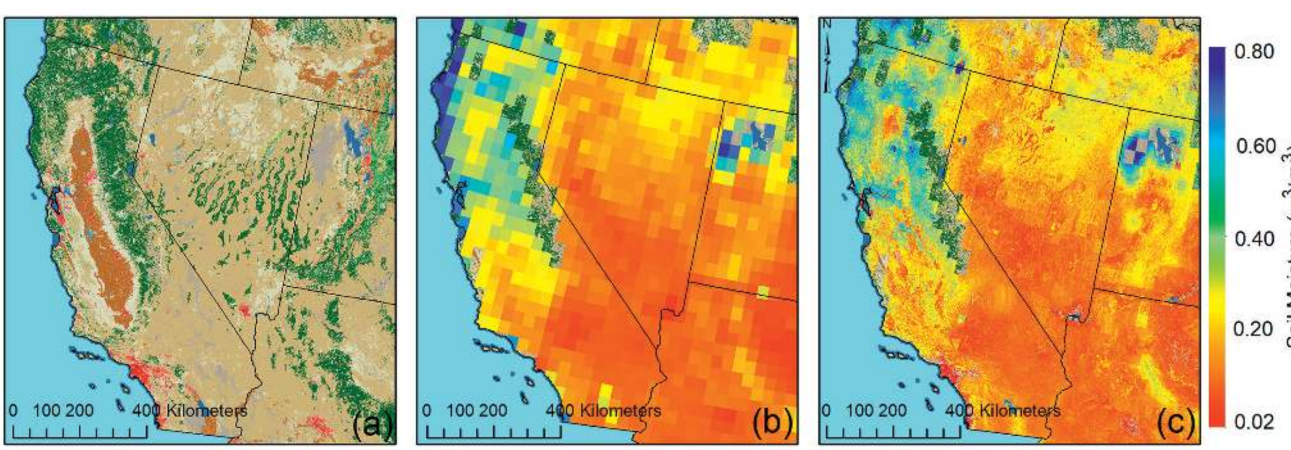

Fig. 4. (a) Land cover distribution over the western United States, (b) original SMAP soil moisture at ~36-km spatial resolution, and (c) downscaled SMAP soil moisture at 1-km spatial resolution for 1 Apr 2018.

colleagues in 2017 using the enhanced SMAP data (at 9 km resolution) does not represent the underlying spatial heterogeneity, which is evident in the maps of Fig. 2.

Figure 3 compares the downscaled soil moisture at 1-km spatial resolution against the original SMAP soil moisture and its interpolated version which are available at 36- and 9-km spatial resolutions, respectively. Please note that the images in Fig. 3 are from the same dates as Fig. 2. To balance the sharp edges at the grid border, we applied an interpolation method similar to that proposed by Montzka and colleagues in 2018 on the downscaled 1-km soil moisture image and generated a dataset with no patch effect that better represents spatial heterogeneity of soil characteristics, vegetation types, and climatic conditions. Further investigation (please see Fig. 1) also revealed that the interpolation approach does not affect the accuracy of the downscaled soil moisture data.

As we discussed earlier, the produced 1-km SMAP soil moisture data correlate well with the in situ observations over different geographical locations with different land–atmosphere regimes. In addition to this, our study also confirms that there is a spatial consistency between the coarse- and fine-resolution soil moisture maps. For example, as seen in Figs. 4a and 4c, the downscaled product provides more detailed soil moisture information consistent with the spatial heterogeneity of soil characteristics and vegetation types. The soil moisture spatial pattern is dependent on the heterogeneity of soil parameters (e.g., soil texture, vegetation, and topography) that are generally not distributed homogenously in the area. This results in an uncertainty in the soil moisture retrievals. Our downscaled soil moisture map could fill this gap through decreasing the discrepancy between the spatial variability of soil parameters and soil moistures. Moreover, the following example shows that the downscaled soil moisture spatial pattern closely follows the climate pattern and weather conditions.

In the state of Texas near Houston, the soil moisture conditions generated by the SMAP satellite before (Figs. 5a,b, 21 August 2017) and after (Figs. 5c,d, 26 August 2017) the landfall of Hurricane Harvey revealed that this dataset is a reliable source in studying the changing soil wetness condition due to heavy rainfall associated with the tropical cyclone. Similar to the original SMAP observation (Fig. 5a), the downscaled soil moisture (Fig. 5b) also indicates that the soil surface was already very wet a few days before the onset of torrential rainfall. This is also consistent with the report of the Southeast Regional Climate Center (SERCC) that Texas, Louisiana, and other southern states have had one of their wettest months on the record before the landfall of Hurricane Harvey (please see https://earthobservatory.nasa.gov/images/90864/soil-moisture-satellite-observes-harveys-wrath). This saturated soil surface decreased the infiltration capacity and therefore escalated the likelihood of flooding. As seen in Figs. 5a and 5c, both SMAP images at 36- and 1-km spatial resolutions confirm that the southwest regions of Houston became exceptionally wet on 26 August 2017, as corroborated by the observed torrential rainfall and widespread flooding. According to the Figs. 5b and 5d, the 1-km

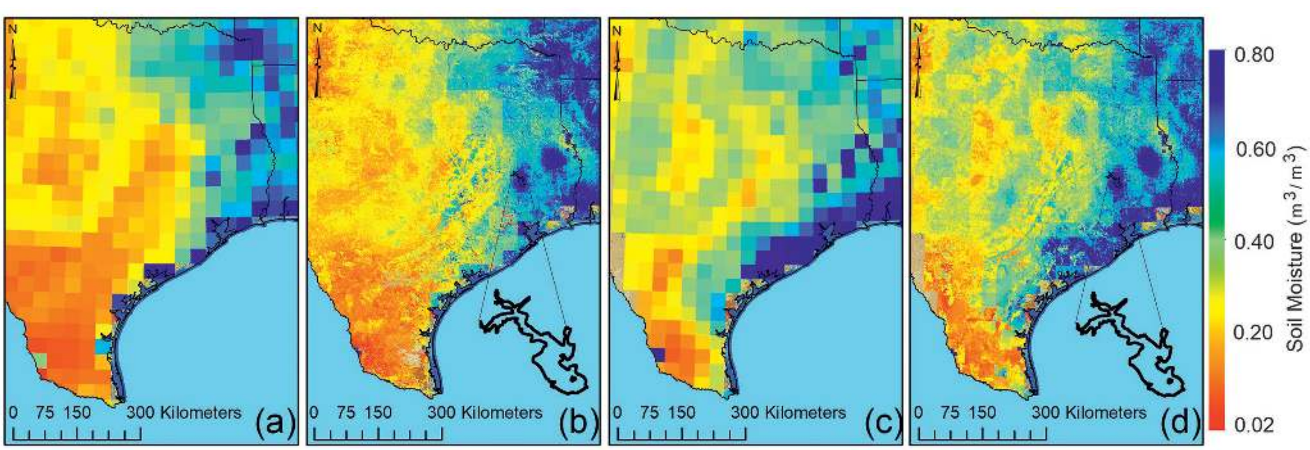

Fig. 5. (a), (b) The soil moisture condition at 36- and 1-km spatial resolutions, respectively, on 21 Aug 2017, before the landfall of Hurricane Harvey over the state of Texas. (c), (d) The soil moisture condition at 36- and 1-km spatial resolutions, respectively, on 26 Aug 2017, after the termination of Hurricane Harvey. The polygons shown in (b) and (d) illustrate Lake Livingston.

soil moisture maps demonstrate the increase of inundated area near the upstream and downstream areas of Lake Livingston during Harvey's rainfall. This information is in accordance with several reports showing that the flooded regions around Lake Livingston caused severe damage to roads and properties due to its overflowing (for more information, we refer the readers to www.khou.com/article/weather/hurricane/harvey/nhc-harvey-caused-125-billion-in-damage-68-deaths-in-texas/285-511430188). Lake Livingston is a reservoir built for water-supply purposes with no flood-control or storage capability. During such an extreme event, knowledge of the soil moisture condition at fine spatial resolution is critical as it can be used to update the antecedent moisture conditions in flood forecasting models. For example, in one of our recent studies, we explored the benefit of using the downscaled SMAP soil moisture product to enhance the Weather Research and Forecasting Hydrological Model (WRF-Hydro) flood forecasting skill. The results showed that assimilating the 1-km soil moisture data into WRF-Hydro significantly improves its ability to accurately predict the onset of Hurricane Harvey flooding.

Unlike in situ networks, land surface models are able to estimate the soil moisture at different spatial scales and continuously over time. The quality of such model estimates is most often limited due to the inaccurate representation of model physics, model parameters, and forcing data. Such uncertainties can be accounted for by constraining the model predictions with high-resolution and near-surface soil moisture observations, such as the dataset provided here. These data are also important for effective irrigation scheduling, crop yield modeling, and the accurate initialization of climate prediction models, which leads to more reliable climate forecasts. Soil moisture interacts with several hydroclimate variables including evapotranspiration, precipitation, land surface temperature, and albedo. Therefore, such data at fine resolution enable better understanding of the processes of the climate system at regional or local scales. The developed soil moisture product at 1-km spatial resolution can be used to identify, assess, and monitor the extent of (flash) drought, especially for agricultural practices. It can also play a key role in operational fire prediction and its risk assessment and management. Our downscaled SMAP soil moisture product has recently been successfully used in few hydroclimate studies. This dataset is currently available over the CONUS from April 2015 to the present and can be accessed via www.moradkhani.net/data/smap-data/.

Acknowledgments

Partial financial support for this project was provided by the National Oceanic and Atmospheric Administration (NOAA) Modeling, Analysis, Predictions, and Projections (MAPP) (Grant NA18OAR4310319). Also, partial financial support was provided by the National Science Foundation (NSF) (Grant EAR-1856054).

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