A SMAP-Based Drought Monitoring Index for the United States

Sara Sadri[UCLA], Eric F. Wood[Princeton University], and Ming Pan[Princeton University]

[University of California, Los Angeles (UCLA)]Department of Geography, 1255 Bunche Hall, Los Angeles, CA 90095
[Princeton University]Department of Civil and Environmental Engineering, 59 Olden St, Princeton, NJ 08540

Correspondence: Sara Sadri (sadri@princeton.edu)

Abstract. Since April 2015, NASA's Soil Moisture Active Passive (SMAP) mission has monitored near-surface soil moisture, mapping the globe between the latitude bands of $85.044°$N/S in 2-3 days depending on location. SMAP Level 3 passive radiometer product (SPL3SMP) measures the amount of water in the top 5 cm of soil except for regions of heavy vegetation (vegetation water content $> 4.5 kg/m^2$) and frozen or snow covered locations. SPL3SMP retrievals are spatially and temporally

5   discontinuous, so the 33 months offers a short SMAP record length and poses a statistical challenge for meaningful assessment of its indices. The SMAP SPL4SMAU data product provides global surface and root zone soil moisture at 9-km resolution based on assimilating the SPL3SMP product into the NASA Catchment land surface model.

Of particular interest to SMAP-based agricultural applications is a monitoring product that assesses the SMAP near-surface soil moisture in terms of probability percentiles for dry and wet conditions. We describe here SMAP-based indices over the

10   continental United States (CONUS) based on both near-surface and root zone soil moisture percentiles. The percentiles are based on fitting a beta distribution to the retrieved moisture values. To assess the data adequacy, a statistical comparison is made between fitting the distribution to VIC soil moisture values for the days when SPL3SMP are available, versus fitting to a 1979-2017 VIC data record. For the cold season (November-April), 57% of grids were deemed to be consistent between the periods, and 68% in the warm season (May-October), based on a Kolmogorov–Smirnov statistical test. It is assumed that

15   if grids passed the consistency test using VIC data, then the grid had sufficient SMAP data. Our near-surface and root zone drought index on maps are shown to be similar to those produced by the U.S. Drought Monitor (from D0-D4) and GRACE. In a similar manner, we extend the index to include pluvial conditions using indices W0-W4. This study is a step forward towards building a national and international soil moisture monitoring system, without which, quantitative measures of drought and pluvial conditions will remain difficult to judge.

1   Introduction

Understanding the risks associated with extreme hydrologic conditions, whether drought or pluvial events, is crucial for effective water management. Drought is an extreme condition when water in one or a combination of water stores (e.g. river, lake, reservoir, snowpack, soil water, or groundwater) or water fluxes (precipitation, evapotranspiration or runoff) drops below an appropriately defined condition for a prolonged period of time (Wilhite and Glantz, 1985; Wilhite, 2000; AMS, 2012). Such a

25   water deficit evolves over weeks to months and can lasts for months and years. Drought's propagation is silent and often without warning until it impacts human lives and environmental activities (Tallaksen and Van Lanen, 2004). Drought conditions

are related to water demand, so local water use plays a central role in defining conditions of scarcity and the resulting impacts. As defined by Wilhite (1985) (Wilhite and Glantz, 1985), drought is classified into meteorological, agricultural or hydrologic drought depending on whether the deficit is measured using precipitation, soil moisture or river discharge, respectively. The reduced supply of precipitation (and subsequently soil moisture) for crops leads to agricultural drought that impacts crop yield,

5   inflicting enormous economic impacts in developed countries and the suffering by millions of people in less developed regions of the world (Université Catholique de Louvain, 2009). Since 1996, the U.S. has seen at least one drought event per year (except for years 1997, 2001, 2004, and 2010), and each year drought costs between billion and 14 billion dollars in damages (in 2015 - adjusted dollars) (NCEI, 2017). In California alone, the 2015 drought was estimated to cause $2 - 5$ billion in damages to the agricultural sector (Howitt et al., 2015).

10   Although the impacts of drought are intimately linked to the vulnerability of a population to adverse conditions (UNDP, 2004) and how society responds within the constraints of changing economies, timely determination of the current level of agricultural drought aids the decision-making process in order to reduce its impacts. Scientifically-based drought monitoring tools and warning systems assist to mitigate the losses caused by droughts, and to plan and manage water shortages that will accompany future droughts (Martinez-Fernandez et al., 2016). Such drought monitoring tools are based on long-term

15   observations of the hydrological variables such as precipitation, streamflow, soil moisture, and groundwater. Pluvial conditions are related to an abundance of precipitation and subsequently wet soil conditions that can affect adversely agriculture by waterlogging the fields, or exacerbating flooding from additional rainfall. Thus, for monitoring extremes (either agricultural drought or pluvial conditions) realistic estimation of soil moisture at regional to continental scales is required. Soil moisture is the central source of information since it reflects recent precipitation and antecedent soil conditions (Sheffield and Wood, 2011).

20   In a sense, soil moisture captures the aggregate balance of all hydrological processes and represents available water, being a buffer between incoming precipitation and throughfall and evapotranspiration and drainage processes (Entekhabi et al., 1996). Unfortunately, soil moisture (and evapotranspiration) are among the least-observed components of the hydrological cycle, especially over large spatial and temporal scales (Reichle, 2017; Sheffield and Wood, 2011).

Many statistical measures, or indices, for extreme conditions have been developed in the U.S.; particularly for drought

25   conditions. This is due to the slow evolution of drought and its economic and social impact, while for pluvial conditions, they show a potential for floods over a relatively short period. Currently, no single drought index has been able to adequately capture the severity and intensity of drought and its impact on different groups of users (Heim, 2002). Heim (2002) summarizes and gives an overview of the major twentieth century U.S. drought indices. The most common ones are the Standardized Precipitation Index (SPI), Palmer Drought Severity Index (PDSI), Standardized Runoff Index (SRI) and the U.S. Drought

30   Monitor (DM or USDM). SPI is recognized by the World Meteorological Organization (WMO) as the standard index for quantifying and reporting meteorological drought. It is used to characterize drought on a range of timescale ranging from 1 to 36 months. SPI quantifies observed precipitation as a standardized departure from an underlying distribution function for precipitation. The raw precipitation is fit to an appropriate distribution function, then transformed into a standardized Normal distribution. The SPI index is expressed as the number of standard deviations by which the anomaly deviates from the long term

35   mean. Usually 30 years of monthly data is recommended for fitting the data. On short timescales, SPI is closely related to soil

moisture while at long timescales it is related to groundwater. The advantages of SPI is that it only relies on precipitation and can characterize both drought and pluvial conditions, and its computation over different timescales can be related to various water resource stores (such as soil moisture and groundwater). The PDSI uses precipitation and an estimate of evaporation in conjunction with a water balance model to estimate relative soil dryness. The original formulation used temperature to estimate

5   a potential evapotranspiration, but it is now recognized that a energy-based estimate such as the Penman-Monteith approach is preferred (Sheffield et al., 2012; Mo and Chelliah, 2006). One weakness of the PDSI is its inability to handle winter-time conditions that include snowmelt and frozen precipitation, which makes its long-term monitoring problematic. The USDM integrates several drought indices and professional input from all levels into a weekly operational drought-monitoring map product (Svoboda, 2000). The limitation of the USDM lies in its attempt to show drought at several temporal scales (from

10   short-term drought to long-term drought) on one map product. Hence, the application of the DM is not to replace any local or state information or subsequently declared drought emergencies or warnings, but rather to provide a general assessment of the current state of drought around the United States, Pacific possessions, and Puerto Rico (Svoboda, 2000). Since the USDM relies on professional inputs from the field, it is difficult to have historical consistency (since the professionals change) or to provide forecasts.

15   Long-term and large scale observations of soil moisture are scarce in the United States and elsewhere, so datasets produced by the North American Land Data Assimilation System (NLDAS) are valuable alternatives. For example, Sheffield et al. (2004) used simulations from the NLDAS Variable Infiltration Capacity (VIC) model forced with observed precipitation and near surface meteorology to develop a soil moisture based drought index. Currently NCEP offer a NLDAS drought monitor (NOAA, 2018) based on four land surface models (LSM): VIC, Noah, Mosaic and Sacramento forced with NLDAS forcings.

20   The approach ((Sheffield et al., 2004)) is to fit the model-simulated soil moisture from a probability distribution, usually a beta distribution, where the percentiles are translate to the index values that range from 0 to 1. Recent drought applications such as the VIC-based Princeton University drought and flood monitoring systems for Africa and Latin America (Sheffield et al., 2014) use model simulated soil moisture based on satellite precipitation (Group, 2013). A major limitation of the indices discussed earlier, as well as the LSM based approaches, is a reliance on quality meteorological data. While precipitation is one of the

25   best observed variables, gauge observations are limited in many regions, especially over much of the developing world (e.g. Africa). Even when they are available, the are often not in near real time, preventing computing indices. This reveals one of the weaknesses of the above indices: their estimates rest on the availability and accuracy of the forcings, specifically precipitation (Reichle, 2017). In places such as U.S. where the quality of the precipitation data is quite high, VIC skill is relatively high also (Pan et al., 2016). However, in regions with sparse networks or low accessibility, such as Africa, the VIC skill can be relatively

30   low (Reichle, 2017). Additionally, Robock et al. (2000) intercompared four NLDAS models and found that soil moisture differs a great deal among models.

    Heim (2002) summarizes four characteristics of a useful operational drought monitoring system. These include: 1) the indices need to be available on a near-real-time basis; 2) the indices need to be monitored on a national scale, which will require the establishment of national networks for some variables; 3) a complete and reliable historical data are needed over

35   a common reference period to allow conversion of the observations to a meaningful form (such as a percentile ranking); and

4) the data need to be adjusted to remove non climatic influences (such as those arising from water management practices) (Friedman, 1957; Heim, 2002).

An alternative approach to using model-derived soil moisture for drought detection and prediction is satellite-derived soil moisture. There are currently four major satellite-based systems that provide soil moisture products at various spatial and

5   temporal resolutions: MetOp with the advanced scatterometer (ASCAT) (Brocca et al., 2010; Wagner and others, 2013), JAXA's Advanced Microwave Scanning Radiometer AMSR2 (Parinussa et al., 2015; Wu et al., 2015) with the C- and X Band passive radiometers on the GCOM-W1 satellite that is a follow-on to the AMSR-E sensor, which failed on 4 October 2011 and was part of NASA's Earth Observing System; ESA's Soil Moisture Ocean Salinity (SMOS) L-band radiometer (Pan et al., 2010; Kerr et al., 2012, 2016) and NASA's Soil Moisture Active Passive (SMAP) L-band radiometer Entekhabi et al. (2010). The radar

10   on SMAP failed after three months, but soil moisture estimates based on the radiometer continue to be produced. Of particular interest, especially for applications in parts of the globe with sparse in-situ data, is to have a SMAP-based monitoring product that expresses soil moisture in terms of probability percentiles for dry (drought) or wet (pluvial) conditions (Entekhabi et al., 2010). In this study, SMAP-based indices are developed and assessed over the continental United States (CONUS) for both a near-surface (5cm) SPL3SMP and root zone SPL4SMAU products. The SMAP data is discussed in section 2.1, including a

15   determination whether its 33 months are sufficient to estimate a drought index. Section 2.2 develops the indices by fitting a beta distribution, with upper and lower bounds, to the time series and using the percentiles as the index. In section 3, comparisons are made to currently available drought indices. To help relate the percentiles to the U.S. Drought Monitor, which uses levels D0-D4 to indicate severity, the percentiles are mapped similarly. This is extended in a similar manner to pluvial conditions using indices W0-W4. Some discussion and conclusions are brought in sections 4 and 5, respectively.

2   Data and Methods

2.1   SMAP Data

Since 31 March 2015, NASA's Soil Moisture Active Passive (SMAP) mission has monitored near-surface soil moisture, mapping the globe (between $85.044° N/S$) using an L-band (1.4 GHz) microwave radiometer. (The radar system failed 3 months into the mission.) The SMAP mission provides a set of operational global data products that include Level 1 brightness temper-

25   atures at a 36 km resolution (Chan et al., 2016), a SPL3SMP daily passive radiometer based surface soil moisture (nominally 5-cm) at 36 km EASE-grid resolution (O'Neill et al., 2016) and a Level 4 (SPL4SMAU),3hrly, 9 km (EASE-grid) assimilated root zone soil moisture(Reichle et al., 2015). In this study the SPL3SMP and SPL4SMAU products are used in the analysis. For SPL3SMP, the operational product provides a composite of daily estimates of global land surface soil moisture conditions (nominally at 5-cm) that are resampled to a global, cylindrical 36 km Equal-Area Scalable Earth Grid, Version 2.0 (EASE-Grid

30   2.0). Regions with frozen ground or snow covered are masked out based on a frozen ground flag using a Normalized Polarization Ration (NPR)-based passive freeze-thaw retrieval. Given the 1000-km swath and 98.5 minute orbit, the retrievals are spatially and temporally discontinuous with 2-3 day gaps depending on location. The SPL4SMAU products are developed by assimilating the SMAP L-band brightness temperature data (from descending and ascending half-orbit satellite passes, approx-

imately 6:00 a.m. and 6:00 p.m. local solar time, respectively) into NASA's Catchment LSM (Reichle, 2017) that is gridded using an Earth-fixed, global, cylindrical 9 km Equal-Area Scalable Earth Grid, Version 2.0 (EASE-Grid 2.0) projection. Both a surface and a root zone SPL4SMAU product are provided but in this study we only use the root zone product. The land surface model component of the assimilation system is driven by a forcing data stream from the global atmospheric analysis system

5 at the NASA GMAO (Rienecker and coauthors, 2008), and disaggregated to the SMAP 9 km EASEv2 model grid. Additional corrections are applied using gauge- and satellite-based estimates of precipitation that are downscaled to the temporal and 9 km scale of the model forcing using the disaggregation methods described in Liu et al. (2011) and Reichle et al. (2011).

The SPL4SMAU algorithm interpolates and extrapolates the information from SMAP observations and the model estimates in time and space, taking into consideration the relative uncertainties of each; the L4 product represents the merged information

10 (Reichle, 2017). The product provides global soil estimates for the surface (0-5 cm) and "root zone" (0-100 cm), and is an effort to provide continuous, daily information without the discontinuous data provided by the SPL3SMP radiometer retrievals. Nonetheless, the only product that doesn't use ancillary meteorological data is the SPL3SMP soil moisture retrievals.

2.1.1 Fitting the SMAP time series

The short SMAP record length (1,009 days, from 2015-04-01 to 2017-12-31) provides a statistical challenge in estimating

15 the drought and pluvial indices, and thus the risk assessments related to these extreme conditions. The approach selected here follows Sheffield et al. (2004) where the soil moisture time series are fit to a beta distribution (with upper and lower bounds) and the distribution percentiles are the index values. To assess the data adequacy, we use a 1979-2017 VIC LSM simulation over CONUS. The VIC runs were carried out at a 4-km spatial resolution, and for the SPL3SMP comparisons averaged up to 36-km and here we refer to it as VIC near surface (VIC-ns). The SPL4SMAU is at 9-km spatial resolution, so VIC data were

20 aggregated from 4 km computing grids, and averaged over 3 soil layers with varying total soil thickness and we refer to it as VIC root zone (or VIC-rz). A statistical comparison is made between fitting a beta distribution to the VIC soil moisture values using only days when SPL3SMP soil moisture retrievals are available and for the complete 1979-2017 VIC data record. The Kolmogorov–Smirnov (KS) statistical test was used to evaluate the consistency of the beta fitted data. We made the assumption that grids that passed the consistency test using VIC data – i.e. the distribution from the SMAP period record and the complete

25 record were deemed statistically the same – then the SMAP time series over that grid was sufficient to provide a index. More discussion of these results are given in section 2.4.

From April 2015 to December 31, 2017, SMAP had a total 33 months of observations. For many grids over CONUS, the soil moisture density histogram showed two peaks with a dry and wet mode. Further analysis showed these to be related to the warm and cold season periods. To capture this inter-seasonal behavior in soil moisture, we divided the record into a warm

30 season (April - September) and a cold season (October - March). Since April 1, 2015, there have been between 144 and 329 SPL3SMP soil moisture retrievals during the warm season and from 16 to 272 retrievals during the cold season. Figure 1 shows that the number of overpasses are related to the latitude, with higher latitudes having higher number of overpasses, and to the season, with fewer values retrieved during winter, especially in the western U.S., due to snow cover and frozen ground. For LSPL4SMAU root zone, there are 457 records for the cold season and 549 records for the warm season for each grid.
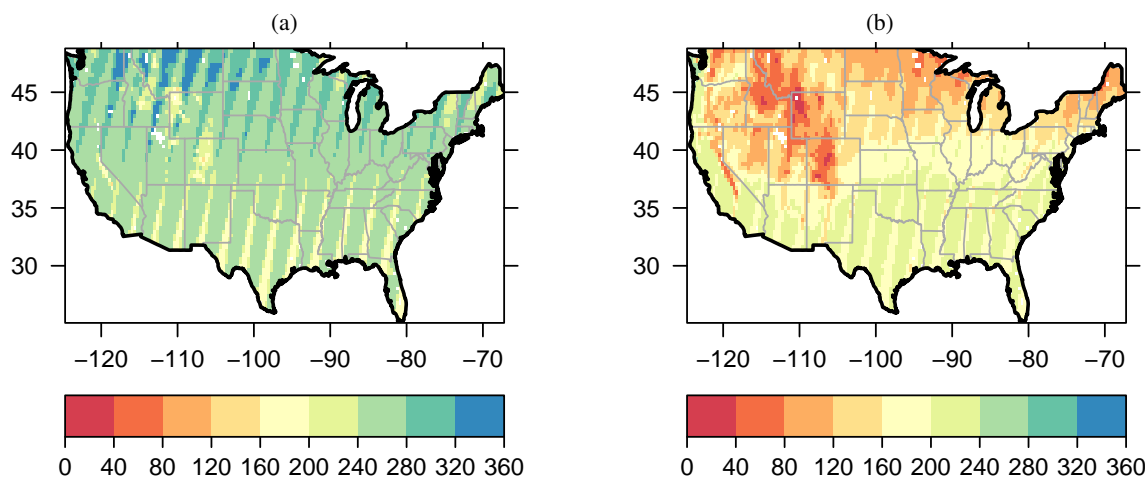
Figure 1. Number of overpasses for each season. (a) is warm season April 1 - September 30; (b) is cold season, October 1 - March 31).

2.2 Fitting the Beta distribution

The beta distribution is a family of continuous distributions. In this paper we use the version with two shape parameters p and q, and two range parameters a and b. It generalizes to a bounded distribution on the interval of $[a, b]$, where a and b usually take on the values of 0 and 1. The beta distribution is flexible enough to accept a wide variety of shapes. The general formula
5 for the beta probability distribution function (pdf) is:

$$f(x) = \frac{(x-a)^{(p-1)}(b-x)^{(q-1)}}{B(p,q)(b-a)^{p+q-1}} \quad a \le x \le b; \quad p, q > 0 \tag{1}$$

where p and q are shape parameters, a and b are lower and upper bounds of the distribution, respectively. In case where $a = 0$ and $b = 1$, this becomes a standard beta distribution (NIST, 2013). The normalizing beta constant $B(p, q)$ is defined by

$$B(p,q) = \int_0^1 t^{p-1}(1-t)^{q-1}dt \tag{2}$$

10 The beta distribution takes on values between a and b. In some literature only the case $a = 0$, $b = 1$ (standard beta distribution) is studied but the general case is more useful here because it allows us to select a distribution matching the observed range of variability. In our study, we compared beta distribution with several parametric distributions (including Normal and Gumble), but given the bounded nature of the distribution, beta distribution is often used as the model of choice for modeling soil moisture time series (Sheffield et al., 2004).

15 Given a set of empirical observations, how should we fit the four parameters? The approach followed in Sheffield et al. (2004) estimated the lower and upper bounds (a and b) by fitting a line to the lower and upper 10% of the data and extrapolating to

where the pdf had zero density. In our study, this approach didn't yield useful results with the estimated limits for a (b), often larger than the smallest value (smaller that the largest value). Alternatively, we could have selected a (b) as the smallest (largest) value approach as suggested by AbouRizk et al. (1994), but given our short record length for SMAP we were concerned that the resulting distribution would be too bounded due to the weather over the SMAP period. The approach taken was to compute for

5   each grid the ratio of the smallest soil moisture value from the full VIC record divided by the smallest soil moisture value from the short VIC record, and then set a for that grid as the smallest SMAP retrieval multiplied by the ratio. The same approach was used for b. This was followed for both the SPL3SMP and SPL4SMAU analysis. When fitting VIC distributions, we set the short VIC and long VIC records $a(b)$ were set to the smallest (largest) value.

Sheffield et al. (2004) used the method of moments to fit the beta distribution to historical soil moisture simulations from

10   the VIC LSM. They computed the first three moments and minimized the difference between the distribution estimates and sample estimates since they were over-constrained. We used the standard method of moments to calculate the parameters p and q. Thus, for each grid location, the beta distribution was fitted to 6 sets of data related to the SPL3SMP product: Short warm season VIC and SMAP (1 April - 30 September for 2015, 2016, 2017; 18 months); Long warm season VIC (1 April - 30 September, 1979-2017; 129 months); Short cold season VIC and SMAP (1 October - 31 March, 2015-2016; and 1 October - 31

15   December 2017; 15 months); Long cold season VIC (1 October - 31 March for 1979 and 2016; and 1 October - 31 December for 2017; 126 months), using the first and second moments:

$$\mu = \frac{p}{p+q} \tag{3}$$

$$CV = \frac{\mu}{\sigma} \tag{4}$$

20   where σ is the standard deviation defined as:

$$\sigma = \sqrt{\frac{p*q}{(p+q)^2*(p+q+1)}} \tag{5}$$

For the SPL4SMAU root zone soil moisture product, the beta distribution was fit to the warm season and cold season using all 457 retrievals. After being fitted to beta distributions, Figure 2 show the 20th percentile, average and 80th percentile soil moisture data in the warm season and cold season respectively for SPL3SMP 5-cm soil moisture product, and similarly in

25   Figure 3 for the SPL4SMAU root zone product.

2.3   Data Adequacy

It is assumed that if the short VIC time series, fitted to the beta distribution is statistically consistent with long VIC time series, then we can assume that short SMAP time series would be consistent with a hypothetical long SMAP time series. This is possible since the correlation between SPL3SMP and VIC is quite high. Correlation mpas are shown in Figure 4 between

30   the SMAP 5-cm SPL3SMP product and VIC upper 10-cm product for the warm season and cold period periods. Overall the
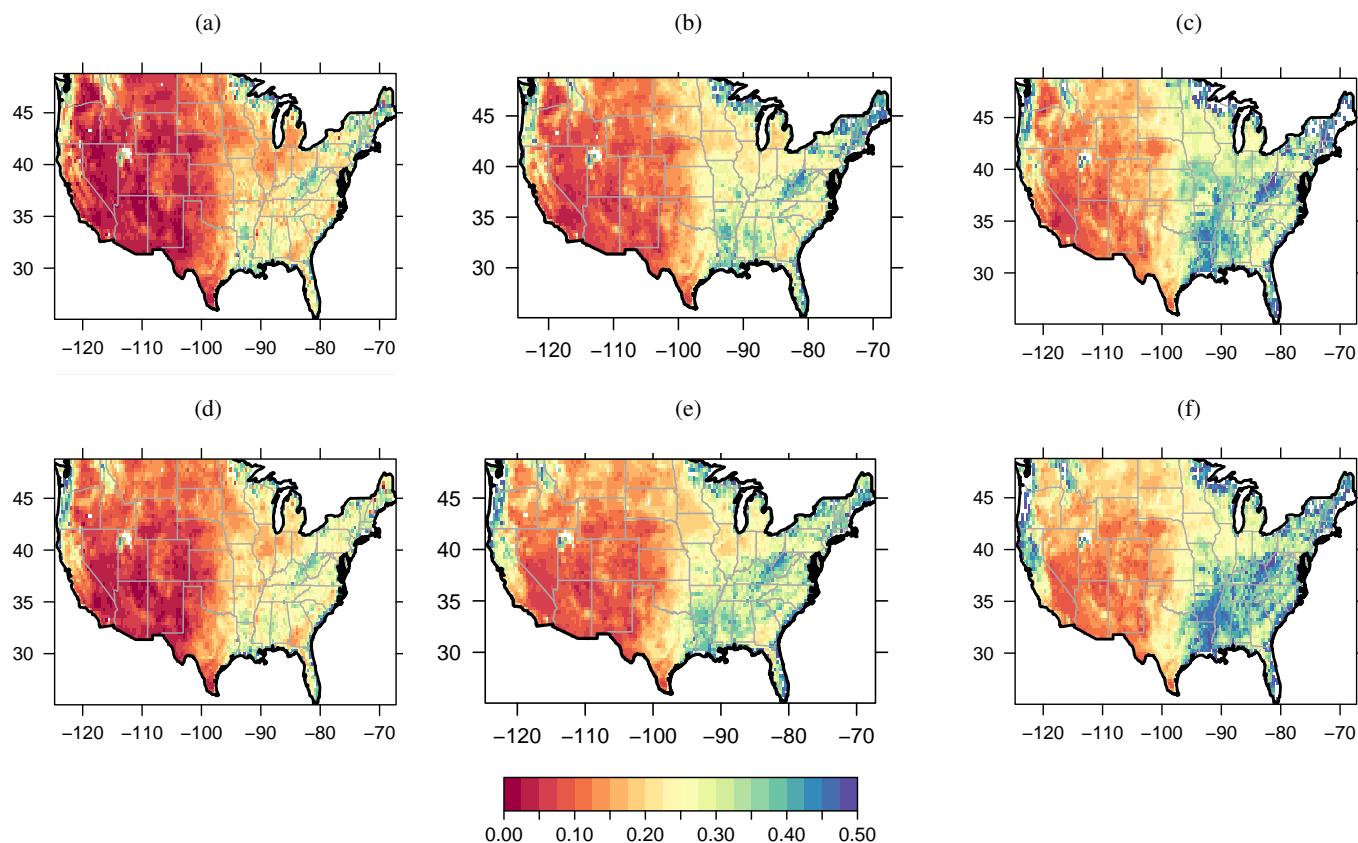
Figure 2. top row: SMAP index for the warm season for during summer for SPL3SMP top 5-cm soil moisture ((a), 20th percentile; (b), average soil moisture; (c), 80th percentile; bottom row: as the top row except for the cold season. Total period is from 2015/04/01 to 2017/12/31

average correlation for both warm and cold seasons are high and around 0.6. During the warm season, the Central Valley and Southern California, Florida, northeastern U.S., and north of Wisconsin and Minnesota show poor correlation with VIC. The extent of this poor correlation increases during the cold season for northeastern U.S., Wisconsin and Minnesota. But contrary to the warm season, southern California shows a high a correlation with VIC during the cold season. We attribute this change to California irrigation that SMAP picks up, but VIC doesn't since the version used here doesn't have water management effects. One would expect to see a similar effect in regions like Nebraska, but it doesn't appear to be as pronounced. While systematic biases do not get revealed in correlations, the temporal consistency among the time series is captured.

A Kolmogorov-Smirnov (KS) test was applied for goodness-of-fit. The KS test is a well known nonparametric statistical test that compares whether two time series are coming from the same continuous distribution. It can also be used to statistically evaluate whether the fitted beta distribution and the retrieved data come from the same (beta) distribution. The KS test was done for six comparisons: between short warm season VIC and long warm season VIC, short cold season VIC and long cold season VIC, short warm season and raw SMAP retrievals, and short cold season and raw SMAP retrievals. The null hypothesis
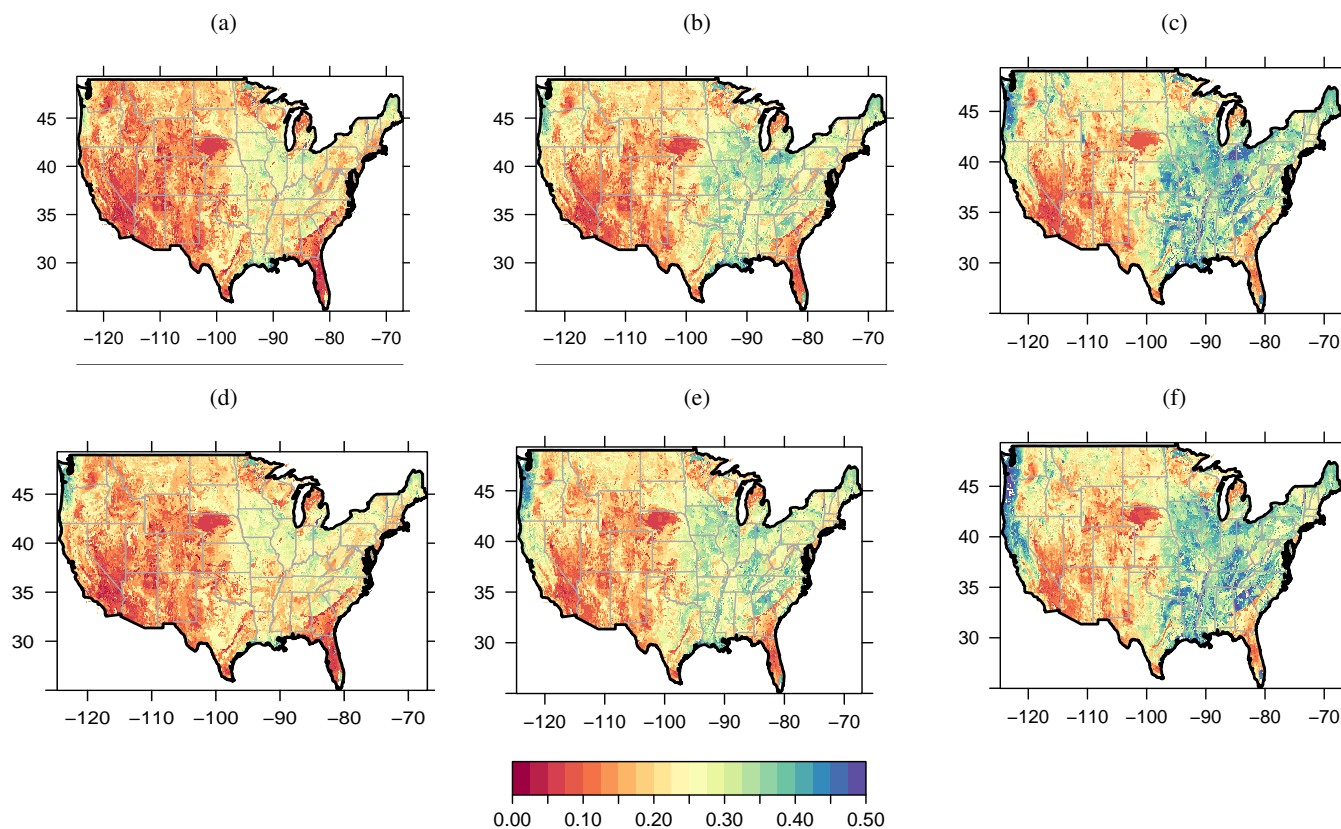
Figure 3. As shown in figure 2 except for SPL4SMAU (root zone soil moisture).

that the soil moisture data were sampled from a beta distribution or that the underlying beta distribution of short soil moisture data is the same as the underlying beta distribution of long soil moisture data is rejected for values of D that exceed a critical value at the 95% significance level. The critical value $D_{critical}$ at the 95% significance level was estimated as:

$$D_{critical} = \frac{1.36}{\sqrt{n}} \tag{6}$$

5 where n is the number of observed variable (Lindgren, 1962).

Figure 5 presents the results where we have confidence that the SMAP drought (pluvial) indices provide reliable risk levels given the current period of record. As the record length gets extended, the above analysis needs to be repeated to see if the adequacy changes. Warm season shows at least 11% more in the number grids whose pass the adequacy test. This might suggest that with the current length of SMAP data, it shows a stronger capability in drought index than pluvial or flood monitoring.The

10 use of the information in Figure 5 should guide water managers in determining if SMAP drought or pluvial risk levels are reliable.
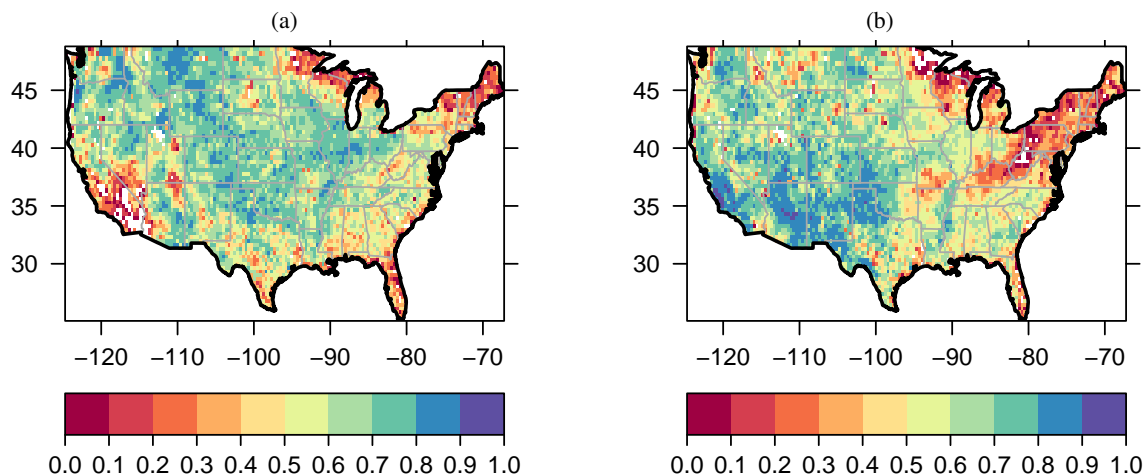
Figure 4. (a) Correlations between VIC and SMAP for the warm season (R=0.63) and (b) cold season (R=0.61). White regions signify negative correlation.
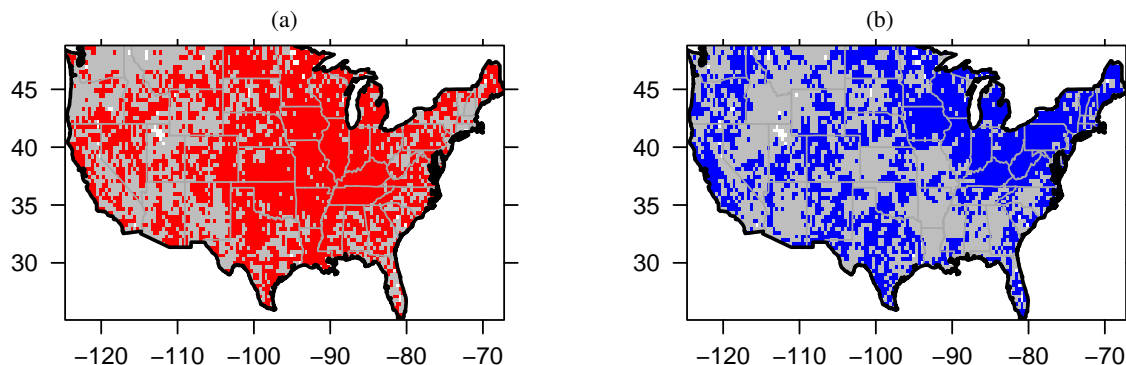

Figure 5. (a) Grids whose short term VIC warm season data has the same underlying beta distribution as the long warm season data shown in red, n = 3560 or 68% of grids; (b) the same as the left figure but for cold season period shown in blue, n = 2927 or 57% of grids.

3 Comparison to other indices

In the introduction we discussed a number of drought index products ; mostly those related to soil moisture. In this section we will compare a selection of soil moisture drought indices for days where the various products were available.

The following indices are compared with the SMAP index. For surface soil moisture index based on level 3 data (SPL3SMP), we provide a 3-day composite to offer a more continuous coverage. This is compared the 1-month SPI (SPI-1) index, a VIC LSM index, and the USDM. For SMAP soil moisture index based on the Level 4 product (SPL4SMAU), comparisons are made with a 3-month SPI (SPI-3) index and a GRACE satellite product. All the products except for GRACE are described in Section 1.

GRACE is NASA's Gravity Recovery and Climate Experiment (GRACE) satellite system that detects small changes in the Earth's gravity field caused by the redistribution of water on and beneath the land surface. Combined with the Catchment Land Surface Model using an Ensemble Kalman smoother data assimilation Zaitchik et al. (2008), GRACE maps root zone soil moisture and groundwater transformed into percentiles (NDMC, 2018b).

5   Figure 6 shows drought during the period from January 4 through October 17, 2017. for both near surface and root zone. In this period, there was one agricultural drought event in Montana, and North and South Dakota, with losses exceeding $1 billion across the United States (NCEI, 2017). The plains of eastern Montana experienced exceptional drought throughout July to October, 2017 and in late October drought started to recover. The peak of the drought was in July 2017 when 20% of Montana was in severe drought and 23% of it in moderate drought. Concurrently, 40% of North Dakota was in extreme drought while
10   70% of the state was under some level of drought, and similarly, 68% of South Dakota was under severe drought (NCEI, 2017).

In Figure 7, drought during the period of October 3 to November 8, 2016 is shown for both near surface and root zone. In 2016, there were three drought events in the western, northeastern and southeastern parts of the U.S.. The drought had mostly been alleviated in northern California by near-normal precipitation during the 2015-16 Winter, and above normal precipitation in the Fall 2016. To the extent that the drought persisted in Southern California after this period, it is reflected in total column
15   soil moisture rather than near-surface soil moisture (Figure 9) .

In general, there is a high correspondence among the drought maps, particularly in the development of the drought in the southeastern U.S. during October and November 2016. Due to heavy rainfall along the Mississippi River in November, the drought migrated eastwards. Also, by November 2016 the drought in southern California was alleviated, which is picked up by SPL3SMP, SPL4SMAU, VIC-ns and VIC-rz, SP-1 and 3, GRACE, and to a much lesser extent by the USDM that showed
20   an increasing area under drought on November 28 compared to SPL3SMP, SPL4SMAU, GRACE, or VIC-ns and VIC-rz. Additionally, for the maps that also include wetness (all except USDM), there is a high correspondence of pluvial regions (example Figure 8).

4   Conclusions

The drought index described in this study provides a consistent estimate of state of drought on a daily basis in high resolution
25   for most of the United States. The scope of this paper is limited since the range of SMAP data is limited (only 33 months composed of 18 months of summer and 15 months of winter, over the course of almost 2.5 years). The data available do not yet represent the range of interannual variability. Therefore, the results should be considered a demonstration of the reliability and usefulness of SMAP for a drought monitoring product and for implementation into an operational drought-monitoring tool.

The study presented initial insights and the potential of using SMAP for monitoring drought and pluvial regional with a first
30   application over CONUS. Soil moisture data from SMAP at both SPL3SMP and SPL4SMAU were fitted to a beta distribution and were used to construct probability distributions for warm and cold seasons. Dividing the year into warm and cold seasons enabled us to track the soil moisture dynamics, and thus the probability distribution and index seasonally.
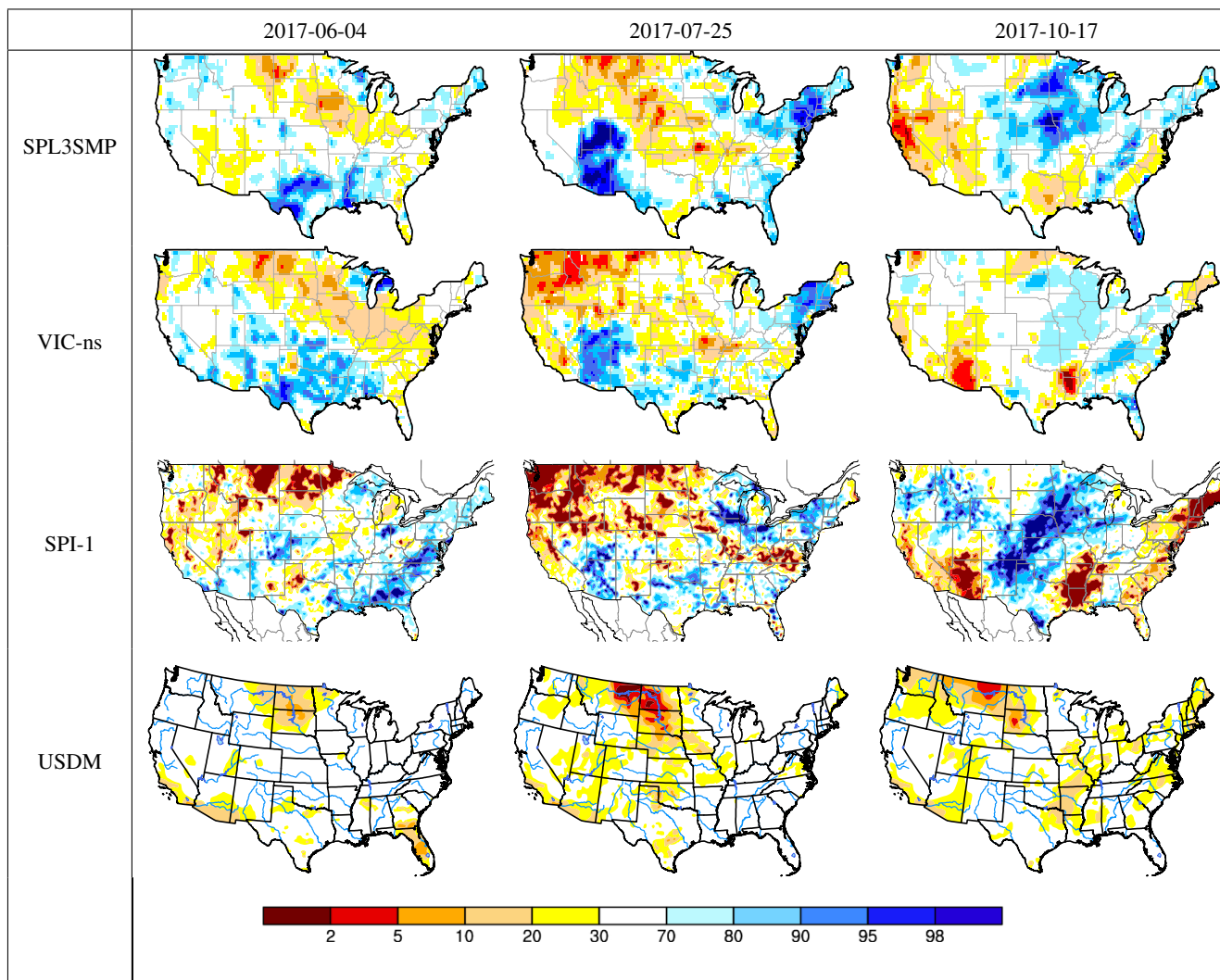
Figure 6. Comparison of 3 dates of SPL3SMP index map with VIC-ns, SPI-1, and USDM in 2017. For USDM, drought levels covering from 30 to 100 are shown in white.

The soil moisture data are a culmination of all hydrological processes and represents available water from incoming precipitation and throughfall to evapotranspiration and drainage processes. Hence soil moisture has been one of the most desirable variables for water management, yet unfortunately sparsely observed. The SMAP satellite is providing global observations of soil moisture of unprecedented quality. This study indicates there is the potential for SMAP data to contribute as a critical monitoring tool globally for both drought and pluvial conditions.

Producing soil moisture drought index in two different soil depths allows for monitoring of agricultural drought in different stages of development. This is important, first, because grid analysis showed that full column soil moisture index can be less, similar, or more than near surface soil moisture index depending on the location. Secondly, depending on the stage of plant
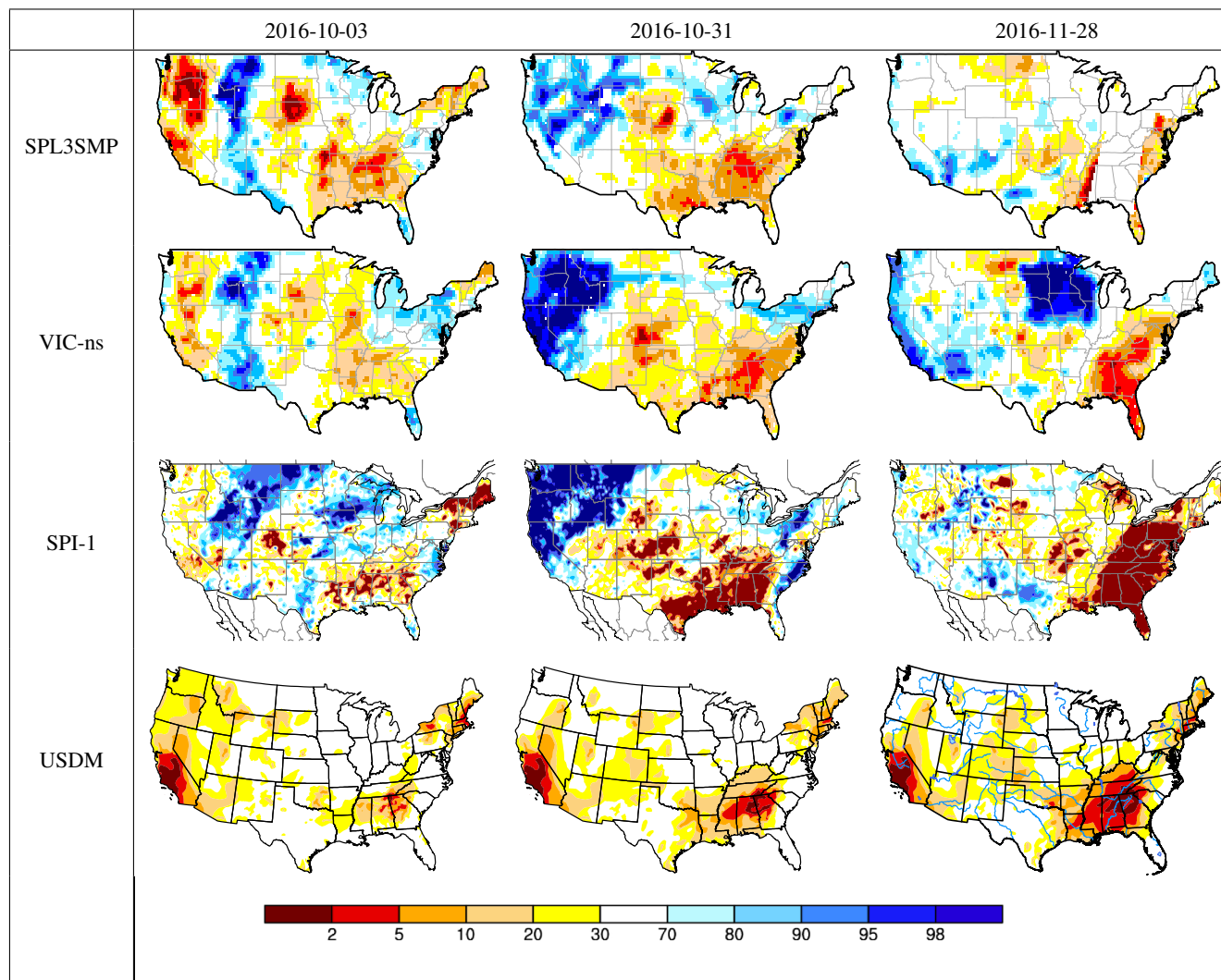
Figure 7. Comparison of 3 dates of SPL3SMP index map with VIC-ns, SPI-1, and USDM in 2016. For USDM, drought levels covering from 30 to 100 are shown in white.

development, surface soil moisture or root zone soil moisture drought index can be more useful in agricultural management. For example, surface soil moisture is important in the germination stage but less so for managing irrigation or in estimating yields. Deficient topsoil moisture at planting may hinder germination, leading to low plant populations per hectare and a reduction of final yield (NDMC, 2018a). At the same time root zone moisture at this early stage may not affect final yield but as the growing

5 season progresses it becomes more important for plant water needs.

The lower and upper percentile maps of soil moisture reveal the dynamics of precipitation in the upper and lower soil levels. For example, Florida and the southeast have higher surface moisture but drier root zone soil moisture at 80%. This can be related to over-extracting from groundwater resources in those regions. On the other hand, some areas in the U.S. such as
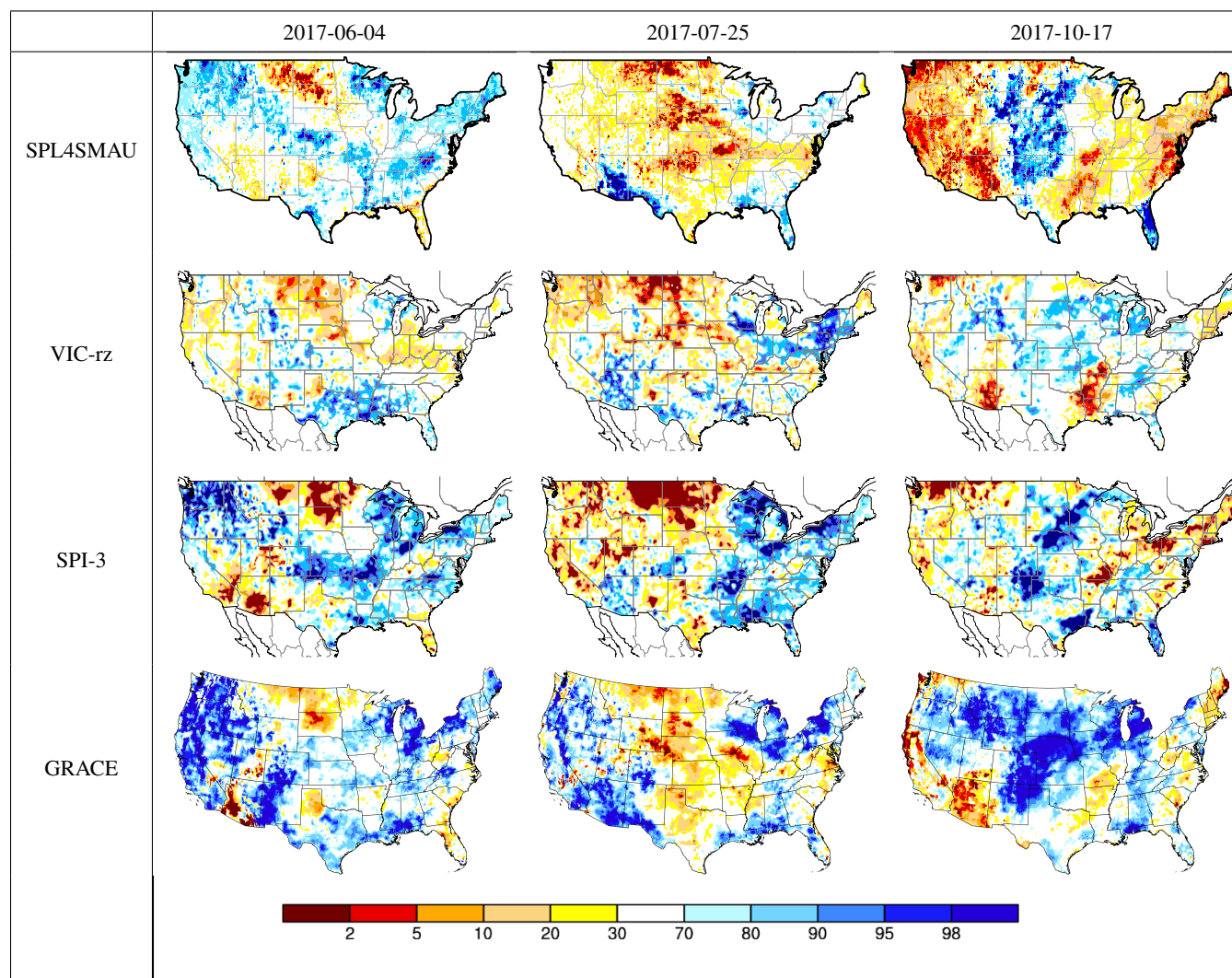
Figure 8. Comparison of 3 dates of SPL4SMAU index map with VIC-rz, SPI-3, and GRACE in 2017.

Wisconsin and Illinois with moderate surface soil moisture show higher root zone soil moisture. While the soil type (silty clay loam) in these areas is one of the most productive type of soil in the world, it seems that the presence of deep bedrock and large aquifers below southern Wisconsin and northern Illinois states contributes largely to groundwater and root zone replenishment to provide higher soil moisture than the surface soil moisture.

5   Besides drought, SMAP can also identify regions of anomalously wet conditions that can be of great use to water and agricultural managers. Wet conditions can indicate potential flood-prone conditions and therefore regions can be put on flood alerts if additional heavy rain occurs. Also, wet conditions can impact farm management, especially in the spring when sowing takes place or during the harvesting period.
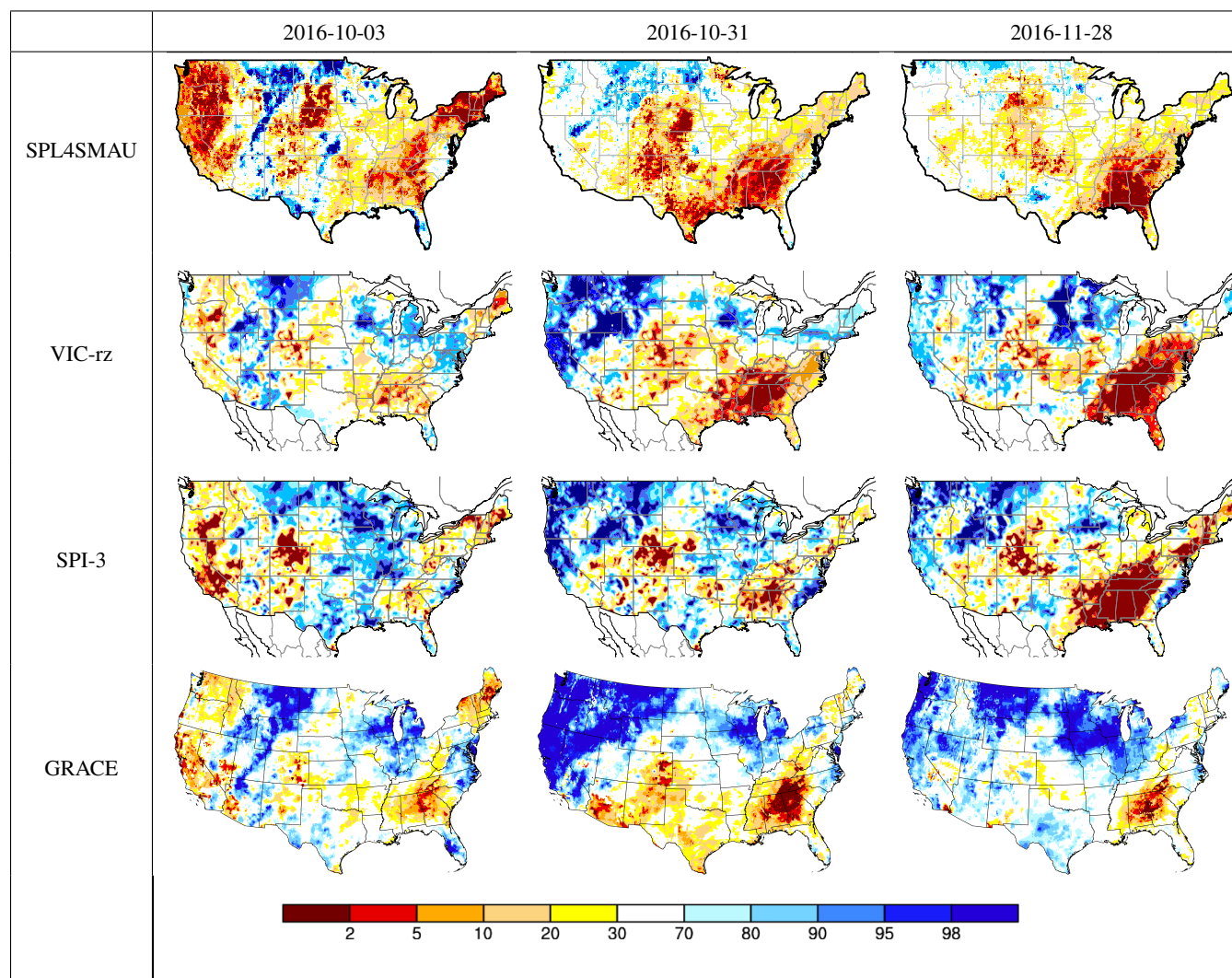
Hydrology and
Earth System
Sciences
Discussions

Figure 9. Comparison of 3 dates of SPL4SMAU index map with VIC-rz, SPI-3, and GRACE in 2016.

Through comparing SMAP based index maps for drought and wet conditions with other index products we see high similarity. Although there can be some errors at different levels, the overall evaluation reveals that SMAP based drought products can be a viable alternative for drought monitoring in the U.S.. One advantage for SMAP is that the index is generated at a daily resolution with almost complete coverage every three days. This enables observing the effect of fluctuations in other hydrological variables, such as precipitation. In comparison, USDM, GRACE, and SPI have low temporal resolution which makes it difficult in studying the shorter-term impacts from the other variables on soil moisture.

Future applications of this study can be coupling plant growth models with near surface and root zone soil moisture drought index products. Plant growth models can take into account the plant water demand, prevailing weather conditions, biological characteristics of the specific plant, its stage of growth, and the physical and biological properties of the soil (NDMC, 2018a).

Both near surface and root zone soil moisture drought products can provide important information about the availability of soil moisture at the stage which plant is developing in order to cultivate the optimum harvest.

Because SMAP monitors soil moisture directly, and provides critical information for drought early warning, it is important that the future developments focus on drought assessment using SMAP in underrepresented parts of the world, such as Africa

5   and the Middle East. The results here provide significant support for a global SMAP drought monitoring system.

Such a system would be an important step towards building an international soil moisture monitoring system, without which, quantitative measures of drought will remain difficult to judge. The fact that SMAP data can be retrieved and drought index maps can be generated in real time is very promising and suggests that a SMAP drought index product can be implemented operationally.

10   *Data availability.*   The SMAP-based drought index product at daily resolution for CONUS is available at http://hydrology.princeton.edu/smap-drought

Hydrology and
Earth System
Sciences

Open Access

EGU

Discussions

References

AbouRizk, S. M., Halpin, D. W., and Wilson, J. R.: FITTING BETA DISTRIBUTIONS BASED ON sample data, Journal of Construction Engineering and Managemen, 120, 5156, 1994.

AMS: Drought, http://glossary.ametsoc.org/wiki/Drought, 2012.

5 Brocca, L., Hasenauer, S., Lacava, T., Melone, F., Moramarco, T., Wagner, W., Dorigo, W., Matgen, P., Martinez-Fernandez, J., Llorens, P., Latron, J., Martin, C., and Bittelli, M.: Soil moisture estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study across Europe, Remote Sens. Environ., 115, 3390–3408, https://doi.org/10.1016/j.rse.2011.08.003, 2010.

Chan, S., Bindlish, R., O'Neill, P., Njoku, E., T.Jackson, Colliander, A., Chen, F., Burgin, M., Dunbar, S., Piepmeier, J., Yueh, S., Entekhabi, D., Cosh, M., T.Caldwell, Walker, J., Wu, X., Berg, A., Rowlandson, T., Pacheco, A., McNairn, H., Thibeault, M., Martinez-Fernandez,

10 J., Gonzalez-Zamora, A., Seyfried, M., Bosch, D., Starks, P., Goodrich, D., Prueger, J., Palecki, M., Small, E., Zreda, M., Calvet, J., Crow, W., and Kerr, Y.: Assessment of the SMAP Passive Soil Moisture Product, IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, 54, 4994–5007, 2016.

Entekhabi, D., Rodriguez-Iturbe, I., and Castelli, F.: Mutual interaction of soil oisture state and atmospheric processes, Journal of Hydrology, 184, 3–17, 1996.

15 Entekhabi, D., Njoku, E. G., O'Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T. J., Johnson, J., Kimball, J., Piepmeier, J. R., Koster, R. D., Martin, N., McDonald, K. C., Moghaddam, M., Moran, S., Reichle, R., Shi, J. C., Spencer, M. W., Thurman, S. W., Tsang, L., and Van Zyl, J.: The Soil Moisture Active Passive (SMAP) Mission Proc., IEEE, 98, 704–716, https://doi.org/10.1109/JPROC.2010.2043918, 2010.

Friedman, D. G.: The prediction of long-continuing drought in south and southwest Texas, Occasional Papers in Meteorology, p. 182, the

20 Travelers Weather Research Center, Hartford, CT, 1957.

Group, P. U. H.: url:http://stream.princeton.edu/CONUSFDM/WEBPAGE/interface.php?locale=en, 2013.

Heim, R. R., J.: A review of twentieth century drought indices used in the United States, Bull. Am. Meteorol. Soc., 83, 1149–1165, 2002.

Howitt, R. E., Medellin-Azuara, J., MacEwan, D., Lund, J. R., and Daniel, A.: Economic Impact of the 2015 Drought on Farm Revenue and Employment Sumner, Agricultural and Resource Update, Giannini Foundation of Agricultural Economics, University of California,

25 Davis., 2015.

Kerr, Y. H., Waldteufel, P., Richaume, P., Wigneron, J. P., Ferrazzoli, P., Mahmoodi, A., Al Bitar, A., Cabot, F., Gruhier, C., Juglea, S. E., Leroux, D., Mialon, A., and Delwart, S.: The SMOS Soil Moisture Retrieval Algorithm, IEEE Trans. Geosc. And Remote Sens., 50, 1384–1403, https://doi.org/10.1109/TGRS.2012.2184548, 2012.

Kerr, Y. H., Al-Yaari, A., Rodriguez-Fernandez, N., Parrens, M., Molero, B., Leroux, D., Bircher, S., Mahmoodi, A., Mialon, A., Richaume,

30 P., Delwart, S., Pellarin, A. A. B. T., Bindlish, R., Rudiger, T. J. C., Waldteufel, P., Mecklenburg, S., and Wigneron, J.: Overview of SMOS performance in terms of global soil moisture monitoring after six years in operation, Remote Sens. Environ., 180, 40–63, https://doi.org/10.1016/j.rse.2016.02.042, 2016.

Lindgren, B.: Statistical Theory, Mac-millan, New York, 1962.

Liu, Q., Reichle, R. H., Bindlish, R., Cosh, M. H., Crow, W. T., de Jeu, R., Lannoy, G. J. M. D., Huffman, G. J., and Jackson, T. J.: The

35 contributions of precipitation and soil moisture observations to the skill of soil moisture estimates in a land data assimilation system, Journal of Hydrometeorology, 12, 750–765, 2011.

Martinez-Fernandez, J., Gonzalez-Zamora, A., Sanchez, N., and A Gumuzzio, .: Satellite soil moisture for agricultural drought monitoring: Assessment of the SMOS derived Soil Water Deficit Index (vol 177, pg 277, 2016), REMOTE SENSING OF ENVIRONMENT, 183, 368–368, 2016.

Mo, K. C. and Chelliah, M.: The modified Palmer Drought Severity Index based on the NCEP North American Regional Reanalysis, J. Appl.
5 Meteor. Climatol., 45, 1362–1375, 2006.

NCEI, N.: U.S. Billion-Dollar Weather and Climate Disasters, url:https://www.ncei.noaa.gov/, https://www.ncdc.noaa.gov/billions/, national Centers for Environmental Information, 2017.

NDMC: National Drought Monitoring Center, Types of Drought, URL: http://drought.unl.edu/DroughtBasics/TypesofDrought.aspx, 2018a.

NDMC: Groundwater and Soil Moisture Conditions from GRACE Data Assimilation, url:http://nasagrace.unl.edu/Archive.aspx, the National
10 Drought Mitigation Center University of Nebraska-Lincoln, 2018b.

NIST: Beta Distribution, url:http://www.itl.nist.gov/div898/handbook/eda/section3/eda366h.htm, 2013.

NOAA: NLDAS Drought Monitor Soil Moisture, url:http://www.emc.ncep.noaa.gov/mmb/nldas/drought/, 2018.

O'Neill, P., Chan, S., Njoku, E. G., Jackson, T., and Bindlish, R.: SMAP L2 Radiometer Half-Orbit 36 km EASE-Grid Soil Moisture, Distributed Active Archive Center Version 4, NASA National Snow and Ice Data Center, Boulder, Colo., doi:10.5067/XPJTJT812XFY,
15 2016.

Pan, M., Li, H., , and Wood, E.: Assessing the skill of satellite-based precipitation estimates in hydrologic applications, Water Resour. Res., 46, https://doi.org/10.1029/2009WR008290, 2010.

Pan, M., Cai, X., Chaney, N. W., Entekhabi, D., and Wood, E. F.: An initial assessment of SMAP soil moisture retrievals using high-resolution model simulations and in situ observations, Geophysical Re, 43, 9662–9668, 2016.

20 Parinussa, R. M., Holmes, T. R. H., Wanders, N., Dorigo, W. A., and de Jeu, R. A. M.: A Preliminary Study toward Consistent Soil Moisture from AMSR2, J Hydromet., 16, 932–947, https://doi.org/10.1175/JHM-D-13-0200.1, 2015.

Reichle, R., Lucchesi, R., Ardizzone, J. V., Kim, G., Smith, E. B., and Weiss, B. H.: Soil Moisture Active Passive (SMAP) Mission Level 4 Surface and Root Zone Soil Moisture (L4SM) Product Specification Document, Tech. Rep. 10 (Version 1.4), NASA Goddard Space Flight Center, Greenbelt, MD, 2015.

25 Reichle, R. H.: Assessment of the SMAP Level-4 Surface and Root-Zone Soil Moisture Product Using In Situ Measurements, Journal of Hydrometeorology, 18, 2621–2645, 2017.

Reichle, R. H., Koster, R. D., Lannoy, G. J. M. D., Forman, B. A., Liu, Q., Mahanama, S. P. P., and Toure, A.: Assessment and enhancement of MERRA land surface hydrology estimates, Journal of Climate, 24, 6322–6338, 2011.

Rienecker, M. and coauthors: The GEOS-5 Data Assimilation System - Documentation of Versions 5.0.1, 5.1.0, and 5.2.0., NASA Technical
30 Report Series on Global Modeling and Data Assimilation NASA/TM-2008-104606, NASA, vol. 28, 101 pp., 2008.

Robock, A., Vinnikov, K., Srinivasa, G., Entin, J., Hollinger, S., Speranskaya, N., Liu, S., and Namkhai, A.: The Global Soil Moisture Data Bank, Bull. Amer. Meteor. Soc., 81, 1281–1299, 2000.

Sheffield, J. and Wood, E. F.: Drought: Past Problems and Future Scenarios, 978-1-84971-082-4, EarthScan., London, UK, 2011.

Sheffield, J., Goteti, G., Wen, F., and Wood, E. F.: A simulated soil moisture based drought analysis for the United States, J. Geophys. Res.,
35 109, D24 108, https://doi.org/10.1029/2004JD005182, 2004.

Sheffield, J., Livneh, B., and Wood, E. F.: Representation of terrestrial hydrology and large scale drought of the Continental U.S. from the North American Regional Reanalysis, J. Hydrometeor., 13, 856–876, https://doi.org/http://dx.doi.org/10.1175/JHM-D-11-065.1, 2012.

Sheffield, J., Wood, E. F., Chaney, N., Guan, K., Sadri, S., Yuan, X., Olang, L., Amani, A., Ali, A., and Demuth, S.: A Drought Monitoring and Forecasting System for Sub-Sahara African Water Resources and Food Security, Bull. Am. Met. Soc., in press, 95, 861–882, 2014.

Svoboda, M.: An introduction to the Drought Monitor, Drought Network News, 12, 15–20, 2000.

Tallaksen, T. and Van Lanen, H. A.: Hydrological Drought, Processes and Estimation Methods for Streamflow and Groundwater, vol. 48, Elsevier Science, 2004.

Université Catholique de Louvain: The OFDA/CRED International Disaster Database, Web, www.emdat.net, louvain - Brussels - Belgium, 2009.

Wagner, W. et al.: The ASCAT Soil Moisture Product: A Review of its Specifications, Validation Results, and Emerging Applications, Meteorologische Zeitschrift, 22, 5–33, https://doi.org/10.1127/0941-2948/2013/0399, 2013.

Wilhite, D. A.: Chapter 1 Drought as a Natural Hazard: Concepts and Definitions, vol. I, National Drought Mitigation Center at Digital Commons at University of Nebraska - Lincoln, Routledge, London, UK, 2000.

Wilhite, D. A. and Glantz, M. H.: Understanding the Drought Phenomenon: The Role of Definitions, Water International, 10:3, 111–120, 1985.

Wu, Q., Liu, H., Wang, L., and Deng, C.: Evaluation of AMSR2 soil moisture products over the contiguous United States using in situ data from the International Soil Moisture Network, Intern. J. App. Earth Observ. And Geoinfo., 45, 187–199, https://doi.org/10.1016/j.jag.2015.10.011, 2015.

Zaitchik, B. F., RODELL, M., and REICHLE, R. H.: Assimilation of GRACE Terrestrial Water Storage Data into a Land Surface Model: Results for the Mississippi River Basin, American Meteorological Society, 9, 535–548, 2008.