Response to Referee #2

Paper's New Title: Developing a drought monitoring index for the Contiguous U.S. using SMAP

September 10, 2018

1. Comments from referee
This shortcoming can be fixed by providing a more direct link between the (very interesting) data adequacy analysis presented in Section 2.3 and the presentation of index comparisons in Section 3. As currently written, the analysis in Section 2.3 reveals that the (current) 3-year SMAP data heritage is insufficient for a substantial fraction of CONUS. However, this inadequacy is never mentioned again in the paper and does not come into the analysis of results presented in Section 3 and discussed in Section This is a real shame.

2. Author's response
We appreciate this comment and agree that more numerical analysis on the adequacy of the SMAP data would have substantially enhanced the scientific merit of the paper. Therefore, we are addressing the issue through introducing two filters and a combination of them. We have done major changes to the paper and added specific sections for in-depth numerical analysis of the confidence of SMAP-based drought index maps and the adequecy of the data. Please see the section Data Adequacy Filters and beyond that for considering all the changes and explanations we provided in the newer version of the paper.

3. Author's changes in manuscript

0.1 SMAP Data

Since April 2015, NASA's SMAP mission has been monitoring near-surface soil moisture, mapping the globe (between 85.044°N/S) using an L-band (1.4 GHz) microwave radiometer in 2-3 days depending on location. The SMAP mission provides a set of operational global data products that include:

- Level 3 (SPL3SMP): a composite based on daily passive radiometer estimates of global land surface soil moisture (nominally 5 cm) that are resampled to a global, cylindrical 36 km Equal-Area Scalable Earth Grid, Version 2.0 (EASE-Grid 2.0) (O'Neill et al., 2016). Regions of heavy vegetation (vegetation water content $> 4.5\ kg/m^2$) or frozen ground or snow covered are masked out using a Normalized Polarization Ratio (NPR)-based passive freeze-thaw retrieval. Given the 1000-km swath and 98.5 minute orbit, the SPL3SMP retrievals are spatially and temporally discontinuous with 2-3 day gaps depending on location; and
- Level 4 (SPL4SMAU): provides global surface and root zone soil moisture by assimilating the SMAP L-band brightness temperature data (for which SPL3SMP is the gridded version) from descending and ascending half-orbit satellite passes, approximately 6:00 a.m. to 6:00 p.m., every 3 hours, local solar time, into NASAs Catchment LSM (Reichle, 2017; Reichle et al., 2015). The SPL4SMAU data product is gridded using an Earth-fixed, global, cylindrical 9 km EASE-Grid 2.0 projection. The land surface model component of the assimilation system is driven by a forcing data stream from the global atmospheric analysis system at the NASA GMAO (Rienecker and coauthors, 2008). 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 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.

In this study, SPL3SMP products from the 6:00 a.m. retrievals and SPL4SMAU products from 6:00 a.m. retrievals, are used in the analysis of soil moisture drought index. Our SMAP data records are from 2015-04-01 to 2017-12-31, which is equivalent to 1,006 days.

The approach selected here is somewhat similar to that from 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. There are, however, differences in our approach from that in Sheffield et al. (2004). Firstly, the basis of the data used in Sheffield et al. (2004) was simulated soil moisture from VIC while ours is remotely sensed data. Secondly, to calculate the bounds of beta distribution [a, b], Sheffield et al. (2004) used the first (last) 10% of the sorted soil moisture values linearly related to the empirical cumulative distribution function. In our study, this approach did not yield useful results with the estimated limits for a (b) for SMAP, often did not cover the full range of observed values, preventing interpretation of the historical data. Our methodology for obtaining beta distribution parameters a and b is discussed in this section.

As mentioned in the introduction by Heim (2002), one of the conditions for index approach is a complete and reliable historical data needed over a common reference period to allow conversion of the observations to a meaningful form. The short SMAP record length of 1,006 days, from 2015-04-01 to 2017-12-31, provides a statistical challenge in estimating the drought and pluvial indices, and thus the reliability assessments related to these extreme conditions are necessary. Therefore, to assess the data adequacy, we used 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. Here we refer to it as VIC near surface (VIC-ns). The SPL4SMAU is at 9 km spatial resolution, so VIC data were 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 KolmogorovSmirnov (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 record were deemed statistically the same – then the SMAP time series over that grid was sufficient to provide an index. More discussion of these results is given in Section: Results.

Furthermore, we looked at the frequency distribution of soil moisture data at each grid. The data seemed to be dominated by low soil moisture in the summertime, and high soil moisture in the wintertime. Therefore, to capture this inter-seasonal behavior in soil moisture, we divided the record into a warm season (April - September) and a cold season (October - March). Dividing the year into warm and cold seasons enabled us to track the soil moisture dynamics, and thus the probability distribution and index seasonally. Ideally, we would have divided it into monthly data but there are insufficient observations.

For our study period, each grid has 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 per grid is 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.

0.2 Fitting the beta distribution to the SMAP time series

The beta distribution is a family of continuous distributions with two shape parameters (p and q). 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 model a wide variety of shapes. In our study,

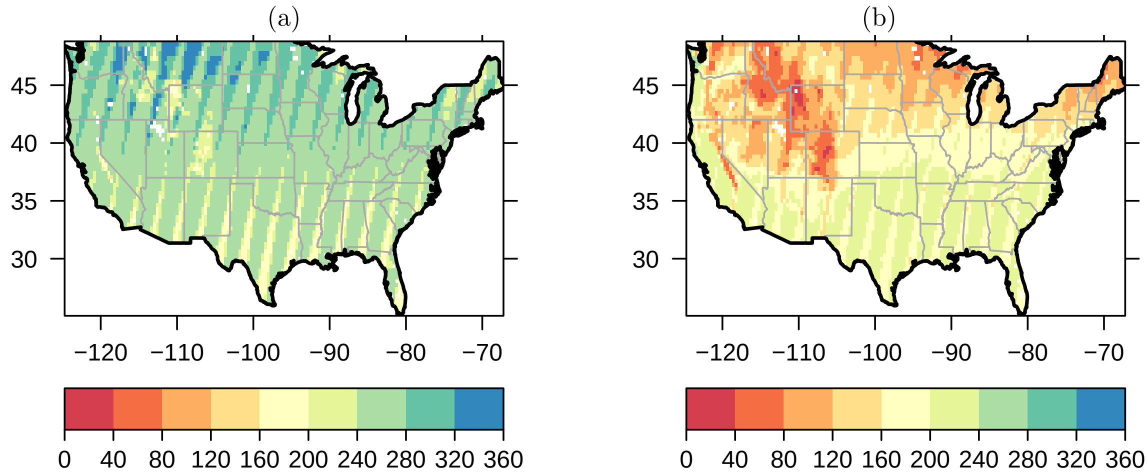


Figure 1: Number of overpasses for each season. (a) is warm season April 1 - September 30; (b) is cold season, October 1 - March 31).

we compared the beta distribution to several parametric distributions (including Normal and Gumbel), but the beta distribution showed the best goodness-of-fit. Furthermore, given the bounded nature of the distribution it is often used as the model of choice for modeling soil moisture time series (Sheffield et al., 2004). The general formula for the beta probability density function (pdf) is:

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

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

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

A main challenge is to fit the four parameters of beta distribution, given a set of empirical observations. Sheffield et al. (2004) used the method of moments to fit the beta distribution to historical soil moisture simulations from 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 also used the standard method of moments to calculate the parameters p and q. But for each grid location, we fit the beta distribution to 6 sets of data related to the SPL3SMP product: 1) Short warm season VIC and 2) Short warm season SMAP (1 April - 30 September for 2015, 2016, 2017; 18 months); 3) Long warm season VIC (1 April - 30 September, 1979-2017; 129 months); 4) Short cold season VIC and 5) Short cold season SMAP (1 October - 31 March, 2015-2016; and 1 October - 31 December 2017; 15 months); 6) 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 $\mu = \frac{p}{p+q}$ and $CV = \frac{\mu}{\sigma}$, where p and q are parameters and its standard deviation defined as:

$$\sigma = \sqrt{\frac{p*q}{(p+q)^2*(p+q+1)}} \tag{3}$$

For the SPL4SMAU root zone soil moisture product, the beta distribution was fit to the warm season and cold season using all 457 and 549 records, respectively.

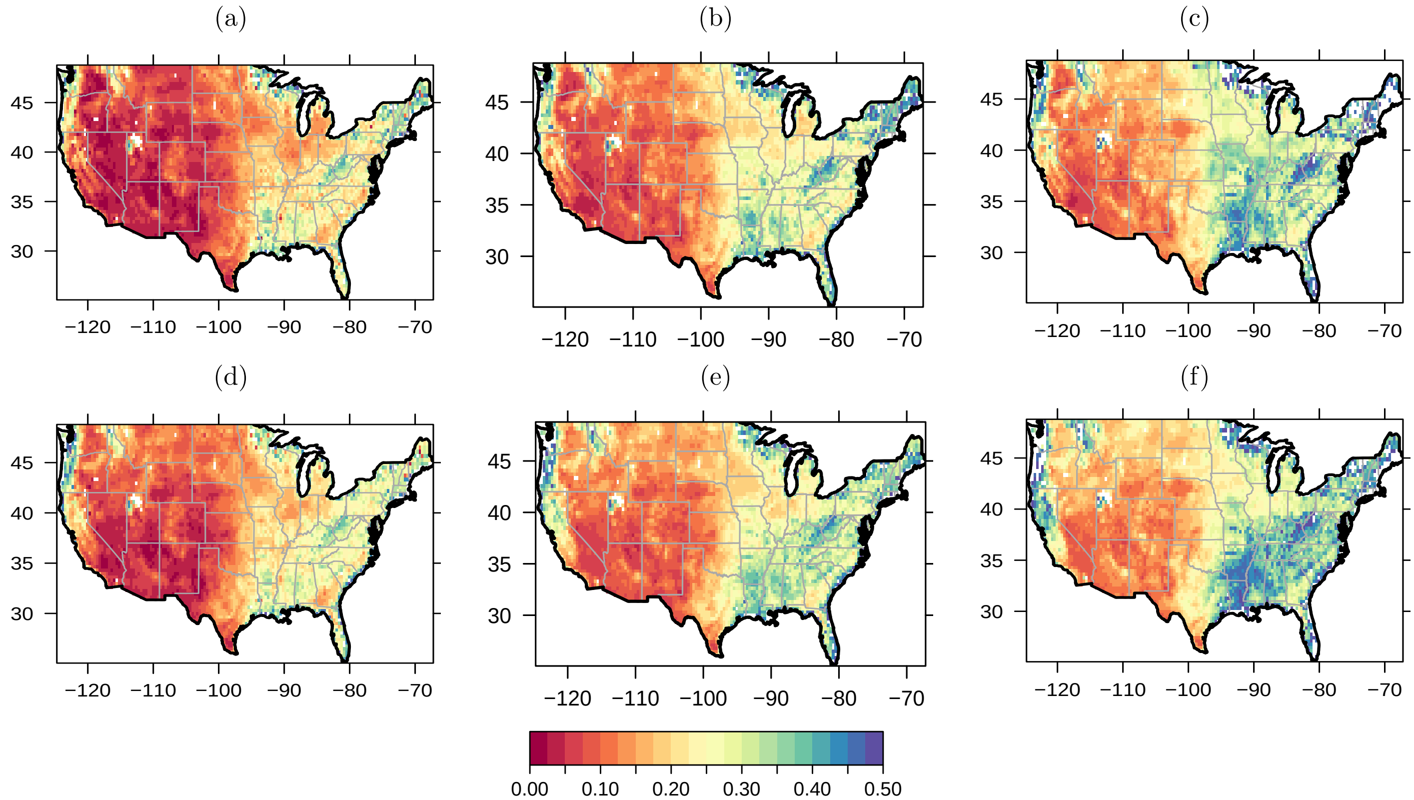


Figure 2: top row: SMAP index for the warm season during summer for SPL3SMP top 5 cm soil moisture (a), 20th percentile; (b), average soil moisture; (c), 80th percentile; bottom row: as the top row but for the cold season. Total period is from 2015/04/01 to 2017/12/31. The soil moisture unit is m^3/m^3.

Figure 2 shows the 20th percentile, average and 80th percentile soil moisture data in the warm season and cold season for SPL3SMP 5-cm soil moisture product, and similarly in Figure 3 for the SPL4SMAU root zone product, after data were fit to the beta distribution.

0.3 Data Adequacy Filters

Insufficient SMAP record length may result in unreliable index values. To be meaningful in using short SPL3SMP data for making confident predictions, we will analyze which grids have the highest certainty in our SMAP drought index. That is, we perform adequacy analysis, and defining filters that separate grids with high reliability in drought monitoring and prediction from ones where we dont expect our predictions to be as accurate. We first define two filters which can separate the 5,815 grids covering CONUS into grids that passed and failed quality control. The two filters are:

(a) The Kolmogorov-Smirnov (KS) test for beta-fitted long-term and short-term VIC with 95% confidence;

(b) Good correlation (≥ 0.4) between beta-fitted VIC and beta-fitted SPL3SMP.

Below we expand upon these two filters and then show how we used them to numerically find the best SPL3SMP filter. We also investigate if combinations of the filters are superior to the individual filters taken alone.

0.3.1 Kolmogorov-Smirnov (KS) filter

The KS test is a well-known nonparametric statistical test that compares whether two samples are coming from the same continuous distribution. We used the KS test for each grid, comparing the modeled

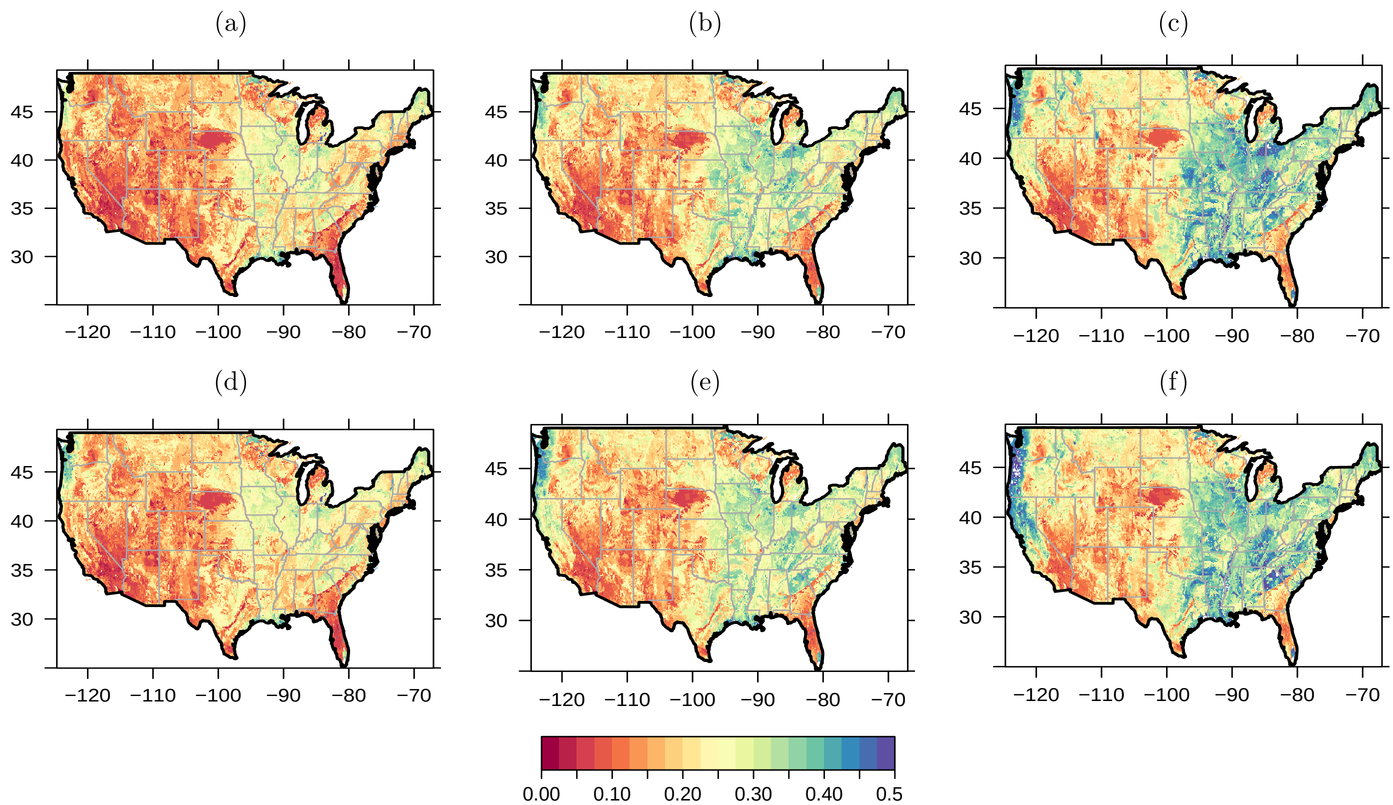


Figure 3: Same as shown in figure 2 but for SPL4SMAU (root zone soil moisture).

beta distribution of the long-term VIC with the modeled beta distribution of the short-term VIC, in both warm and cold seasons. This shows if the long-term and short-term distributions are statistically indistinguishable. If this strong condition is satisfied for a grid, then it is reasonable to assume for that grid that the short SMAP time series would be consistent with a hypothetical long SMAP time series. The null hypothesis – that the underlying beta distribution of short-term soil moisture data is the same as the underlying beta distribution of long-term soil moisture data for VIC – is rejected for values of the KS statistic D that exceed a critical value at the 95% significance level: $D_{critical} = \frac{1.36}{\sqrt{n}}$ where n is the number of observed variable (Lindgren, 1962).

0.3.2 Correlation Filter

As mentioned earlier, one of the key assumptions of this paper is that if the beta distribution fit to the short-term VIC series is statistically consistent with beta fit to the long-term VIC time series, then we assume that the short-term beta-fitted SMAP series is consistent with the hypothetical long-term beta-fitted SMAP time series. This is possible because VIC modeled soil moisture is validated by ground measurements (Pan et al., 2016; Cai et al., 2017), and it is most plausible where the correlation between SPL3SMP and VIC is highest. Correlation maps are shown in Figure 4 between SPL3SMP and VIC-ns product for the warm season and cold season periods. This suggests another filter to use: require that the correlation of beta-fitted SPL3SMP and beta-fitted VIC soil moisture be relatively high. We examined the distribution of correlation values across all grids in order to pick the cutoff between high and low correlation. We chose the mean correlation, minus the standard deviation of correlation (across all grids), as a threshold. Thus grids whose correlation is close to average or better than the average pass the filter. For both the warm and cold seasons, this value was very close to 0.4 and as a result we picked this as the common threshold.

0.3.3 Mean Distance (MD)

To evaluate whether the KS-based filter, the correlation filter, or a combination of both is best, we define a simple Mean Distance (MD) metric. Assuming VIC index at 36 km resolution is the ground truth, we can calculate a distance between VIC and SMAP. For every day that SMAP provided a retrieval, if $smap_i$ is the drought index percentile of grid i that passes the filter, and VIC_i is the VIC drought index percentile of the same grid, and in total n_g grids on day d passed the filter, then the mean distance MD_d is defined as the average of absolute distances between the SPL3SMP drought index percentiles and the VIC drought index percentiles. For the candidate date d and for a given filter:

$$MD_d = \frac{\sum_{i=1}^{n_g} |\,VIC_i - smap_i|}{n_g} \tag{4}$$

In equation (4), VIC_i and $smap_i$ are VIC and SMAP drought index values for grid i, n_g is the total number of grids that passed the filter, and MD_d is the mean distance for date d.

For each filter the final pass and fail distance scores are calculated by averaging MD_d values over the number of days, especially for both dry or wet seasons:

$$MD = \frac{\sum_{i=1}^{n_d} |MD_d|}{n_d} \tag{5}$$

where n_d is the total number of days for which the MD_d value is available. While n_g varies every day, since the number of overpasses varies every day, the value of n_d was constant (549 for warm season and 457 for cold season). The MD value obtained from grids failed a filter is called MD_{fail} and the MD value from grids passed a filter is called MD_{pass}. For each filter a difference (*Diff*) was computed by reducing the MD_{pass} from the MD_{fail}: $Diff = MD_{fail} - MD_{pass} > 0$

0.3.4 Combination filters

In addition to the KS filter and the correlation filter, we investigate two filters defined by the following combination rules:

- Intersection filter: a grid cell g passes the intersection filter if it passes both the KS filter *and* the correlation filter. Otherwise, if fails;
- Union filter: A grid cell g passes the union filter if it passes *either* filter, or both. Note that using the union filter gives the best coverage of the grids throughout CONUS, while the intersection filter has the strongest requirements for passing.

1 Results and Discussion

1.1 Data adequacy metrics

1.1.1 Correlation filter

Figure 4 shows that the 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, around 0.2. The extent of this poor correlation increases during the cold season for northeastern U.S., Wisconsin and Minnesota. Snow season results in poor SMAP coverage during winter time in those areas. In addition, the low number of overpasses (presented in Figure 1) during winter in northeast can play a role in low amount of data and poor correlation during cold season. Contrary to the warm season, southern California shows a high a correlation with VIC

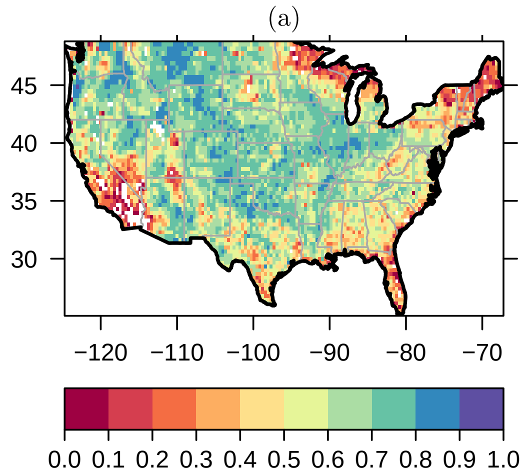


Figure 4: (a) Correlations (R) between VIC and SMAP beta models for the warm season (average R=0.57) and (b) cold season (average R=0.56). White regions signify negative correlation.

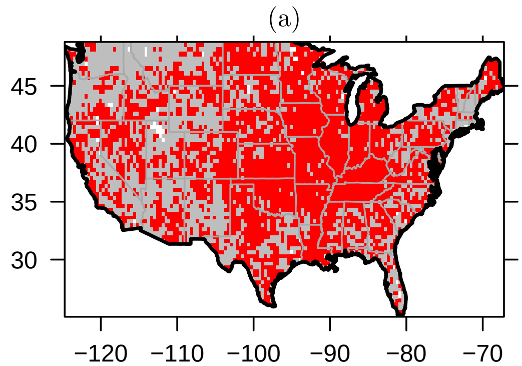


Figure 5: (a) Grids in red show areas whose short term VIC in warm season data has the same underlying beta distribution as the long-term VIC in warm season data (n = 3560 or 68% of grids are red); (b) the same as the left figure but for cold season period shown in blue (n = 2927 or 57% of grids). Gray areas are grids where the short term VIC does not have the same beta distribution as their long term VIC.

during the cold season, around 0.9. We attribute this change in southern and south central California from cold season to warm season to irrigation that SMAP picks up, but VIC doesn't since the version used here doesn't have water management effects. Land use/land cover map shows that about one third of these areas are irrigated vegetation and another third is forests and woodlands (USGS, 2018). There are also as many as 2 million water wells in California that contribute to irregularity of groundwater and affecting the soil moisture. They range from hand-dug, shallow wells to carefully designed large-production wells drilled to great depths (California Dept. of Water Resources, 2018). More data is needed before we can recognize further attributions to low correlation between VIC and SMAP in that region. While systematic biases do not get revealed in correlations, the temporal consistency among the time series is captured.

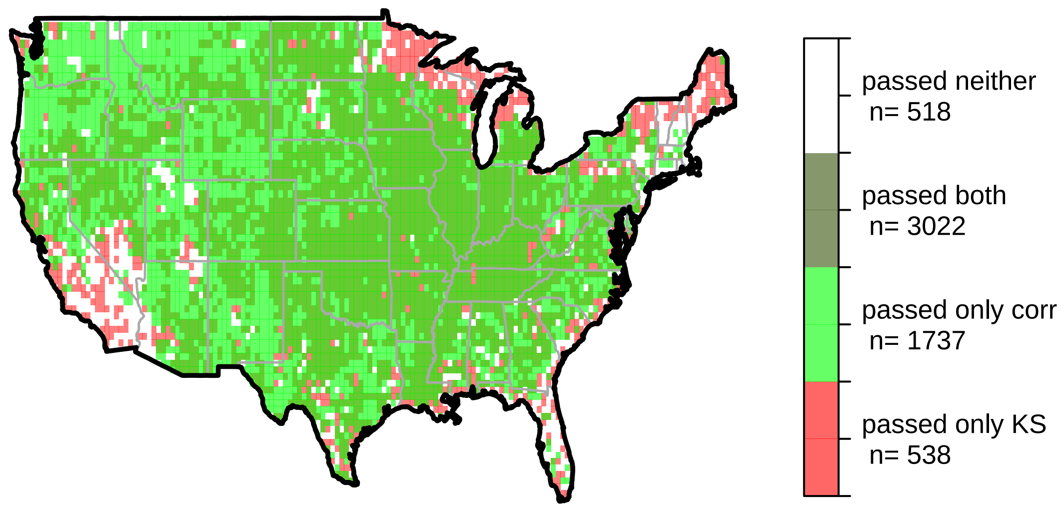
1.1.2 KS filter

Figure 5 shows which grids passed the 95% KS test: there, we have confidence that the SMAP drought (pluvial) indices provide reliable risk levels given the current period of record. The warm season shows 11% more grids passing the adequacy test than the cold season. Note that as the record length gets extended, the above analysis needs to be repeated to see if the adequacy changes.

1.1.3 Combined filters

Figure 6 represents the results of Correlation filter and KS filter together for both warm (top figure) and cold (bottom figure) seasons over all 5,815 grids. We use these filters (passed/failed grids) on a daily basis for MD_d measures; though the value changes every day depending on the number of overpasses for that date. Table 1 summarizes how many grids pass or fail each filter.

(a)



(b)

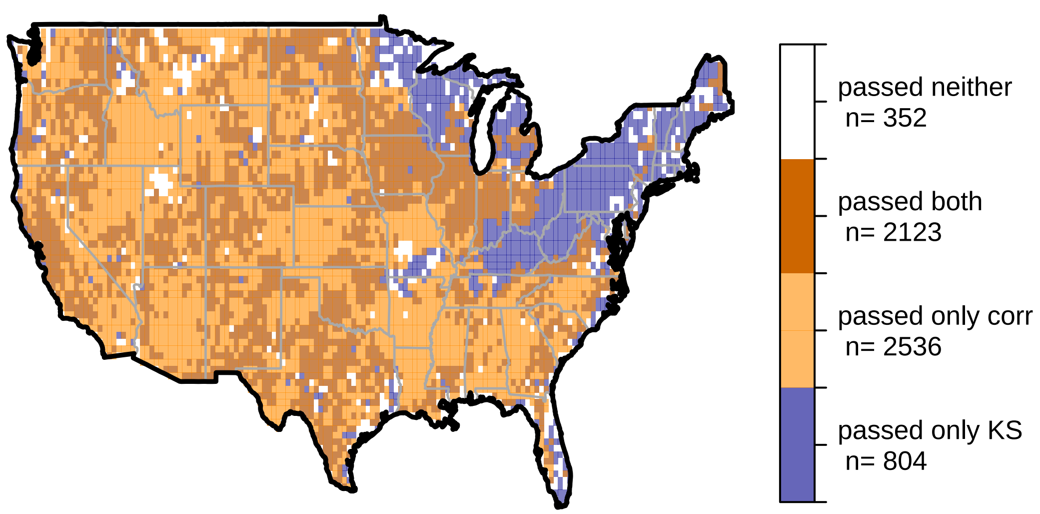


Figure 6: (a): warm season grids that pass the correlation filter and/or the KS filter. Dark green grids include grids that pass intersection filters. (b): cold season grids that pass the correlation filter and/or the KS filter. Dark orange grids include grids that pass intersection filters. In both figures white grids show the grids that pass neither filters and will be crossed hatched in index maps.

Table 1: Number of grids, out of total 5,815, that fail and pass the quality control for each filter. Note: Per day, the n_g numbers are less because of SMAP overpass missing grids.

n_g	KS filter	Correlation filter	Intersection filter	Union filter
Warm season fail	2,255	1,056	2,793	518
Warm season pass	3,560	4,759	3,022	5,297
Cold season fail	2,888	1,156	3,692	352
Cold season pass	2,927	4,656	2,123	5,463

Table 2: DS of four tests averaged over 549 days of warm season.

	KS filter	Correlation filter	Intersection filter	Union filter
MD_{fail}	24.1	26.5	24.5	26.8
MD_{pass}	21.9	21.9	21.1	22.3
Diff	2.2	4.5	3.4	4.5

1.2 Evaluation of Results Under Different Filters

For each filter, the values of MD_d were averaged to calculate MD_{fail} and MD_{pass} for all CONUS over the 549 days of warm season and 457 days of cold season. The summary result of all 4 tests is shown in Table 2 and Table 3. To test if having a filter is better than having no filter, for each season, we performed two sided null hypothesis. The tests used 95% confidence limits between the MD of all grids – which was 22.7 in warm season and 22.6 in cold season – versus the MD of only passed grids. The results showed that all four filters are significantly different than the MD of all CONUS. Thus, regardless of the type of the filter, having some sort of filter is better than having no filter.

In warm season, the KS filter did better (i.e. larger *Diff* values, or better skill in separating high/low performance grids) than the correlation filter for only 115 days out of 546 days, mostly in April. For almost half of the dates (260 days out of 546), the union filter did better than the correlation filter. This outperformance of the union filter occurs evenly throughout the warm season.

In the cold season, for only 48 days out of 457 days, the KS filter did better than the correlation filter and for 198 days the union filter did better than the correlation filter. These results suggest that for the cold season, the correlation filter is providing the most effective filter. However, if we only accept the grids that pass the correlation filter, we lose 804 grids. This area involved almost all of the northeast coast and mid coast, as well as northern Wisconsin and northeast Minnesota. Although this is not a concerning problem for drought since most of the cold season these areas are covered by snow. We still decided to generate a cold season filter by including the KS filter with the correlation filter, thus we used the union filter for the cold season.

Three considerations for doing so are:

(a) The Diff values: The correlation filter *Diff* value and union filter *Diff* Value during cold season are similar and close;

(b) The nature of our tests: It is not that surprising that the correlation filter has a higher *Diff* than that from union filter. The MD metric measures how the SMAP index resemble the VIC index. Thus, we find that the most important predictor is that the SMAP values should be correlated with the VIC values.

(c) Optimum coverage: Although the cold season east coast drought index is not a matter of concern for this study, cold season soil moisture variability can affect warm season soil moisture and consequently agricultural drought. The goal is to create a filter that does not lose important information while provides the best knowledge of soil moisture data.

Table 3: DS of four tests averaged over 457 days of cold season.

	KS filter	Correlation filter	Intersection filter	Union filter
MD_{fail}	22.8	29.0	24.1	29.2
MD_{pass}	22.4	21.2	20.1	22.1
Diff	0.4	7.8	4.0	7.1

During the warm season, most of the grids that failed the test were in southern California and south Nevada, in northeast (New Hampshire, Massachusetts, and Connecticut), and in the southeast along the east coast of Florida. These are attributed to both lack of correlation between SMAP and VIC, and high variability between short term and long term soil moisture. These areas show non-stationarity in soil moisture meaning that soil moisture distribution is subject to change over time either due to climate or human interventions. During the cold season most of the areas are covered using the union filter. However, as discussed we use this filter with caution knowing that at least according to our numerical analysis, the correlation filter did better than the union filter. Most of northeast, including Minnesota and the mid-east regions do not show a high correlation between VIC and SMAP in this season. This is because of the snow coverage and that SMAP does not have a good coverage of soil moisture and has less number of overpasses per grid. However, the KS filter complements the map by showing that the long term and short term VIC during cold season stay pretty stationary over time. This means that the soil moisture in this area has been less subject to change during cold season at least for the past 40 years.

This information can be used to inform an interpretation of SMAP soil moisture percentiles maps based on $<$ 10 years of data, as presented in Figures 7 and 8 for a selection of soil moisture drought and flood indices. The grids that fail both KS and correlation tests (white grids in Figure 6) will be omitted and are where we have the highest uncertainty of the quality of the data. This includes about 500 grids in the warm season and about 350 grids in cold season over the CONUS.

1. Comments from referee
   At best, SMAP will last for 10 years; therefore, data adequacy will always be a pressing concern for the calculation of soil moisture climate percentiles. Given this pressing need - how can the analysis in Section 3 be used to inform an interpretation of SMAP soil moisture percentile maps based on <10 years of data (e.g., as a tool for generating data quality flags, as a data mask or as a source of uncertainty information)?

2. Author's response
   From our numerical tests and results provided the information can be used to inform an interpretation of SMAP soil moisture percentiles maps based on <10 years of data, as presented in Figures 7 and 8 for a selection of soil moisture drought indices. The grids that fail both KS and correlation tests (white grids in Figure 6) will be flagged as crossed and are where we have the highest uncertainty of the quality of the data. This includes about 500 grids in the warm season and about 350 grids in cold season over the CONUS.

3. Author's changes in manuscript
   Please see the extensive analysis and maps provided in the previous section. In our new version we have created a mask to filter grids where we don't have enough certainty in SPL3SMP drough index.

1. Comments from referee
   Does the fit between these new SMAP-based indices and existing drought/pluvial indices noticeably degrade for areas flagged as inadequate in Figure 5? Are there specific events there where the 3-year SMAP data record injects spurious percentile patterns into drought/pluvial events? If so, are the locations of these events adequately flagged as being problematic by results in Figure 5?

2. Author's response
   For this question, we changed Figure 7 and 8 and showed the inadequate areas (based on our new results)

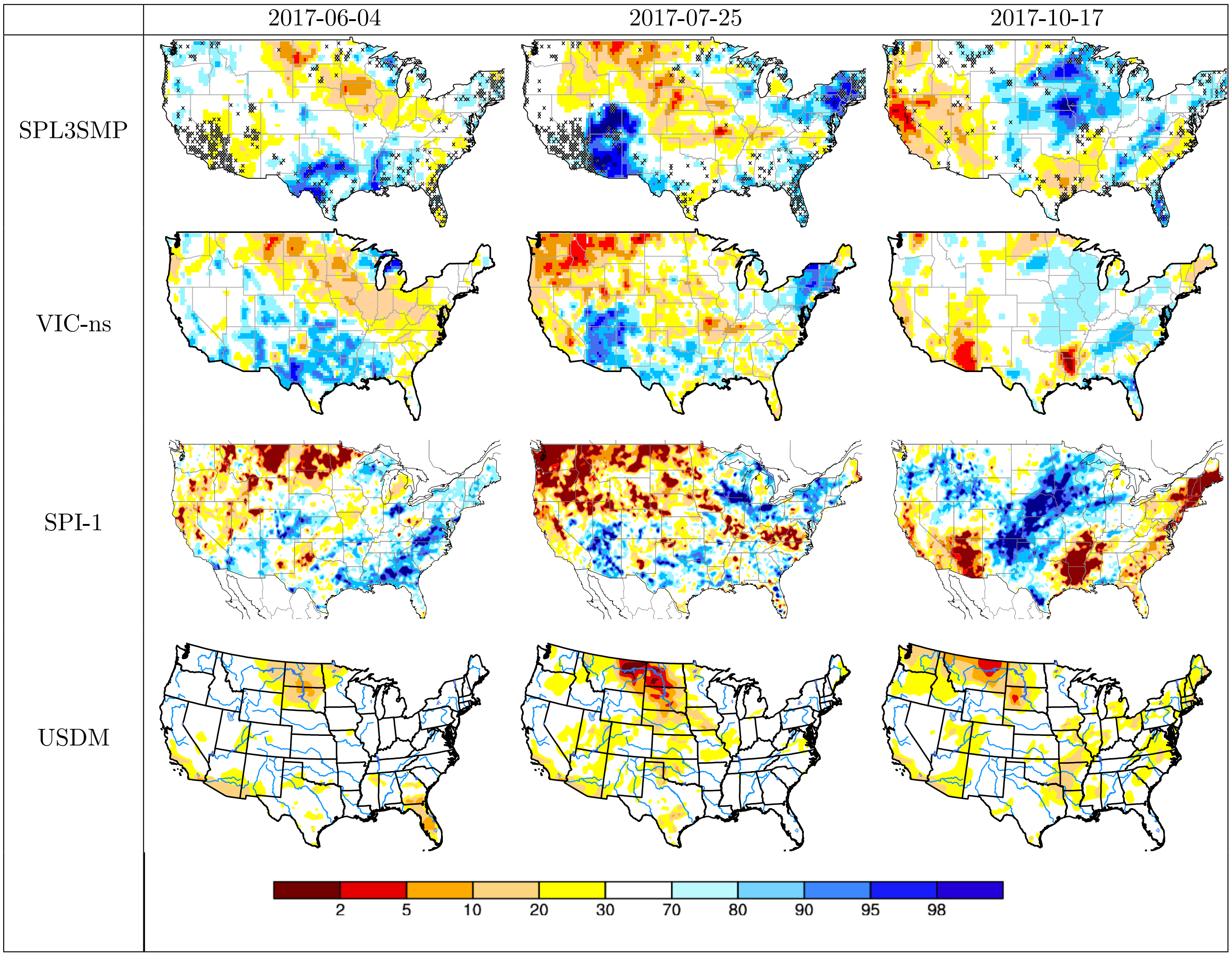


Figure 7: Comparison between SPL3SMP index map and VIC-ns, SPI-1, and USDM in 2017. For USDM, drought levels from 30 to 100 are shown in white.

omitted. The results show that the fit between new SMAP-based indices and existing drought/pluvial indices noticeably degrade for areas failing the filter (cross hatched).

3. Author's changes in manuscript

1.3 Comparison among the drought indices

In Figure 7 to Figure 10, several indices are compared to the SMAP-based drought index. For surface soil moisture index based on SPL3SMP, we provide a 3-day composite SMAP to offer index more continuous coverage. The union filter is applied to omit the grids that do not have reliable estimates. Our index SPL3SMP index produc maps are compared with the 1-month SPI (SPI-1) index, a VIC-ns index, and the USDM. For SMAP soil moisture index based on the SPL4SMAU, comparisons are made with a 3-month SPI (SPI-3) index and a GRACE satellite product. All the products except for GRACE were described in Introduction. 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).

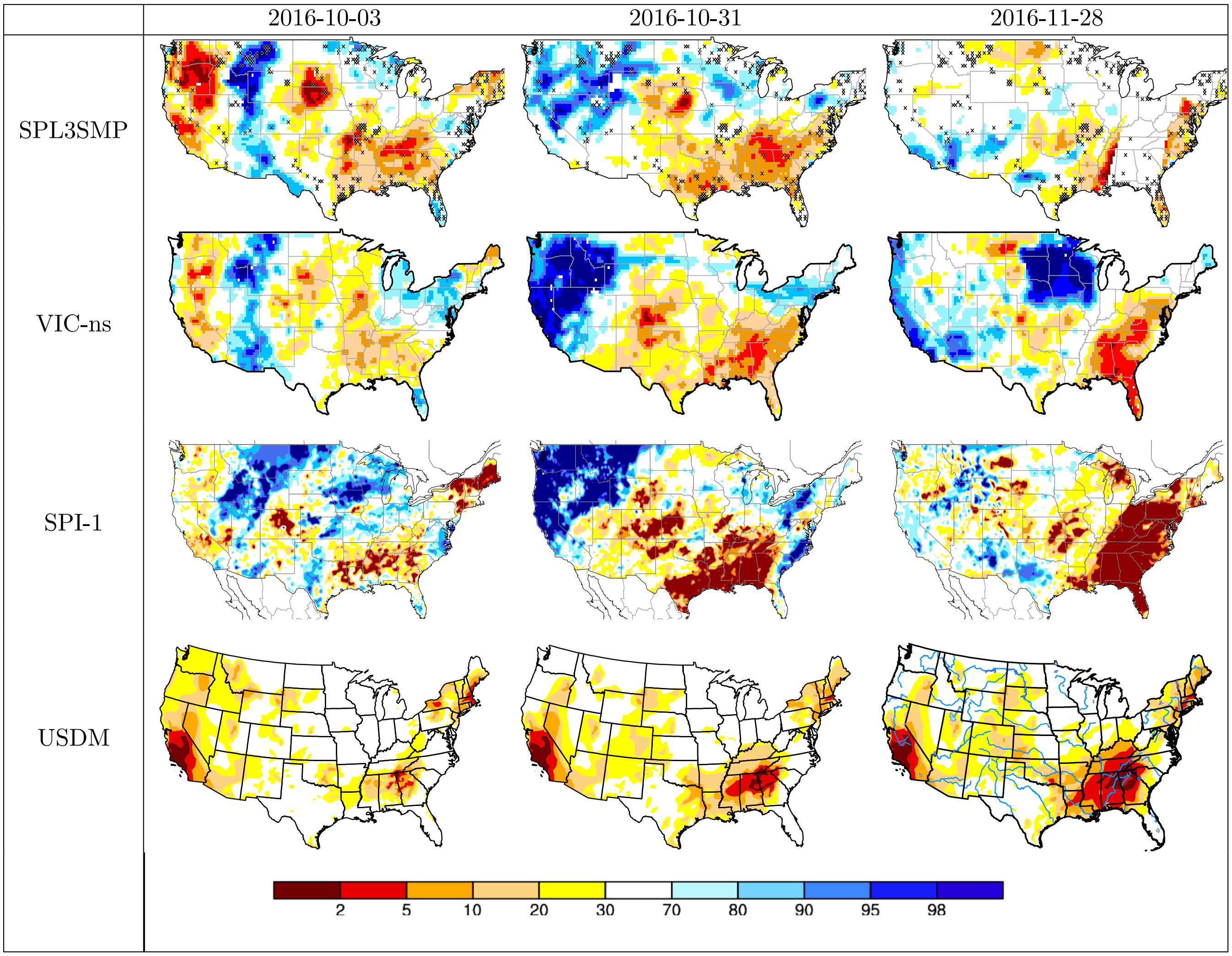


Figure 8: Comparison between SPL3SMP index map and VIC-ns, SPI-1, and USDM in 2016. For USDM, drought levels from 30 to 100 are shown in white.

Figure 7 and Figure 9 show drought during the period from June 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 (NOAA, 2018). 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 70% of the state was under some level of drought, and similarly, 68% of South Dakota was under severe drought (NOAA, 2018). Both SPL3SMP and SPL4SMAU index maps seem to catch this drought event.

In Figure 8 and Figure 10, 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. which are captured by both SPL3SMP and SPL4SMAU index maps. 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 soil moisture rather than near-surface soil moisture (Figure 9).

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

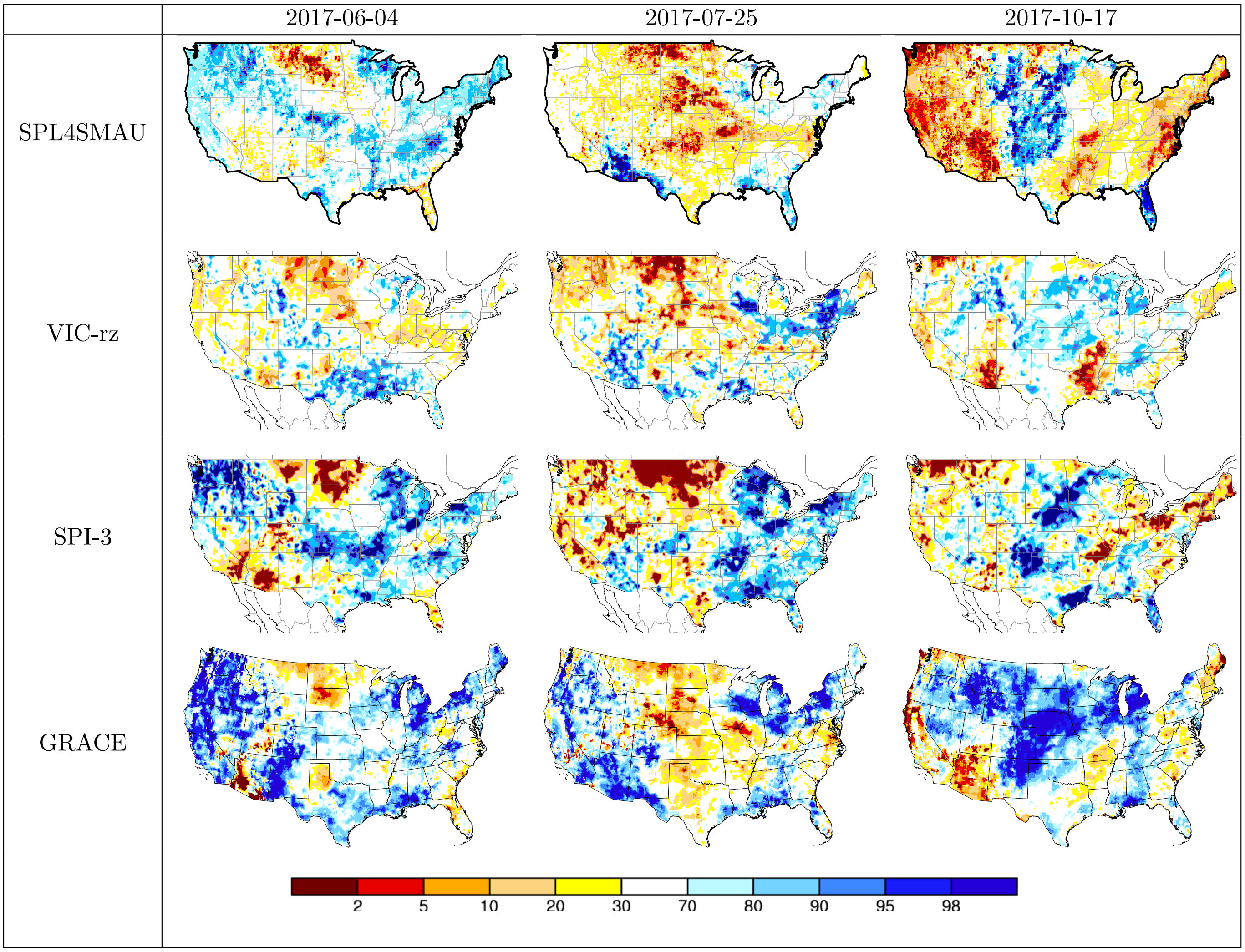


Figure 9: Comparison between SPL4SMAU index map and VIC-rz, SPI-3, and GRACE in 2017.

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 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 7).

Most of grids where we do not have confidence in the accuracy of predictions are in Southern California and Nevada during the warm season (eg. SPL3SMP index map on 2017-06-04 and 2017-07-25 in Figure 7). In fact, there is visible discrepency between SPL3SMP and VIC-ns index maps during that period in Southern California. We believe this is due to lack of correlation between SPL3SMP and VIC-ns in that area since VIC does not model regulation. Human interference and use of groundwater wells during warm season can play a major part in what VIC models and what SMAP sees. For that reason, we think SMAP's metrics in the area are more accurate than from VIC-ns.

1. Comments from referee
   Figure 2 A major issue is calculating percentile products is always determining the seasonal intervals over which climate is considered stationary. Here, the authors choose to (implicitly) assume stationary climate within hot and cold 6-month portions of the year. Some discussion supporting this choice would be helpful. For instance, the warm versus cold season soil moisture differences in Figure 2 are (surprisingly)

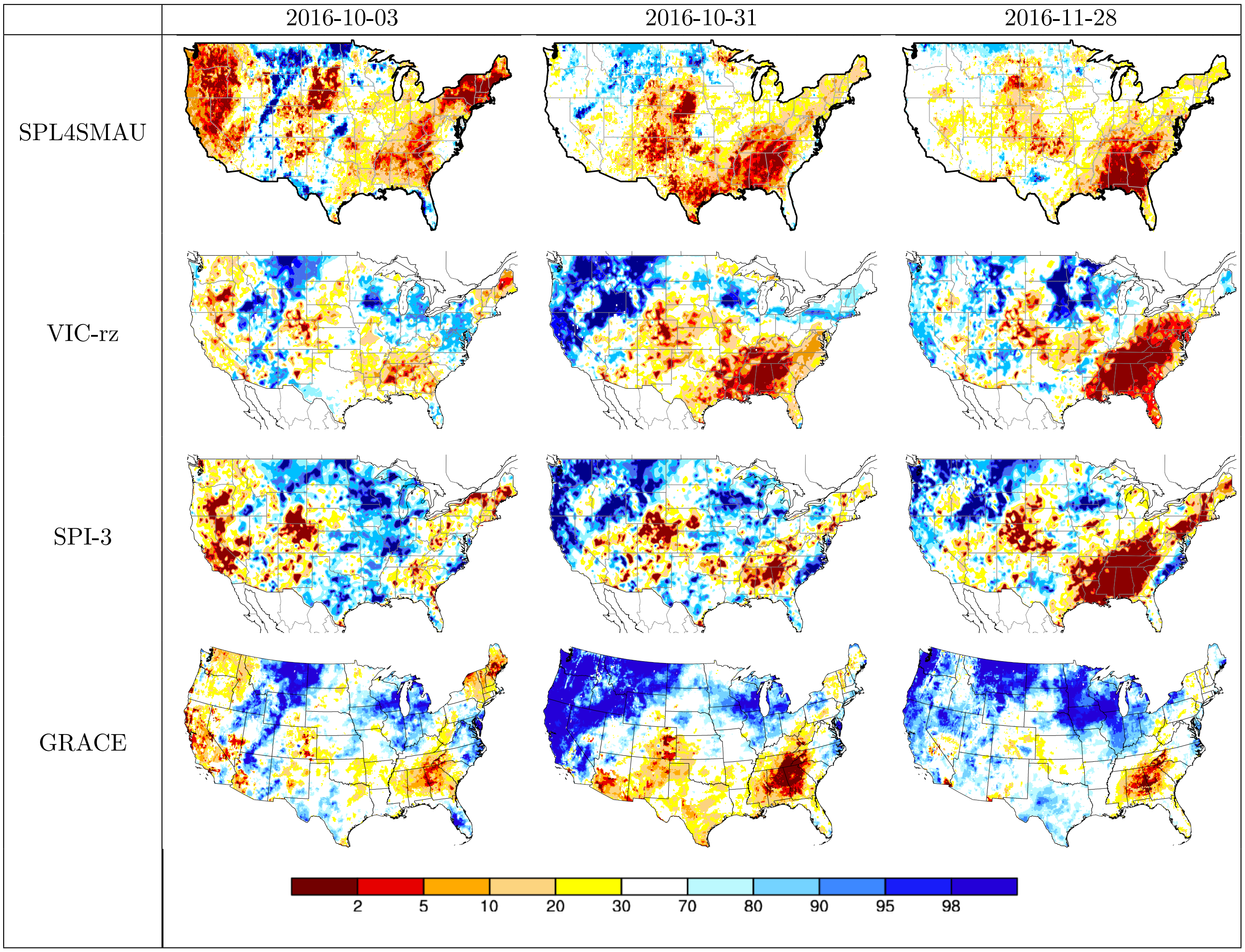


Figure 10: Comparison between SPL4SMAU index map and VIC-rz, SPI-3, and GRACE in 2016.

quite small. On the face of it, this lack of seasonality probably supports the authors decision to consider seasonality in a relatively simple way.

2. Author's response
When we looked at the frequency distributions of soil moisture data at each grid, the data seemed to be dominated by either low soil moisture (summer time) or high soil moisture data (winter time). Further analysis showed these to be related to the warm and cold season periods. Therefore, to capture this inter-seasonal behavior in soil moisture, we divided the record into a warm season (April - September) and a cold season (October - March). Dividing the year into warm and cold seasons enabled us to track the soil moisture dynamics, and thus the probability distribution and index seasonally. Ideally, we would have divided it into monthly data but there are insufficient observations. Ideally we would have divided it into monthly data but there were insufficient observations to do that. This lead to our decision to divide the data into two seasons.

3. Author's changes in manuscript
We looked at the frequency distribution of soil moisture data at each grid. The data seemed to be dominated by low soil moisture in the summertime, and high soil moisture in the wintertime. Therefore, to capture this inter-seasonal behavior in soil moisture, we divided the record into a warm season (April - September) and a cold season (October - March). Dividing the year into warm and cold seasons enabled us to track the soil moisture dynamics, and thus the probability distribution and index seasonally. Ideally,

we would have divided it into monthly data but there are insufficient observations.

1. Comments from referee
   Page 8/Lines 4-7 The attribution of this Southern California signal to an irrigation effects is problematic. The area fraction of Southern California that is irrigated is actually quite low. It is much more likely that the lack of (VIC/SMAP) correlation in these areas is due to thermal problems with 6 pm retrievals over arid/semi-arid regions (which is why the problem does not re-occur in Nebraska) during the summer (basically, summertime pm conditions violate the soil/canopy isothermal assumption that SMAP uses to retrieve soil surface moisture). One way to test this, would be to re-generate Figure 4a using only 6 am retrievals and see if the effect goes away.

2. Author's response
   We are a little bit confused on this comment. We did not use a 6pm retrievals. We have used 6 am retrievals for any location. Regarding Southern California comment, we can recognize that there is an attribution to irrigation in southern and south central California and the high number of private and state owned groundwater wells (there are also as many as 2 million water wells in California that contribute to irregularity of groundwater and affecting the soil moisture. They range from hand-dug, shallow wells to carefully designed large-production wells drilled to great depths) which makes the area regulated and hence what SMAP sees is different what a LSM like VIC expects to be the case, however, we are unsure about other reasons for this. On the other hand, our new analysis and filter doesnt show a very strong confidence during Warm season on Southern California and we explained it in the text. More data is needed before we can recognize further attributions to low correlation between VIC and SMAP in that region. In the northeast and during winter we have the problems of ground covered by snow which doesnt result in good SMAP coverage and the low number of days and overpasses (presented in Figure **??**) during winter in northeast can play a role in low amount of data and poor correlation during cold season. We added this content to the paper and provided references.

3. Author's changes in manuscript
   In one part: In this study, SPL3SMP products from the 6:00 a.m. retrievals and SPL4SMAU products from 6:00 a.m. retrievals, are used in the analysis of soil moisture drought index. Our SMAP data records are from 2015-04-01 to 2017-12-31, which is equivalent to 1,006 days.

   In another part: Figure 4 shows that the 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, around 0.2. The extent of this poor correlation increases during the cold season for northeastern U.S., Wisconsin and Minnesota. Snow season results in poor SMAP coverage during winter time in those areas. In addition, the low number of overpasses (presented in Figure 1) during winter in northeast can play a role in low amount of data and poor correlation during cold season. Contrary to the warm season, southern California shows a high a correlation with VIC during the cold season, around 0.9. We attribute this change in southern and south central California from cold season to warm season to irrigation that SMAP picks up, but VIC doesn't since the version used here doesn't have water management effects. Land use/land cover map shows that about one third of these areas are irrigated vegetation and another third is forests and woodlands (USGS, 2018). There are also as many as 2 million water wells in California that contribute to irregularity of groundwater and affecting the soil moisture. They range from hand-dug, shallow wells to carefully designed large-production wells drilled to great depths (California Dept. of Water Resources, 2018). More data is needed before we can recognize further attributions to low correlation between VIC and SMAP in that region. While systematic biases do not get revealed in correlations, the temporal consistency among the time series is captured.

1. Comments from referee
   Bottom of page 8. . .what exactly is meant by raw SMAP retrievals? Also, the list here seems to contain 2 (as stated in the text). Finally, the exact link between these 6 comparisons and plotted results in Figure 3 is a bit unclear. A couple more explanatory sentences would help here.

2. Author's response
   We fixed the number from 6 to 2 to avoid confusion and over explaining the details. Raw SMAP is SMAP Level 3, and the word raw is removed.

3. Author's changes in manuscript
   We used the KS test for each grid, comparing the modeled beta distribution of the long-term VIC with the modeled beta distribution of the short-term VIC, in both warm and cold seasons. This shows if the long-term and short-term distributions are statistically indistinguishable.

1. Comments from referee
   Bottom of page 13/of page 14. It is not clear to me how the SMAP L4 product could possibly detect the impact of groundwater extraction (using a land model which does not consider the impact of well pumping on saturated zone calculations and assimilation observations sensitive to only the top 5 cm of the soil column). Therefore, the attribution presented here seems potentially misguided. This discussion should be either strengthened or removed.

2. Author's response
   Since this is beyond the scope of the paper we decided to remove this argument from the paper.

3. Author's changes in manuscript
   NA

1. Comments from referee
   The abstract spends too much time discussing SMAP background (in the first paragraph) and too little time defining the contribution of this particular manuscript (see major point above).

2. Author's response
   We agree with that, now the abstract is revised to embody more informative aspects of the information provided in the paper.

3. Author's changes in manuscript
   Abstract: Since April 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 in 2-3 days depending on location. 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. However, the short SMAP record length poses a statistical challenge for meaningful assessment of its indices. This study presents initial insights about using SMAP for monitoring drought and pluvial regions with a first application over the Contiguous United States (CONUS). SMAP soil moisture data from April 2015 to December 2017 at both near-surface (5cm) SPL3SMP, or Level 3, at ∼36 km resolution; and root zone SPL4SMAU, or Level 4, at ∼9 km resolution were fitted to beta distributions and were used to construct probability distributions for warm (May-October) and cold (November-April) seasons. To assess the data adequacy and have confidence in using short-term SMAP for drought index estimate, we analyzed individual grids by defining two filters and a combination of them, which could separate 5,815 grids covering CONUS into passed and failed grids. The two filters were: (1) The Kolmogorov-Smirnov (KS) test for beta-fitted long-term and short-term Variable Infiltration Capacity (VIC) LSM with 95% confidence; and (2) Good correlation (≥ 0.4) between beta-fitted VIC and beta-fitted SPL3SMP. To evaluate which filter is the best, we defined a Mean Distance (MD) metric, assuming VIC index at 36 km resolution is the ground truth. For both warm and cold seasons, the union of the filters – which also gives the best coverage of the grids throughout CONUS – was chosen to be the most reliable filter. We visually compared our SMAP-based drought index maps with metrics such as U.S. Drought Monitor (from D0-D4), SPI 1 month and VIC near surface from Princeton University. The root zone drought index maps were shown to be similar to those produced by the VIC at root zone, SPI 3 month, and GRACE. 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. Comments from referee
   The SMAP product version names in the manuscript differ from the official product names/acronyms (see https://smap.jpl.nasa.gov/data/). . . good to use the official versions.

2. Author's response
   We used the product names from NSIDC (https://nsidc.org/data/smap/smap-data.html) and not the names from NASA. Since people should go to NSIDC, that naming seems to the best. The inconsistency between JPL and NSIDC is a problem.

3. Author's changes in manuscript
   NA

1. Comments from referee
   Page 3/Line 20. . . double parentheses.

2. Author's response
   That is fixed!

3. Author's changes in manuscript
   The approach (Sheffield et al., 2004) took was to fit the VIC-simulated soil moisture to probability distributions, usually beta distributions, where the percentiles are translated to the index values that range from 0 to 1.

1. Comments from referee
   Page 7/Line 4. . . better to say too tightly bounded.

2. Author's response
   This whole paragraph is reworded.

3. Author's changes in manuscript
   Please read the next comment's Author's changes.

1. Comments from referee
   Page 7/Lines 9-11. . . reword to clarify. . . unclear how the moment matching approach applied here differences from that of Sheffield et al. (2004).

2. Author's response
   We made the explanation clearer under Fitting the beta distribution to the SMAP time series section.

3. Author's changes in manuscript
   There are, however, differences in our approach from that in Sheffield et al. (2004). Firstly, the basis of the data used in Sheffield et al. (2004) was simulated soil moisture from VIC while ours is remotely sensed data. Secondly, to calculate the bounds of beta distribution [a, b], Sheffield et al. (2004) used the first (last) 10% of the sorted soil moisture values linearly related to the empirical cumulative distribution function. In our study, this approach did not yield useful results with the estimated limits for a (b) for SMAP, often did not cover the full range of observed values, preventing interpretation of the historical data. Our methodology for obtaining beta distribution parameters a and b is discussed in this section.

1. Comments from referee
   Figure 5 needs a color key. . . not clear what grey shading indicates.

2. Author's response
   We have explained this in the caption and furthermore, we have a Figure 6 now that includes the information of Figure 5 in it and it is color coded. To avoid confusion with different colors codes in Figure 5 and Figure 6 and redundancy of the same numbers, we explained what gray area is in the caption of Figure 5.

3. Author's changes in manuscript
   Please see Figure 6 and the caption of 5.

1. Comments from referee
   Bottom of page 12. . .where exactly is this grid analysis presented? Unclear what is being referred to here.

2. Author's response
   We removed grid analysis phrase to avoid confusion and rephrased it.

3. Author's changes in manuscript
   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. Secondly, depending on the plant development stage, 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 season progresses it becomes more important for plant water needs.

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