Response to Referee #1

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

September 10, 2018

1. Comments from referee
   With interest I have read the manuscript entitled "A SMAP-Based Drought Monitoring Index for the United States", it is interesting and well written (although I am not a native English speaker!). It is certainly of interest for HESS readers. The manuscript details a new SMAP-based index for drought monitoring over the Continental US (although the title mentions [...] the United States).
2. Author's response
   Thank you for this comment. We have changed the title to the one above. We believe is targeting the content of the paper.
3. Author's changes in manuscript
   Paper's New Title: Developing a drought monitoring index for the Contiguous U.S. using SMAP

1. Comments from referee
   The methodology stems on previous work from Sheffield et al., 2004 and is applied to the recent SMAP data. The resulting drought index is then compared to other already existing index like SPI-1&3, and another one GRACE-based. While the article is clear (at least to me), I am missing some more analyses of the drought Index for the manuscript to go from [...] a demonstration of the reliability [...] with lot of text to a proper journal article (There is no results section?).
2. Author's response
   There are some differences between our approach and those from Sheffield et al., 2004. After carefully revisiting there paper, we made major numerical analysis on the added value of the drought index using SMAP and expanded our Results section. 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. The new reliability analysis is described under Data adequacy filter section.
3. Author's changes in manuscript

   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.

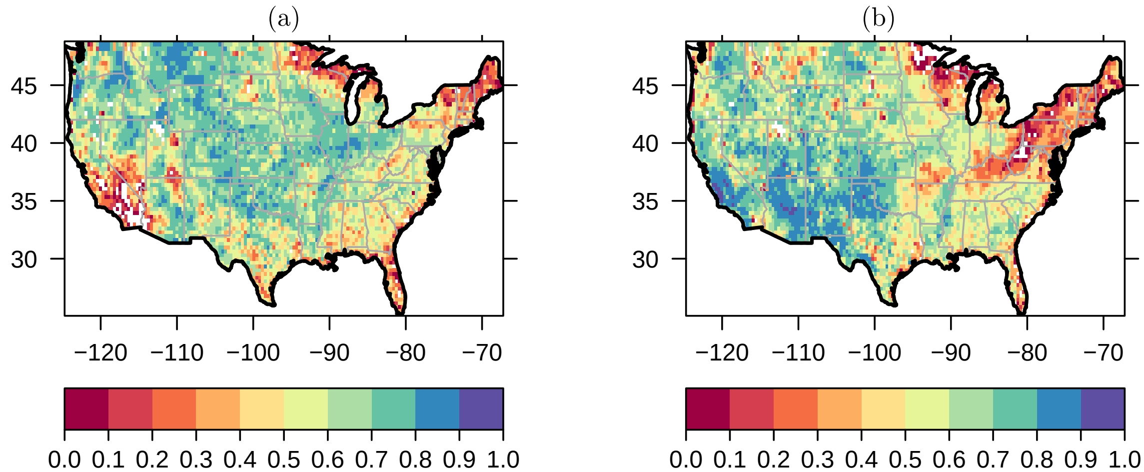

Figure 1: (a) Correlations (R) between VIC and SMAP beta models for the warm season (average R=0.57) and (b) cold season (average R=0.56). White regions signify negative correlation.

0.1 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:

1. The Kolmogorov-Smirnov (KS) test for beta-fitted long-term and short-term VIC with 95% confidence;
2. 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.

0.1.1 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 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). Figure 2 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.

0.1.2 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.,

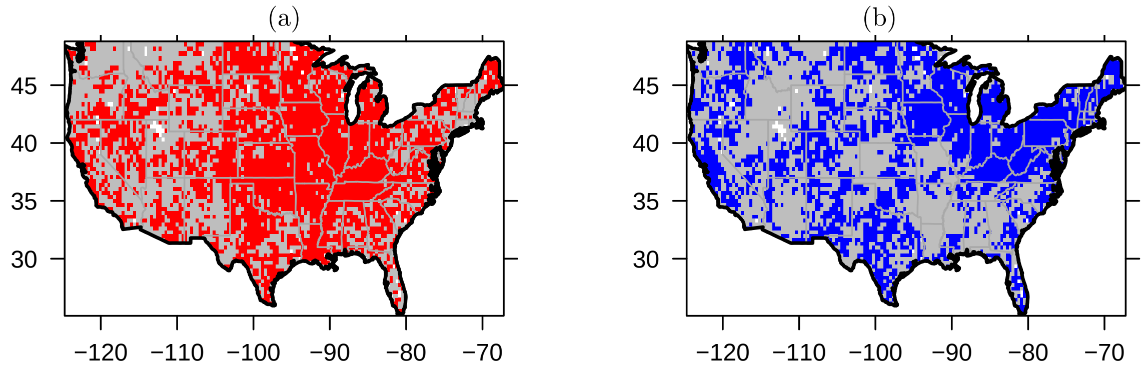

Figure 2: (a) Grids in red show areas whose short term VIC in warm season data has the same underlying beta distribution as the long-term VIC in warm season data (n = 3560 or 68% of grids are red); (b) the same as the left figure but for cold season period shown in blue (n = 2927 or 57% of grids). Gray areas are grids where the short term VIC does not have the same beta distribution as their long term VIC.

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 1 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.

0.1.3 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:

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

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:

$$MD = \frac{\sum_{i=1}^{n_d} |MD_d|}{n_d} \tag{2}$$

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}: $Diff = MD_{fail} - MD_{pass} > 0$

0.1.4 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. Comments from referee
   Authors present several comparisons but not a proper evaluation of the added value of this index. Some more in depth analyses of the added value of the new Index otherwise it is simply one Index amongst many other. For example, if you were using NASAs Catchment LSM (i.e., without assimilation of any SMAP data) would you have different results? How could you / would you quantify/highlight the added value of SMAP?
2. Author's response
   We agreed that some more in-depth analysis of the usefulness of the index would have added more value to the process and the paper. Hence we did extensive analysis on the reliability of our work by analyzing 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 VIC with 95% confidence; and (2) Good correlation (> 0.4) between beta-fitted VIC and beta-fitted SPL3SMP. The process is described in the previous response. Below we should the numerical analysis results. The index without NASA's LSM looks like Level 3 data.
3. Author's changes in manuscript

   Figure 1 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 3) 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.

   #### 0.1.5 KS filter

   Figure 2 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.

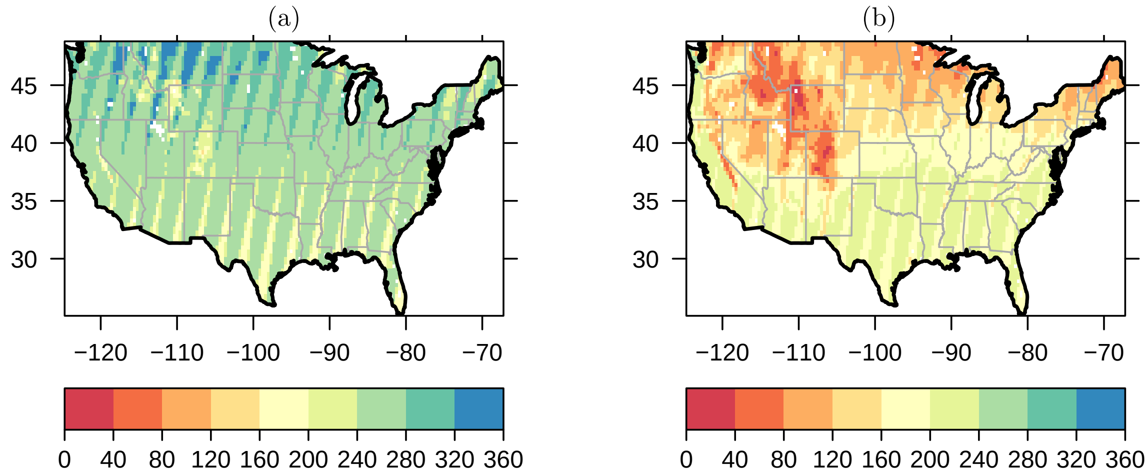

Figure 3: Number of overpasses for each season. (a) is warm season April 1 - September 30; (b) is cold season, October 1 - March 31).

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

0.1.6 Combined filters

Figure 4 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.

0.2 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

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

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

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.

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 4) 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.

0.3 Comparison among the drought indices

In Figure 5 to Figure 8, 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 Section **??**. 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 **?**, GRACE maps root zone soil moisture and groundwater transformed into percentiles (**?**).

Figure 5 and Figure 7 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 6 and Figure 8, 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 7).

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 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 5).

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 5). 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
   Abstract General comment : Some parts seem awkwardly written and are not self explanatory, not all acronyms are given and some very specifics information are given making it difficult to follow for the Reader.
2. Author's response
   In addition to carefully addressing your specific comments about all the acronyms, we re-read and

reevaluated the abstract and rewrote it to make sure it is written in more fluent and scientific way. Please see the new version.

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 $85.044^{\circ} N/S$) 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 $\sim$36 km resolution; and root zone SPL4SMAU, or Level 4, at $\sim$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
P.1,L.5: [...] so the 33 months [...], when doesn't it starts and when does it stops?
2. Author's response
Since we rewrote the abstract this sentence has been changed.
3. Author's changes in manuscript
Please read the new abstract in previous response.

1. Comments from referee
P.1,L.6: Please clarify SPL4SMAU, while I assume it is the level 4 products it might not be obvious for everyone.
2. Author's response
Since we rewrote the abstract this sentence has been changed.
3. Author's changes in manuscript
The sentence changed to: SMAP soil moisture data from April 2015 to December 2017 at both near-surface (5cm) SPL3SMP (36km res.) and root zone SPL4SMAU (9km res.) were fitted to a beta distribution and were used to construct probability distributions for warm (May-October) and cold (November-April) seasons.

1. Comments from referee
P.1,L.10: if your intention is to say that your drought index is based on the level 4 product (SPL4SMAU), simply say it.

2. Author's response
Since we rewrote the abstract this sentence has been changed here. Regardless, our drought indices are both based on Level 3 and Level 4.
3. Author's changes in manuscript
Since we changed the previous sentence to address the issue, this sentence was removed.

1. Comments from referee
P.1,L.13: [...] 57% of grids[...], please clarify.
2. Author's response
The abstract is rewritten to fit the new numerical analysis and hence, doesnt include this part any longer.
3. Author's changes in manuscript
The 57% is clarified more in caption of Figure 2. Please see Figure 2.

1. Comments from referee
P.1,L.16-17: Not obvious what is D0-D4, GRACE and W0-W4, please clarify. Introduction General comment: Some paragraphs are a bit long and could be shortened (it is just my opinion so I let this comment to Authors discretion).
2. Author's response
The sentence changed to: W0-W4 was removed.
3. Author's changes in manuscript
NA

1. Comments from referee
P.2, L.8: what is NCEI?
2. Author's response
This was addressed and changed to NOAA. In the references more information is given.
3. Author's changes in manuscript
Example: In the U.S. since 1996, there has been at least one drought event per year except for years 1997, 2001, 2004, and 2010, and each year drought cost between 1 billion and 14 billion dollars in damages (in 2015 - adjusted dollars) (NOAA, 2018).

1. Comments from referee
P.2, L.10: what is UNPD
2. Author's response
Sorry for the typo. It was UNDP and regardless are more recent UN-ISDR article was more relevant. We referenced UN-ISDR instead.
3. Author's changes in manuscript
Although the impacts of drought are intimately linked to the vulnerability of a population to adverse conditions (UN/ISDR, 2007) 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.

1. Comments from referee
P.3, L30: [...] differs a great deal [...], please consider rephrasing.
2. Author's response
Reworded to differs considerably.
3. Author's changes in manuscript
Additionally, intercomparison of the four NLDAS models showed that soil moisture differs considerably among models (Robock et al., 2000).

1. Comments from referee
   P.4, L.5: [...] and others [...], please consider using et. al.
2. Author's response
   This is fixed.
3. Author's changes in manuscript
   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 temporal resolutions: MetOp with the advanced scatterometer (ASCAT) (Brocca et al., 2010; Wagner et al., 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).

1. Comments from referee
   P.4, Is the last paragraph of the introduction in agreement with the four point described above (I am thinking of point 3 in particular). Maybe a link could be made with long data record of soil moisture from satellite derived surface soil moisture like the ESA-CCI data set (e.g., Dorigo et al., 2017, see reference below).
2. Author's response
   Shortness of data availability for SMAP is a challenge, However, we numerically figured out how to address this challenge. We looked at the correlation between SMAP and VIC and distribution parameters between long term VIC and short term VIC and could make reasonable conclusion on how to overcome the challenge and how reliable our estimates of the drought index using SMAP can be. We wrote about these approaches in the Data adequacy, Result, and Discussion sections. We have decided not to include the ESA-CCI in the analysis.
3. Author's changes in manuscript
   Please refer to above methodology explanations.

1. Comments from referee
   P.4, L.18 : please clarify W0-W4 (I guess W is for week)
2. Author's response
   We removed this expression from the paper. They refer to the drought levels in the USDM. We don't know what W stands for (perhaps wet?).
3. Author's changes in manuscript
   NA

1. Comments from referee
   Data and Methods General comment : I believe consistency is a key element that could be improved.
2. Author's response
   We also appreciate noticing that and we have worked through the text and made sure all the dates are consistent from April 1, 2015 through December 31, 2017.
3. Author's changes in manuscript
   Various locations

1. Comments from referee
   P.4, L.22: Since 31 March [...], in the introduction it is since April.
2. Author's response
   This is fixed and all through the paper April 1st is indicated as the first day of SMAP analysis.

3. Author's changes in manuscript
   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.

1. Comments from referee
   P.4, L.26-27: please rephrase to mention Level 3; Level 4...
2. Author's response
   Fixed!
3. Author's changes in manuscript
   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.

1. Comments from referee
   P.4, L.33: If it is he case (and I think it is from the introduction), the SMAP L-band Tb that are assimilated to produce the SPL4SMAU are the SPL3SMAU data (?) if so, please simply say it.
2. Author's response
   This paragraph is changed to the one brought up in the previous response.
3. Author's changes in manuscript
   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).

1. Comments from referee
   P.5,L.9, what is L4, please clarify.
2. Author's response
   L4 is SPL4SMAU. I changed it to be consistent with the rest of the text.
3. Author's changes in manuscript
   This part of text is changed. Additionally I checked that everywhere in the text is consistent and is using either Level 4 or SPL4SMAU.

1. Comments from referee
   P.5, L.27, 33 months sometimes, 1009 days some others, please be consistent if you are talking about the same thing.
2. Author's response
   This was clarified and now it is consistent throughout the text as 1,006 days (not 1,009).
3. Author's changes in manuscript
   Our SMAP data records are from 2015-04-01 to 2017-12-31, which is equivalent to 1,006 days.

1. Comments from referee
   P.6, L.15, please rephrase question.
2. Author's response
   It was rephrased.
3. Author's changes in manuscript
   A main challenge is to fit the four parameters of beta distribution, given a set of empirical observations.

1. Comments from referee
   P.6, L.29, what is mpas ? Please correct typo (maps I guess)
2. Author's response
   Yes, fixed!
3. Author's changes in manuscript
   NA

1. Comments from referee
   Figure 2: units?
2. Author's response
   The unit is m^3/m^3 and it is added to the text.
3. Author's changes in manuscript
   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.

1. Comments from referee
   P.8, L.1: Please comment on correlation values and their significance.
2. Author's response
   The significance of the correlation values between VIC and SPL3SMP is that is allows us to use VIC as a tool for fitting beta distribution to SPL3SMP. Under section titled Correlation Filter we explained the significance of it in the revised version.
3. Author's changes in manuscript
   Please refer to the section "correlation filter" above.

1. Comments from referee
   Comparison to other indices General comment : I am missing some in depth analyses of the added value of the new Index otherwise it is simply one Index amongst many other. For example, if you were using NASA's Catchment LSM (i.e., without assimilation of any SMAP data) would you have different results? P.10, I think a word is missing in the second sentence (?)
2. Author's response
   This comment of the reviewer was brought up on the first page. Please see the repeated version above. In addition, in the revised version we added very interesting and in-depth numerical analysis, introducing the Mean Distance metrics and filters to find the most reliable grids for SMAP-based drought predictions, which adds greatly to the value of research. The development of a drought index

using SMAP has not been done before. Although other drought indices exists, they are model based being forced by precipitation. SMAP drought index is unique to be an index solely based on remotely sensed satellite data.

3. Author's changes in manuscript
The drought index described in this study provides a reliable estimate of the state of drought on a daily basis for the CONUS using SMAP. We fitted beta distributions to the SMAP data and used correlation, KS, and a combination of those two filters to numerically assess the adequacy of the short term SMAP data for each grid cell. The areas that passed neither the KS nor correlation tests were flagged in the final SMAP drought index. These areas are grids where we have less confidence in reliable drought index estimates: the are non-stationary and thus their soil moisture has been changing over the past 40 years. The flagged grids can be seen as adjustment to the model to remove non-climatic influences or water management practices, although more in-depth research is needed to confirm such changes. Given the limited scope of the data, 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.

   Besides drought, SMAP can also identify regions of anomalously wet conditions that can be of great use to water and agricultural managers. Wet indices 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.

   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. This is advantageous since SMAP 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 to study the shorter-term impacts from the other variables on soil moisture.

   Both near surface and root zone soil moisture drought products can provide important information about the availability of soil moisture at the stage where plants develop in order to cultivate the optimum harvest. Future applications of this study can be coupling plant growth models with near surface and root zone soil moisture drought index products (**?**).

   The soil moisture data are a culmination of all hydrological processes and represent available water from incoming precipitation and throughfall to evapotranspiration and drainage processes. The SMAP satellite is providing global observations of soil moisture of unprecedented quality. 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. Thus results here provide significant support for a global SMAP drought and pluvial conditions monitoring system. since SMAP data can be retrieved and maps can be generated in near-real time, it is very promising that a SMAP drought index product can be implemented operationally.

1. Comments from referee
P.11, why are the figures embedded in the conclusion?
2. Author's response
Thank you for pointing that out. That was an error with how LATEX compiled. That is fixed now.
3. Author's changes in manuscript
Changes are made in the new manuscript.

1. Comments from referee
Conclusions Some sentences really look like introduction to me.
2. Author's response
That is fixed as well! Please see the revised version.

3. Author's changes in manuscript
   The drought index described in this study provides a reliable estimate of the state of drought on a daily basis for the CONUS using SMAP. We fitted beta distributions to the SMAP data and used correlation, KS, and a combination of those two filters to numerically assess the adequacy of the short term SMAP data for each grid cell. The areas that passed neither the KS nor correlation tests were flagged in the final SMAP drought index. These areas are grids where we have less confidence in reliable drought index estimates: the are non-stationary and thus their soil moisture has been changing over the past 40 years. The flagged grids can be seen as adjustment to the model to remove non-climatic influences or water management practices, although more in-depth research is needed to confirm such changes. Given the limited scope of the data, 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.

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References

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.

Cai, X., Pan, M., Chaney, N. W., Colliander, A., Misra, S., Cosh, M. H., Crow, W. T., Jackson, T. J., and Wood, E. F.: Validation of SMAP soil moisture for the SMAPVEX15 field campaign using a hyper-resolution model, Water Resources Research, 53, 3013–3028, 2017.

California Dept. of Water Resources: Wells, url:https://water.ca.gov/Programs/Groundwater-Management/Wells, 2018.

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.

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, 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 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.

NOAA: U.S. Billion-Dollar Weather and Climate Disasters, urlhttps://www.ncdc.noaa.gov/billions, URL `https://www.ncdc.noaa.gov/billions/`, national Centers for Environmental Information (NCEI), 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, 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.

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.

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

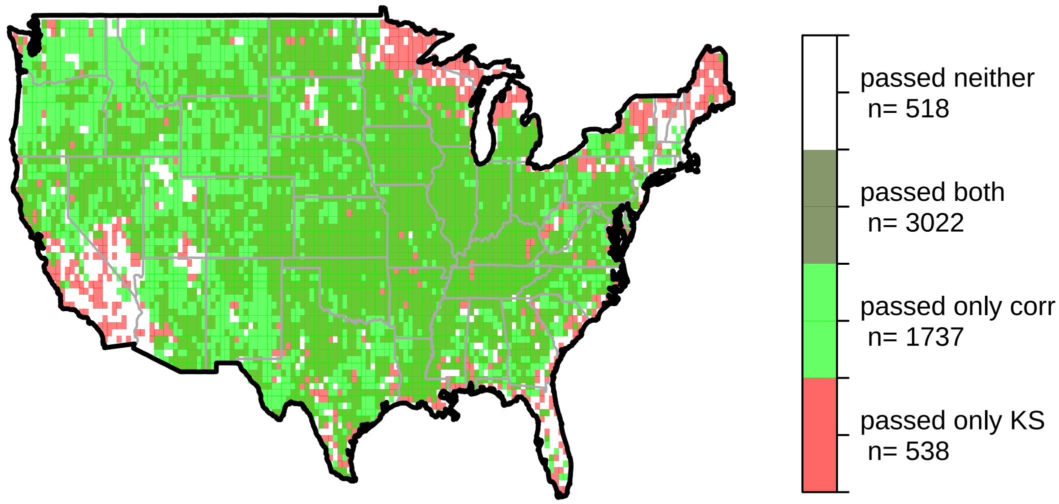
UN/ISDR: Drought Risk Reduction Framework and Practices: Contributing to the Implementation of the Hyogo Framework for Action. United Nations secretariat of the International Strategy for Disaster Reduction (UN/ISDR), Tech. Rep. 98+vi pp, United Nations secretariat of the International Strategy for Disaster Reduction (UN/ISDR), Geneva, Switzerland, 2007.

USGS: National Gap Analysis Program, Land Cover Data Viewer, url:https://goo.gl/rntijg, 2018.

Wagner, W., Hahn, S., Kidd, R., Melzer, T., Bartalis, Z., Hasenauer, S., Figa-Saldaña, J., de Rosnay, P., Jann, A., Schneider, S., Komma, J., Kubu, G., Brugger, K., Aubrecht, C., Züger, J., Gangkofner, U., Kienberger, S., Brocca, L., Wang, Y., Blöschl, G., Eitzinger, J., and Steinnocher, K.: 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.

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.

(a)



(b)

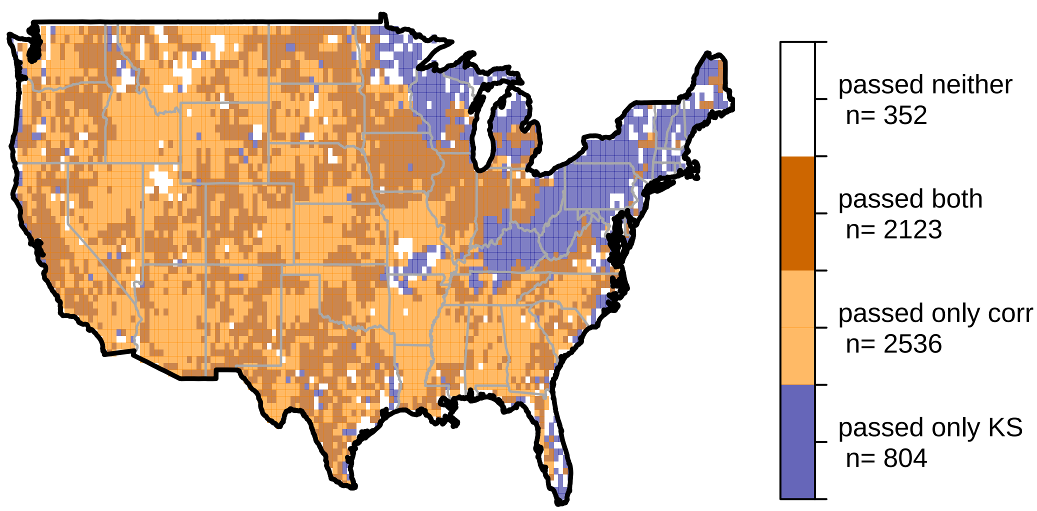


Figure 4: (a): warm season grids that pass the correlation filter and/or the KS filter. Dark green grids include grids that pass intersection filters. (b): cold season grids that pass the correlation filter and/or the KS filter. Dark orange grids include grids that pass intersection filters. In both figures white grids show the grids that pass neither filters and will be crossed hatched in index maps.

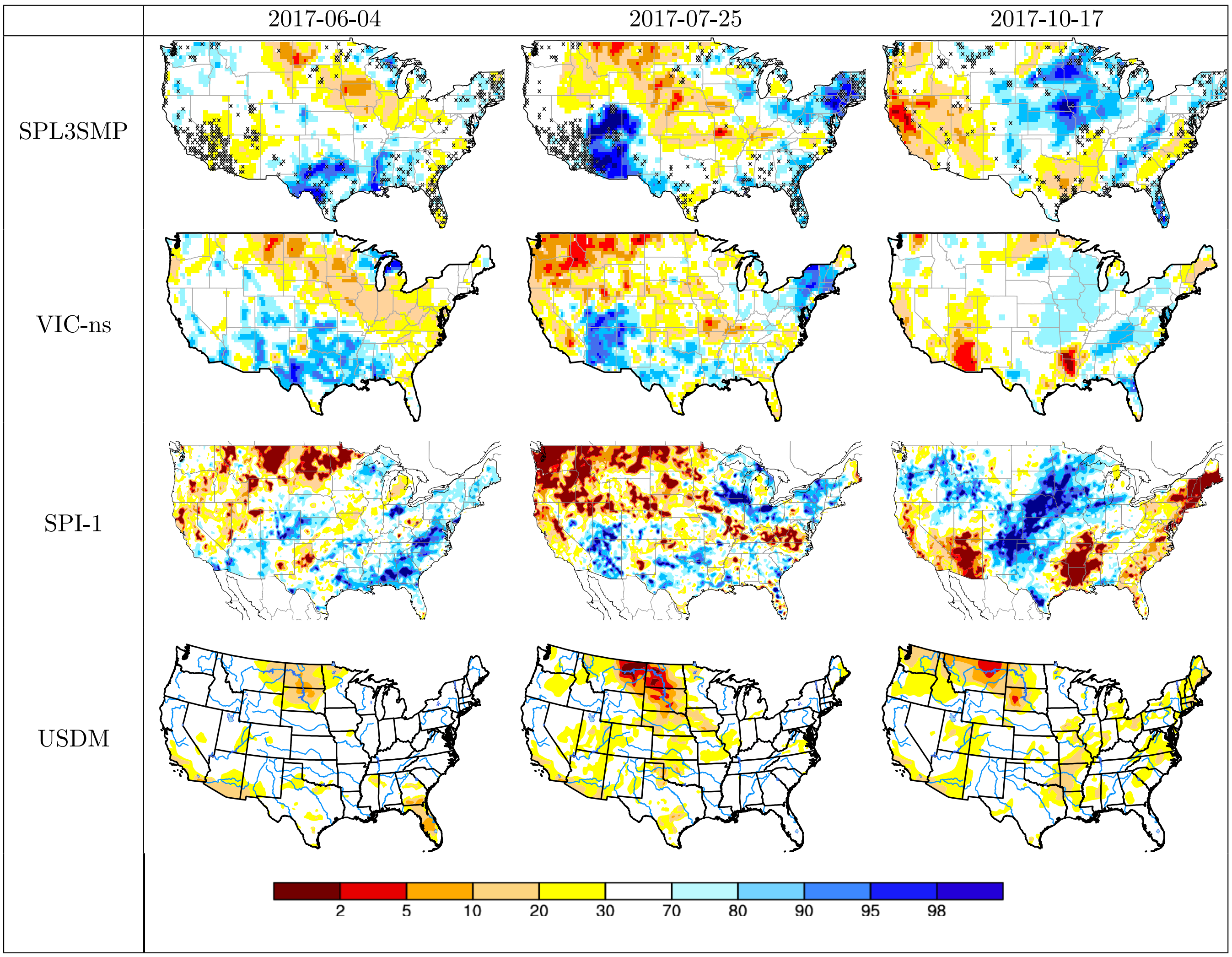


Figure 5: Comparison between SPL3SMP index map and VIC-ns, SPI-1, and USDM in 2017. For USDM, drought levels from 30 to 100 are shown in white.

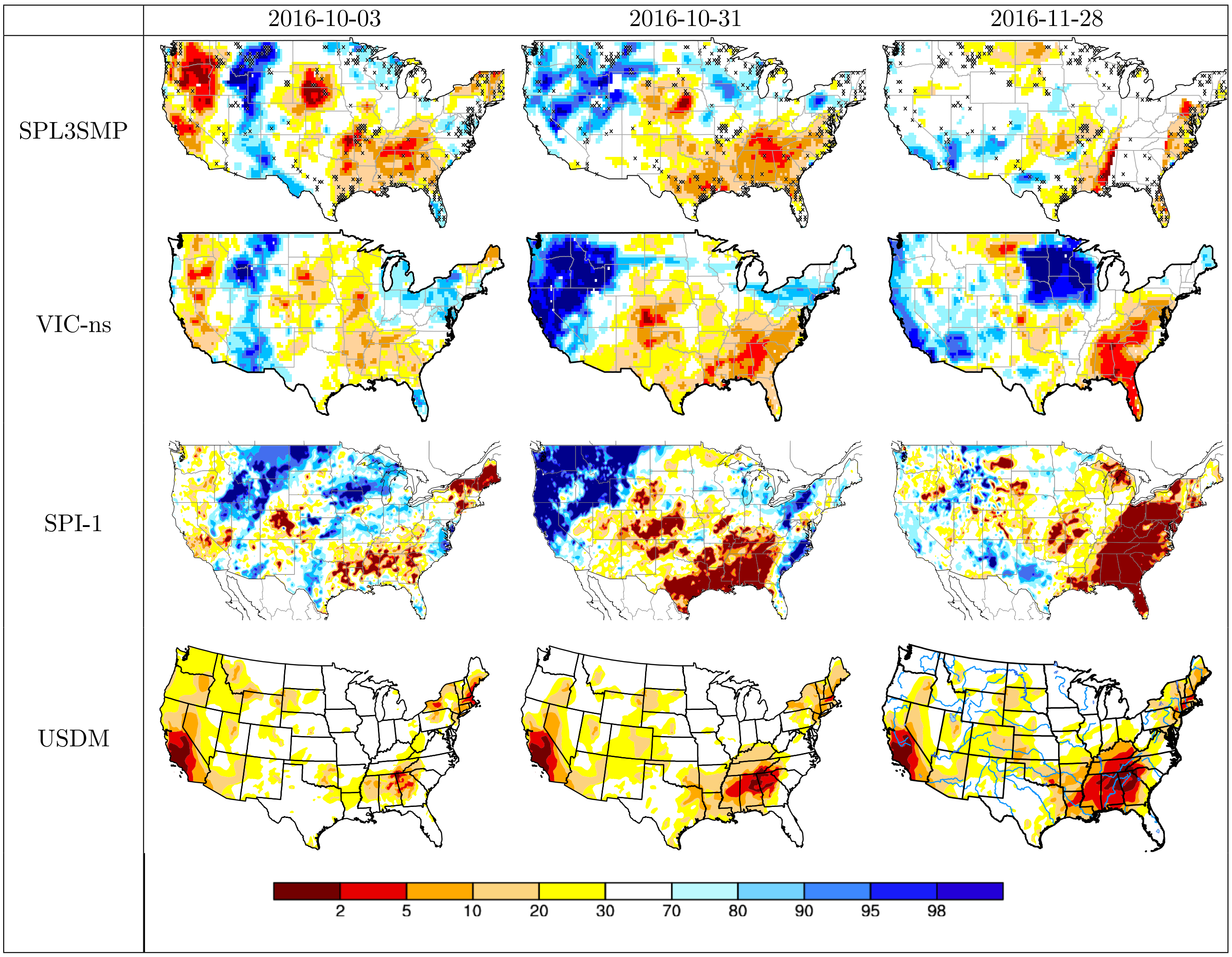


Figure 6: Comparison between SPL3SMP index map and VIC-ns, SPI-1, and USDM in 2016. For USDM, drought levels from 30 to 100 are shown in white.

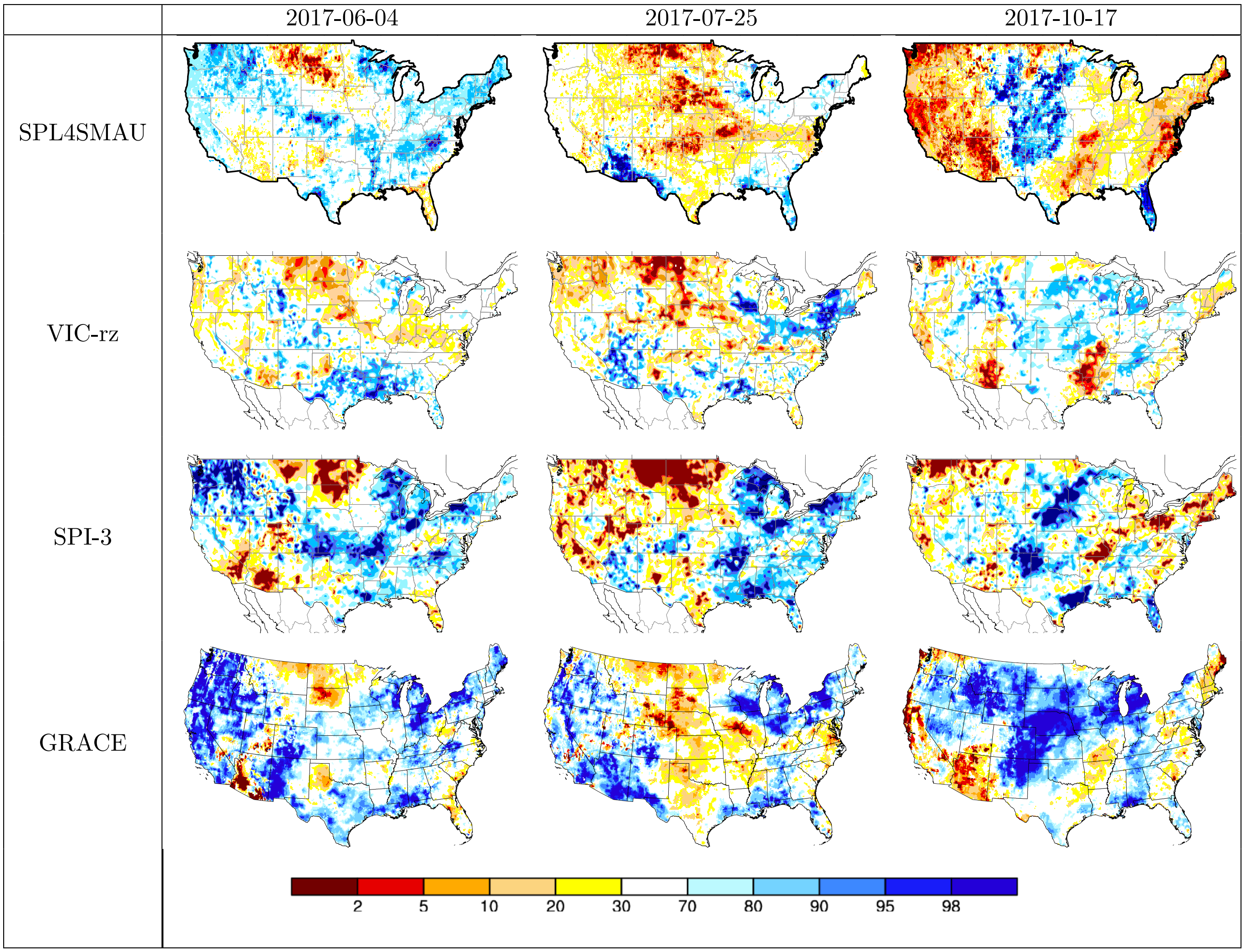


Figure 7: Comparison between SPL4SMAU index map and VIC-rz, SPI-3, and GRACE in 2017.

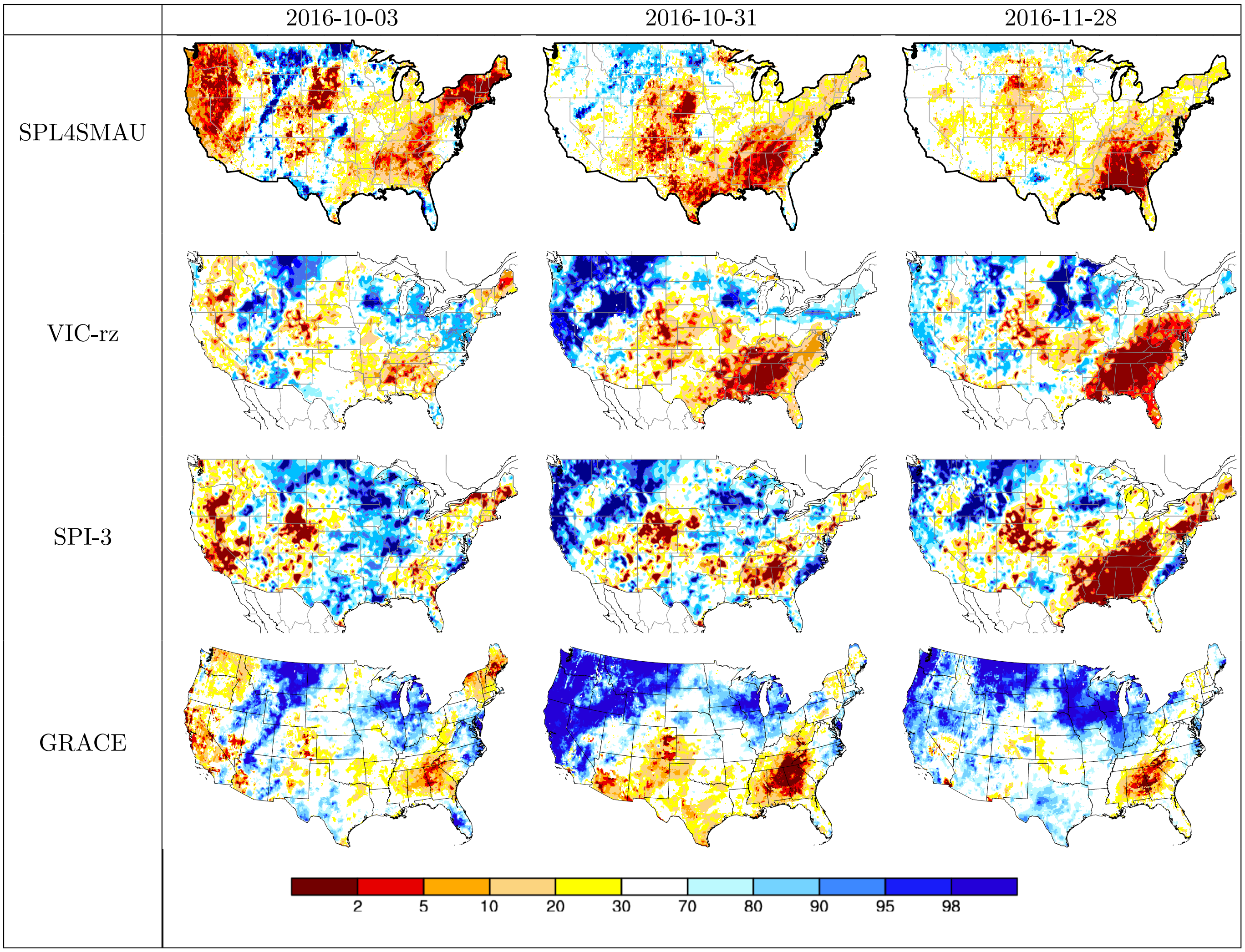


Figure 8: Comparison between SPL4SMAU index map and VIC-rz, SPI-3, and GRACE in 2016.