Length Scales of Hydrological Variability as Inferred from SMAP Soil Moisture Retrievals

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ABSTRACT

Hydrological variability at a given location is characterized in part by a horizontal length scale—a measure of how far one can travel from that location and still see similar time variations of a hydrological variable of interest. Here, using Level-2 soil moisture retrievals produced by the NASA Soil Moisture Active Passive (SMAP) mission, we compute global distributions of these length scales for the Northern Hemisphere warm and cold seasons (May–September and November–March, respectively). The length scales show significant spatial and seasonal variability, with, as expected, much larger values (e -folding scales of greater than 500 km) often seen in the cold season, when convective rainfall is less prominent. The SMAP-derived length scales are found to be largely consistent with those derived directly, where possible, from precipitation measurements. This suggests a unique value of the retrievals: outside of well-instrumented areas, satellite-based soil moisture datasets have the potential to provide otherwise unattainable estimates of the horizontal length scales of hydrological variability.

1. Introduction

The importance of the mean hydrological cycle—how much rain tends to fall during summer in a given region, for example, or the average seasonal cycle of streamflow in a given basin—is indisputable, as it helps to define where ecosystems can thrive and people can live. Arguably just as important, though, is the variability in this cycle. While a region's long-term mean precipitation may, at first glance, seem adequate to support a particular biome, such biomes may also require reliability in their yearly water supply, and higher variability implies reduced reliability and thus reduced growth (e.g., Koster et al. 2014a). Like vegetation, society also requires a reliable water supply, and with this in mind, humans have built vast networks of reservoirs to guard against water deficits during dry years as well as against flooding during wet years. The footprint of hydrological variability, however, can nevertheless prove too much for human controls, as exemplified by the 1993 flooding

in the central United States (NOAA 1994) and the drought that plagued California in recent years (Seager et al. 2015). The importance of hydrological variability, and the need in particular to prepare ahead of time for specific hydrological variations, provides much of the motivation for the development of forecasting systems at weather, subseasonal, and seasonal time scales (NRC 2010).

Given its importance, the characterization of hydrological variability is fundamental to any proper description of the global hydrological cycle. Human attempts at quantifying this variability indeed go back thousands of years, for example, to ancient measurements of Nile River stage (Dooge 1988). Nowadays, extensive datasets of precipitation, streamflow, and derived evapotranspiration, some covering multiple decades, allow for detailed statistical characterizations of hydrological variability in well-measured areas [e.g., Gu et al. (2007) and Mo and Lettenmaier (2018) are two of a great many examples]. Modeling tools, particularly atmospheric reanalysis systems that merge model results with observations in a mathematically optimal

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way (e.g., [Dee et al. 2011](#); [Gelaro et al. 2017](#)), provide comprehensive, multidecadal datasets well suited to studies of hydrological variability (e.g., [Maussion et al. 2014](#); [Collow et al. 2016](#)).

Hydrological variability, however, is a complex and multifaceted concept, and some aspects of it are still relatively unexplored. One largely undocumented facet of the variability, at least on the global scale, is the horizontal length scale over which hydrological variations are similar. Consider, for example, the time series of precipitation at two locations a kilometer apart. The two time series would presumably be strongly correlated, since the two sites would tend to see the same sequence of storms and dry periods over a period of years. Such similarity would probably also be seen for locations 10 km apart, but locations 200 km apart would begin seeing different storms at different times, and the agreement in their precipitation time series would accordingly be reduced. Using statistical techniques, a distance (basically, a length scale) associated with a specified reduction in agreement between the time series could be computed from the precipitation data collected at different locations (e.g., [Cayan and Georgakakos 1995](#)). Presumably this length scale would vary both geographically and with season and would imprint itself onto the length scales characterizing the variabilities of soil moisture, evapotranspiration, and streamflow. As outlined in [section 4](#) below, the overall spatial connectedness of hydrological variations can have important impacts on measurement strategies as well as on hydrological and climatic processes that influence society; it is more than a statistical curiosity.

Available relatively recently to the hydrological community are global gridded datasets of satellite-derived moisture in the top several centimeters of soil ([Kerr et al. 2010](#); [Entekhabi et al. 2010](#)). While moisture deeper in the soil (e.g., through the root zone) may appear to be more central to variations in the overall hydrological cycle, the near-surface moisture measured via satellite has unique value for hydrological analysis (e.g., [McColl et al. 2017a](#)). This is because surface moisture lies at the interface between the atmospheric and land branches of the global hydrological cycle. The water content within the near-surface soil regulates both the direct evaporation of soil water into the atmosphere and the ability of incident precipitation water to infiltrate into deeper layers of the soil. As a result, variations in near-surface moisture, properly interpreted, can reveal much about variations in the hydrological cycle itself. Time series of near-surface soil moisture variations have been successfully processed into estimates of precipitation ([Brocca et al. 2014](#); [Koster et al. 2016a](#)), streamflow ([Koster et al. 2018](#)), and

evapotranspiration ([Purdy et al. 2018](#)), demonstrating unequivocally the strong connection between near-surface moisture as measured by satellites and large-scale hydrological fluxes.

The present study applies gridded, 36-km resolution soil moisture retrievals from the National Aeronautics and Space Administration (NASA) Soil Moisture Active Passive (SMAP) mission ([Entekhabi et al. 2010](#); see [section 2a](#) below) to the problem of quantifying horizontal length scales of soil moisture variability across the globe. [A corresponding analysis of Soil Moisture Ocean Salinity (SMOS) data ([Kerr et al. 2010](#)) is left for future work.] Different processes control soil moisture variability at different length scales ([Robock et al. 1998](#); [Entin et al. 2000](#); [Famiglietti et al. 2008](#)); given the spatial resolution of the SMAP data, the focus here is on what are mainly large-scale, meteorology-based soil moisture variations as opposed to subgrid-scale variations induced by surface features such as soil properties and topography. We will show how the soil moisture-based length scales vary geographically and with time of year, and we will examine them for consistency with those computed (where possible) from in situ precipitation data. Note that in situ measurements of precipitation, soil moisture, streamflow, or ET are far from globally comprehensive. Also, hydrological fluxes do not have a direct, mechanistic impact on the radiances measured by satellite, and as a result, satellite-based estimates of hydrological fluxes, while of great value, have built into them a number of assumptions that can imprint themselves on length scale calculations. Given these considerations, a global quantification of these length scales using SMAP data can be considered a unique and important contribution to the overall characterization of the global hydrological cycle.

We emphasize that this is a purely statistical study. While we do speculate on some of the physical processes underlying our computed length scales, we do not attempt here to verify these speculations or explain the computed length scales in terms of, for example, the soil's ability to transform or modify the length scales inherent in the atmospheric forcing (e.g., precipitation and evaporative demand). We consider the presentation of these length scales to be valuable in itself, because again, such a characterization from a single, global-scale hydrological dataset is not readily available in the literature. The length scale we employ does not capture all aspects of hydrological spatial variability (e.g., it effectively averages out anisotropy in the spatial statistical structures), but this is in some ways a strength, as this length scale has the advantage of simplicity—it captures, in a highly intuitive way, the first-order character of these structures.

Our analysis of horizontal length scales utilizes the data sources and methodology detailed in [section 2](#). Results are provided in [section 3](#), with emphasis on the SMAP-derived length scales in the Northern Hemisphere warm and cold seasons ([section 3a](#)) and on comparisons of SMAP-derived length scales with precipitation-derived length scales ([section 3b](#)). Further discussion, along with a description of how our results fit in with existing studies, is provided in [section 4](#), followed by a summary in [section 5](#).

2. Data and methods

a. Soil moisture data

For this study we examine version 4 of the SMAP Level-2 soil moisture retrievals ([O'Neill et al. 2016](#)), which represent average soil moisture conditions in the top several centimeters of soil. Specifically, we use the baseline retrievals derived from vertically polarized brightness temperatures using the single-channel algorithm. Extensive evaluations of the retrievals against independent in situ soil moisture data have been performed since the mission's launch in early 2015 (e.g., [Chan et al. 2018](#)); these evaluations show that the retrievals successfully meet mission accuracy requirements. For analysis tractability, we examine here the data provided on the 36-km Equal Area Scalable Earth (EASE) grid (version 2; [Brodzik et al. 2012](#)), a resolution that approximates the true underlying resolution of the data. Also, for simplicity, we use only the descending branch [0600 local time (LT) overpass] data; using the ascending (1800 LT overpass) data as well would add a diurnal component to the signal that would be difficult to interpret in the context of our analysis. We attain the extensive data coverage needed for the analysis by employing retrievals flagged as having either "recommended" or "uncertain" quality. We eliminate from consideration, however, soil moisture data in deep tropical rain forests, for which the SMAP soil moisture signal is known to be especially poor. The tropical rain forest data (and some of the boreal forest data) are removed by requiring the maximum vegetation water content (VWC) over the year, as used in the processing of the SMAP Level-2 retrievals, to be below 10 kg m^{-2} .

In effect, then, aside from the elimination of tropical forest data and some boreal forest data, we use the same data employed by [Koster et al. \(2018\)](#) but extended through September 2018. Analyses for the Northern Hemisphere warm season [May–September (MJJAS)] are thus based on 4 years of data (2015–18), whereas analyses for the Northern Hemisphere season [November–March (NDJFM)] are based on 3 years of data.

The return time for a descending branch SMAP soil moisture measurement is up to 3 days, and the Level-2 retrievals provided by the project are accordingly missing data on the off days. A given "snapshot" of SMAP-based soil moisture thus consists of swaths of land with data separated by swaths of land with no data, with larger swaths of missing data in the tropics. Because our length scale calculation for a grid cell will be based on time series correlations between soil moisture at the cell and that at a large number of remote cells (see below), and because such calculations require contemporaneous data, we deemed it appropriate to "gap fill" the data—to produce daily soil moisture fields with complete and isotropic spatial coverage. For this study we filled in missing data at a given grid cell using data for that cell at neighboring retrieval times, using simple linear interpolation in the time domain. We examined, by the way, the impact of this gap filling strategy by performing two supplemental length scale analyses (results not shown): one in which no gap filling was performed, so that length scale computations relied on far fewer pairings of points, and one in which interpolation in time was replaced by simple persistence, meaning that the soil moisture at a given grid cell was always set to the most recently retrieved value. The length scales produced under the persistence approach were similar to those produced with the time-interpolation approach, being close to identical in midlatitudes. The "no gap filling" approach produced roughly equivalent length scales in midlatitudes but somewhat reduced length scales in parts of the tropics, presumably due to the particularly reduced data coverage there.

The single-channel algorithm used to produce the baseline retrievals examined here relies in part on the prescription of a climatological VWC to obtain needed vegetation opacity information ([Chan et al. 2013](#)). If VWC in nature has large-scale spatial anomalies that vary from year to year, the spatial structure of these anomalies could potentially embed itself in the error field of the retrievals (see, e.g., [Dong et al. 2018](#)), and this may in turn affect the length scales we compute, perhaps inflating them. To avoid this problem, retrievals produced with the dual-channel algorithm ([O'Neill et al. 2015](#)) could be used. This algorithm solves for soil moisture and vegetation opacity simultaneously, but the retrievals obtained with the current version of the algorithm are known, in general, to be less accurate (e.g., [Chan et al. 2018](#)), which would also affect our computed length scales. We proceed with the single-channel algorithm product, offering the caveat that the impact of VWC variability structures on our results are unknown though expected to be minor.

Finally, in the correlation analysis, we want to avoid focusing on correlations associated with variations of the climatological mean seasonal cycle within the MJJAS and NDJFM time frames. We thus perform a crude, first-order removal of the mean seasonal cycle in the SMAP data. The multiyear mean (4 years for May–September and 3 years for October–April) of the soil moisture at a grid cell is computed for each day of the year, and a 30-day filter is applied to the resulting mean annual cycle. This filtered mean seasonal cycle at the grid cell is then removed from the grid cell’s time series.

b. Precipitation data

The precipitation data analyzed here are taken from the Climate Prediction Center Unified Gauge-Based Analysis of Global Daily Precipitation (CPCU; Xie et al. 2007; Chen et al. 2008). This rain gauge-based dataset provides global daily fields of precipitation at a resolution of $0.5^\circ \times 0.5^\circ$; we regrid each daily field to the 36-km SMAP EASE grid prior to deriving our precipitation-based length scales. (We examined, by the way, the impact of this regridding by computing length scales from the precipitation data on their original $0.5^\circ \times 0.5^\circ$ grid. The results, not shown, turn out to be essentially the same.) For further consistency with the MJJAS soil moisture data examined, we focus on the precipitation data for MJJAS during 2015–18, and we remove from the precipitation data a crude but filtered estimate (i.e., based on these 4 years of data) of the mean seasonal cycle at each grid cell using the approach described above for the soil moisture data. Besides daily precipitation amounts, the CPCU dataset also provides information on the number of gauges that contributed to each daily precipitation estimate at each grid cell.

Note that in contrast to our earlier studies (Koster et al. 2016a, 2017), we smooth the precipitation data (prior to computing and removing the estimate of the mean seasonal cycle) with a 3-day filter instead of with a 5-day filter. The 3-day filter is used here to mimic the effective time-filtering performed on the SMAP data as a result of the interpolation of soil moisture values on days between overpasses.

c. Length scale estimation

The time series of soil moisture at two distinct grid cells A and B will presumably be similar if A and B lie close each other, and the time series will be independent if A and B are very far apart. We assume here that to first order, the time correlation between the time series $\rho(A, B)$ decreases exponentially with the distance between the two grid cells $L(A, B)$:

$$\rho(A, B) = e^{-L(A, B)/\lambda}, \quad (1)$$

where λ represents the spatial (horizontal) length scale of correlation. A similar approach was applied by Entin et al. (2000) to the analysis of in situ soil moisture data.

The calculation of the average length scale λ operating at a given SMAP grid cell A_0 , proceeds as follows. We first identify all SMAP grid cells (from A_1 through A_N) that both (i) lie within 1000 km of A_0 , (a nominal distance large enough to encompass important large-scale correlation structures, as illustrated below in Fig. 1; note that for a location at least 1000 km away from the coast, this typically amounts to more than 2000 contributing cells) and (ii) contain a suitably large set of data contemporaneous with that of A_0 (100 days of contemporaneous data, corresponding to roughly 33 independent SMAP measurements; note, however, that the number of days going into the calculation is typically much greater). We then find the unique value of λ that minimizes the error ERR, where

$$\text{ERR} = \sum_{n=1}^N \left[\rho_{\text{actual}}(A_0, A_n) - e^{-L(A_0, A_n)/\lambda} \right]^2. \quad (2)$$

Here, $\rho_{\text{actual}}(A_0, A_n)$ represents the correlation, computed directly from the SMAP data, between the soil moisture time series at grid cells A_0 and A_n . Given that we assume an exponential decrease of correlation with distance, negative values of $\rho_{\text{actual}}(A_0, A_n)$ are assumed here to be dominated by sampling error and are zeroed before they are used in (2). If the number of independent SMAP measurements (i.e., before time interpolation) at A_0 itself within a seasonal period falls below an average of 25 per year (i.e., a total of 100 SMAP measurements for the four MJJAS periods and 75 for the three NDJFM periods), as often happens at high latitudes during winter, the length scale is reset to an undefined value.

A separate value of λ (referred to hereafter as λ_{SMAP}) is found in this way for each SMAP grid cell, allowing the production of a global map of λ_{SMAP} values. An equivalent procedure is used in section 3b to extract horizontal length scales λ_{PRCP} from the gridded CPCU precipitation data.

3. Results

a. Soil moisture length scales

Figure 1a shows how the SMAP-based time series of soil moisture during the Northern Hemisphere warm season (MJJAS) at a grid cell in the central United States

Correlations Between Soil Moisture Time Series at White Dot and That at Remote Locations

FIG. 1. (a) Map showing how the daily time series (during May–September of 2015–18) of SMAP near-surface soil moisture at a central U.S. grid cell (marked by a white dot) correlates with the soil moisture time series elsewhere across the continent. (b) As in (a), but for a grid cell in the western United States. (c) As in (a), but for soil moisture during November–March. (d) As in (b), but for soil moisture during November–March. In all plots, the black ring consists of SMAP grid cells on the edge of the 1000-km circle that encompasses the grid cells contributing to the length scale calculation. Values based on less than an average of 25 SMAP measurements per year (100 for MJJAS over 4 years and 75 for NDJFM over 3 years) are whited out. Most of the correlations shown are based on more than 200 measurements, for which an absolute value of greater than 0.2 is significantly different from zero at the 99.5% confidence level.

(located in the figure with a white dot) correlates with contemporaneous soil moisture time series across North America. Correlations as high as 0.5 are seen almost 10° latitude to the north. This implies that about 25% of the variance of soil moisture at the white dot is “explained” by the variance of soil moisture close to 1000 km away—the time variations of hydrological processes at these distant locations are not independent. Correlations exceed 0.3 over an area that spans much of the central Great Plains.

Note that the spatial pattern of the temporal correlation field in Fig. 1a is not isotropic; the relevant

length scales appear to be somewhat longer in the north–south direction, particularly toward the north. Thus, although the form of (2) assumes isotropic behavior, this assumption is not strictly satisfied by the data. Nevertheless, (2) has the advantage of providing a single, “average” estimate of length scale to characterize the overall spatial pattern of correlation. Using (2), a λ_{SMAP} value of 459 km is found for the indicated grid cell (based on an N of 2332). For comparison, Fig. 1b shows the spatial field of temporal correlation against the soil moisture time series at a southwest United States location, again for MJJAS. The operative length

scale at this location is clearly shorter, and this is captured with (2), which produces here a λ_{SMAP} value of 283 km (based on an N of 1641).

Figures 1a and 1b thus illustrate that the SMAP-based length scales vary geographically. These panels can in turn be compared with Figs. 1c and 1d, which show the corresponding results for the Northern Hemisphere cold season (NDJFM). This comparison reveals a strong seasonality in the length scale—at both indicated locations, λ_{SMAP} tends to be much larger in winter (844 km for the central U.S. point and 533 km for the southwestern U.S. point). This distinction is not surprising given the fundamentally different characters of summer and winter precipitation and the fact that precipitation length scales strongly imprint themselves on soil moisture length scales. Simply put, the spatial scale of convection, which dominates summertime precipitation at these latitudes, tends to be smaller than that of the large-scale storms that dominate the wintertime precipitation.

We repeat the length scale calculations using each SMAP grid cell in turn as the target grid cell. Some details of these calculations are provided first in Fig. 2. Figure 2a shows the number of grid cells contributing to the calculation of λ_{SMAP} at each point using (2). This distribution of N has the expected smooth pattern, without unusual discontinuities; roughly 2000 cells contribute to each value in continental interiors, and even along the coasts, λ_{SMAP} is derived from at least 500 correlation estimates. Figures 2b and 2c show, for MJJAS and NDJFM respectively, the spatial distribution of the root-mean-square error of the correlation estimation underlying (2):

$$\text{RMSE} = \sqrt{\frac{\text{ERR}}{N}}. \quad (3)$$

In essence, this RMSE provides an indication of the degree to which a simple exponential fall-off in correlation, as embodied in (1), is valid. Figures 2b and 2c show generally low values of RMSE, of order 0.1, in the summer hemispheres and somewhat larger values (of order 0.15–0.2) in the winter hemispheres (see below). We must naturally keep these errors in mind when interpreting the global fields of λ_{SMAP} , remembering that λ_{SMAP} is designed only to capture, with a single number, the first-order character of the hydrological spatial correlation structures. A single length scale obviously cannot capture the numerous facets of such structures, such as the anisotropy illustrated in Fig. 1, and such facets will necessarily lead to nonzero RMSE. We consider the first-order character of spatial correlation to be important in its own right. Global fields of λ_{SMAP}

calculated with (2) should show how this basic character varies in space.

Figure 3a accordingly shows the global distribution of λ_{SMAP} for the Northern Hemisphere warm season, as derived from the SMAP data using (2). Different locations are seen to have distinctly different length scales. The lower length scales in the Sahel, generally less than 200 km, presumably reflect the nature of precipitation there, which is largely convective during summer (Yang and Smith 2008); according to the SMAP data, hydrological variations in the Sahel at locations just a couple of hundred kilometers apart are largely independent. Particularly low values are also seen, for example, in parts of India, in much of China, and in northeastern Siberia. Particularly high length scales (>600 km) are seen in a number of places, including the eastern Sahara, southeastern Brazil, southern Africa, and eastern Australia. A small negative correlation ($r = -0.42$) is seen across the globe between length scale and mean MJJAS soil moisture (not shown), reflecting in part the large values of λ_{SMAP} found in various deserts. No obvious correlation is seen between λ_{SMAP} and N in Fig. 2a.

Note that even the “particularly low” length scales mentioned above still exceed, by a comfortable margin, the ~36-km resolution of the SMAP retrievals used to compute them. This supports the idea the SMAP resolution is adequate to address the length scale problem. Still, it is wise to keep in mind the potential impacts of resolution on the computed length scales. As a simple test of such impacts, we repeated our MJJAS calculation after coarsening the SMAP data from 36 to 108 km through the use of a 3×3 averaging window. The length scales obtained from the aggregated (108 km) SMAP data were slightly larger (typically by about 50 km, as might be expected by the effective spreading out of the data), with all spatial features of the fields otherwise retained. In essence, this test suggests that our computed length scales are, in fact, tied somewhat to the resolution of the SMAP data. We accordingly infer that if the SMAP instrument had been able to provide data at, say, a 10-km resolution, our computed warm season length scales may have been smaller, though (presumably) they would still be similar in magnitude to those shown in Fig. 3a.

Figure 3b shows the corresponding results for NDJFM, and Fig. 3c shows the MJJAS minus NDJFM length scale differences. A salient feature of the field in Fig. 3c is the large increase in λ_{SMAP} in going to the Northern Hemisphere cold season throughout the southern tier of North America, where enough winter data exist to allow a comparison. Similarly, a corresponding decrease in λ_{SMAP} is seen for NDJFM in many parts of Southern

FIG. 2. (a) The value of N in (2) at each grid cell for the MJJAS calculation of λ_{SMAP} . (b) The RMSE of the correlation estimates underlying the MJJAS λ_{SMAP} calculation, as computed with (3). (c) As in (b), but for the NDJFM λ_{SMAP} calculation.

Hemisphere midlatitudes (e.g., much of Australia and southern Africa). Again, this presumably reflects the importance of convection during summer.

Going beyond simple considerations of convection to explain the patterns in Fig. 3 is challenging. The various atmospheric phenomena that control the time and length scales of precipitation (and accordingly affect the time and length scales of soil moisture) include convective cloud systems, sea-breeze thunderstorms, low level jets, mesoscale convective systems, tropical storms, and extratropical cyclones and anticyclones, all of which vary in importance with season. These phenomena

can also be modulated at times by larger-scale teleconnections such as the Madden–Julian oscillation, the Pacific–North American (PNA) pattern, the North Atlantic Oscillation (NAO), and the El Niño–Southern Oscillation cycle (ENSO), leading to a complex interplay of space and time scales. Further complicating the problem is the impact of other facets of the climate system (radiation, wind speed, etc.) on soil moisture length scales through the evapotranspiration process as well as the presence of potentially relevant length scales in the assigned soil and vegetation parameters underlying the retrievals.

(a) Spatial Correlation Length Scale from SMAP (km): MJJAS

(b) Spatial Correlation Length Scale from SMAP (km): NDJFM

(c) Differences: MJJAS minus NDJFM

FIG. 3. (a) Spatial correlation length scales computed with (2) from SMAP near-surface soil moisture data covering the period May–September of 2015–18. (b) As in (a), but for the Northern Hemisphere cold season (NDJFM). (c) Differences. Values based on less than an average of 25 SMAP measurements per year (100 for MJJAS over 4 years and 75 for NDJFM over 3 years) are whitened out.

Even given this complexity, the length scales shown in Fig. 3 for a number of regions appear to be consistent with our understanding of the prevailing controls on local hydrodynamical variability. For example, North America during the summer (MJJAS) shows a swath of higher length scales (>400 km) down the center of the continent, with particularly high values in Texas (>500 km) (Fig. 3a). These high values are presumably linked to the controlling influences of the southerly low level jet (e.g., Helfand and Schubert 1995; Walters and

Winkler 2001) on moisture transport and precipitation, which would tend to produce high precipitation correlations (and thus soil moisture correlations) at a distance in the north/south direction, consistent with the example in Fig. 1a. The eastern part of the continent would not be so influenced by the jet, and the lower summertime length scales there simply reflect the dominance of convection. During winter (Fig. 3b), the relatively long length scales over much of the southern United States are consistent with the impact of ENSO

(note that 2015/16 was a strong event), which induced a more active storm track in this region (e.g., Schubert et al. 2008), and consequently more large-scale precipitation events.

Over northern Eurasia during summer, synoptic storm systems (cyclones) play an important role in defining precipitation length scales, though surface evaporation is also an important moisture source for the precipitation (e.g., Serreze and Etringer 2003). In that regard, it should be noted that a key source of surface drying during boreal summer is the occurrence of slow-moving anticyclones (a major source of short-term drought in Eurasia; e.g., Schubert et al. 2014) that act to suppress precipitation and produce at their periphery dry and hot low-level winds (“Sukhovoy”; see Lydolph 1964) that produce intense transpiration and drying of the soil, especially in the steppe and semidesert zones of northern Eurasia (e.g., just north of the Black and Caspian Seas). This drying mechanism may have contributed to the enhanced soil moisture length scales seen for boreal summer relative to boreal winter in those regions (Fig. 2c).

The long length scales over Australia are consistent with the strong impact of ENSO on those regions, especially during austral winter. In fact, the pattern of large length scales shown in Figs. 3a and 3b over Australia bear a strong resemblance to the correlation maps of the linkages between precipitation and the southern oscillation during those two seasons (e.g., Becker et al. 2013).

This possible ENSO linkage is an example of a potentially important contributor to a region’s calculated length scale, namely, interannual variations in large-scale precipitation regime. If sea surface temperatures (SSTs), for example, induce large year-to-year variations in the precipitation falling in a given continental-scale region, the result would be a large length scale for the region. Consider, for example, a region that as a whole is generally wet in one MJJAS and is generally dry in the other three MJJAS periods due to SST influences (e.g., ENSO). The SMAP data would show, for distant locations within that region, strong temporal correlations across the four MJJAS periods, even though such large correlations would not be seen within a single year.

To examine this possibility, we repeated our length scale calculations with a twist: we used (2) to compute λ_{SMAP} for MJJAS within each SMAP year individually and then combined the four year-specific λ_{SMAP} fields into a single average field. Such a field, in effect, focuses on within-year agreement between neighboring soil moisture time series (reflecting the size of individual storms) rather than on across-year agreement (which

might instead reflect SST influences on the overall, continental-scale precipitation regime). We show the results of this supplementary calculation in the form of a difference map—we show in Fig. 4a the difference between the λ_{SMAP} values in Fig. 3a and those obtained with the year-by-year calculation. A large difference thus implies a large impact of interannual variability in continental-scale precipitation regime on the computed value of λ_{SMAP} . We indeed see large differences in eastern Australia, supporting the idea, posited above, that SST influences (presumably ENSO) are responsible for the high Australian λ_{SMAP} values shown in Fig. 3a. Interannual variability in large-scale precipitation regime is also seen to affect the λ_{SMAP} values computed in North Africa and the Middle East and in southern Africa.

The corresponding difference map for NDJFM is provided in Fig. 4b. The differences are smaller overall but still show some interesting features. Note in particular the differences that appear in the southeastern United States. These differences are fully consistent with the idea, suggested above, that ENSO effects contribute to the large NDJFM length scales computed for this region.

b. Comparisons to precipitation-based length scales

CPCU gauge-based precipitation data for MJJAS of the years 2015–18 are processed into horizontal length scales λ_{PRCP} using a procedure identical to that used for λ_{SMAP} . For proper comparison with the soil moisture length scales, precipitation data at locations and times for which soil moisture data were excluded (e.g., due to snow cover or high VWC) were not used in the calculations. The global field of λ_{PRCP} is presented in Fig. 5a, and the corresponding field for NDJFM is provided in Fig. 6a. Given that precipitation is the dominant forcing of soil moisture, one might expect some consistency between the fields of λ_{PRCP} and λ_{SMAP} (from Figs. 3a,b). The difference maps in Figs. 5b and 6b show the degree to which these fields are indeed consistent.

The precipitation-based length scales differ from those for soil moisture in many places; Fig. 5b shows large differences, for example, throughout Africa, in the Middle East, and in the eastern half of Australia, and Fig. 6b shows large differences as well in China. Figure 5c provides a map of the rain gauge density underlying the CPCU product for MJJAS. (The field for NDJFM is similar.) Rain gauges are indeed spotty across much of the globe; see Kidd et al. (2017) for further discussion. [Note that the aforementioned Becker et al. (2013) study utilized precipitation data from an earlier period during which the CPCU rain gauge coverage in Australia was more extensive.] It is presumably not a

FIG. 4. (a) Impact of interannual variability on the length scale calculation: the value of λ_{SMAP} obtained using all years together, as in Fig. 3a, minus the value obtained when λ_{SMAP} is computed separately for each year and the yearly values are then averaged. (b) As in (a), but for NDJFM.

coincidence that the areas with particularly large length scale differences (absolute value of λ_{SMAP} minus λ_{PRCP}) line up for the most part with areas having questionable precipitation estimates due to low gauge density, given that values of λ_{PRCP} are accordingly untrustworthy in these areas.

Note that we are not saying here that precipitation-based and soil moisture-based length scales would be identical in a perfectly measured world. Soil moisture processes can presumably transform the statistical character of precipitation processes in space, at the very least by transforming (“reddening”) the variability of precipitation in time at each local point within a large-scale region (Delworth and Manabe 1988). We argue again, though, that precipitation is the primary driver of soil moisture variability, and this implies that their statistics should be strongly connected. Given the low rain gauge density over most of Africa, it seems safe to posit that λ_{SMAP} values better characterize the length scales of hydrological variability (including precipitation variability) than the λ_{PRCP} values that can be derived from the CPCU data. Of course, a direct comparison of Figs. 5b and 5c is not straightforward, given

that the length scale calculation, through (2), for even well-gauged grid cells can be affected by poor precipitation estimates in remote grid cells with low rain gauge densities. This may explain in part the large λ_{SMAP} minus λ_{PRCP} values along the east coast of Australia, where gauges are plentiful—the values of λ_{PRCP} there rely in large part on precipitation estimates in the interior of Australia, which is poorly gauged and for which CPCU data has in fact been shown to be poor in the context of SMAP data assimilation (Reichle et al. 2017).

Conversely, with a few exceptions, λ_{SMAP} and λ_{PRCP} tend to agree in well-gauged areas. The gray areas in Fig. 5b show, for MJJAS, where λ_{SMAP} and λ_{PRCP} lie within 100 km of each other; the agreement generally appears strong in the United States, Europe, western Asia, India, and eastern China, all of which feature expansive rain gauge coverage. Agreement is weaker in NDJFM (Fig. 6b), again, particularly in China; still, large areas of agreement across well-gauged areas in the western United States and Europe are clearly seen. In such regions, at least to first order, the SMAP soil moisture data do capture the length scales

FIG. 5. (a) Spatial correlation length scales computed with (2) from CPCU rain gauge–based precipitation data covering the period May–September of 2015–18. (b) Differences: SMAP-based length scale for MJJAS minus CPCU-based length scale for MJJAS. Grid cells containing less than 100 SMAP measurements for MJJAS over 4 years are whited out. (c) Map of average rain gauge density underlying the CPCU product during the period examined.

that characterize precipitation. Again, we would not expect the soil moisture–based and precipitation–based length scales to match perfectly. Nevertheless, Figs. 5b and 6b indicate that they are, as might be expected, generally similar.

Some of the differences that do exist in Figs. 5b and 6b are worth examining further. Somewhat large differences are seen, for example, in Texas during MJJAS despite the extensive set of rain gauges in the area.

Differences here (and in some other areas that are generally well gauged, such as eastern Brazil and the Sukhovey area north of the Caspian Sea) appear to involve, at least in part, the different characters of precipitation and soil moisture under conditions of high precipitation. This is illustrated by the comparison of time series in Fig. 7. Figure 7a shows the precipitation time series for 2017 at two locations in the Texas region that are separated in distance by about a longitudinal

(a) Spatial Correlation Length Scale from CPCU Precip (km): NDJFM

(b) Differences: SMAP-based λ Minus CPCU-based λ (NDJFM)

FIG. 6. (a) As in Fig. 5a, but for NDJFM. (b) As in Fig. 5b, but for NDJFM. Grid cells containing less than 75 SMAP measurements for NDJFM over 3 years are whited out.

degree. The phasing of storm events is very similar at the two locations, and yet the relative magnitudes of the rainfall pulses over time are not. The more eastern location (red curve), for example, receives much more water from the storms in late May, whereas the more western location (blue curve) receives much more of the storm water at the beginning of August and at the end of September. Such distinctions in storm magnitude reduce the correlation between the precipitation values at these cells.

The corresponding soil moisture time series at these locations (Fig. 7b), however, are not similarly distinct. For example, despite the fact that the more eastern grid cell gets more than twice the rainfall of the more western grid cell near the end of August (during Hurricane Harvey), the corresponding soil moisture in both cases goes up to about the same value, presumably an effective maximum for the soils considered. Simply put, a soil can only get so wet during a storm, and this mitigates the degree to which large differences in heavy rainfall amounts can induce large differences in soil moisture. As suggested by the example in the figure, the upper bound to soil moisture wetting during large storms allows the correlation between soil moisture at the two sites to be significantly larger than that between the

precipitation values at the two sites. This translates to a longer length scale computed for soil moisture (relative to that for precipitation) in the Texas area.

Of course, it is also worth remembering that the “point” character of the precipitation measurements—even for grid cell areas with multiple rain gauges—does not completely capture the true areal mean precipitation of a grid cell. Such representativeness issues could induce additional noise into the calculation of precipitation correlations, and for this reason alone we may underestimate precipitation length scales from the available data.

4. Discussion

a. Comparison to length scales found in the literature

To our knowledge, Figs. 3 and 4 provide a unique global look at the horizontal length scales characterizing soil moisture (and indeed, hydrological) variability in different seasons. Other studies, however, have effectively derived soil moisture length scales from observations, some from networks covering relatively small areas (e.g., Brocca et al. 2007; Lakhankar et al. 2010) but others based on samples obtained across

FIG. 7. (a) Time series of CPCU precipitation (mm day^{-1}) during the warm season of 2017 at two locations in Texas separated by about 1° of longitude. (b) Corresponding time series of SMAP-based near-surface soil moisture.

continental-scale regions (e.g., Entin et al. 2000; Nicolai-Shaw et al. 2015). Here we discuss our results in the context of the latter studies.

Entin et al. (2000) analyze in situ soil moisture measurements collected in networks spanning Russia, Mongolia, and China, as well as measurements in Illinois and Iowa. Although their length scale calculation procedure differs from that embodied in (2), there are strong similarities—they produce (for Mongolia, China, and Illinois) meteorology-related soil moisture length scales for the 0–10-cm soil layer by effectively assuming an exponential decrease of correlation with distance. We find their values for Mongolia (200–400 km) and Illinois (380–490 km) to be reasonably consistent with the values seen in Figs. 3a and 3b. They produce, however, distinctly larger values for China (500–550 km). The reason for this discrepancy is unclear, though to some extent a proper comparison is precluded due to their use of soil moisture data from all months of the year (with the mean seasonal cycle removed) in a single length scale calculation (except for the Illinois data, see below) and the different sampling rates underlying their data—their site measurements were collected once every ten days and thus, relative to the SMAP data, would be unable to capture all aspects of the synoptic-scale (subweekly) storms affecting the study area. Perhaps just as important, SMAP data in China may be subject to additional noise (relative to that in most other areas) due to corrections made in the area for radio frequency interference (Mohammed et al.

2016). These corrections involve the blanking out of pixels within a given satellite footprint and thereby lead to increased uncertainty in the brightness temperature estimates (P. Mohammed 2019, personal communication). This contributes to quality flags of “uncertain” seen for the Level-2 SMAP soil moisture retrievals across much of China. Any high frequency noise in the Chinese data would translate to reduced λ_{SMAP} values.

Entin et al. (2000) do process the Illinois in situ data separately by season and find, for summer relative to winter, shorter length scales for precipitation (again as expected, given the dominance of convection) but longer length scales for soil moisture, in direct conflict with our results—soil moisture length scales in their study ranged from 575–650 km in summer to 300–350 km during winter. Here again the difference might relate to sampling and associated difficulties in capturing synoptic events (in fact, the few measurements per month they used here were collected on different days for different sites). Also, their data for this particular calculation were relatively limited in spatial extent, being contained within Illinois (along with one location in Iowa); our calculations for the Illinois region included soil moisture information from as far as 1000 km away and can thus capture the impacts on soil moisture of very large-scale winter storms. The importance of this latter consideration is clearly illustrated by a supplemental analysis in which SMAP-based length scales in a region roughly encompassing Illinois (88° – 91°W , 37° – 42°N)

were computed with (2) using only SMAP data contained in that limited region. Length scales produced under this geographic restriction look more in line with the findings of Entin et al. (2000), at least in terms of the relative magnitudes in summer versus winter; whereas the average summer length scale in the Illinois region remained roughly the same (376 km, compared to 390 km from the calculation underlying Fig. 3), the winter length scale decreased significantly from 641 km (from the calculation underlying Fig. 3) to 284 km. That is, with the severe geographic restriction—essentially the same restriction as that imposed by the availability of in situ measurements used by Entin et al. (2000)—we are unable to produce the large winter length scales of the type represented in Fig. 1c.

Nicolai-Shaw et al. (2015) employ a somewhat different approach to quantifying the spatial scale of agreement between soil moisture time series. The approach, taken from Orlowsky and Seneviratne (2014), involves computing Spearman's rank-based correlations between soil moisture time series at different locations and then continually eliminating the farthest stations from consideration until a specified fraction of the remaining stations show a correlation above an assigned threshold. They applied the approach to in situ soil moisture and to gridded satellite-based soil moisture over the conterminous United States (CONUS).

When they applied their analysis to gridded satellite data over the CONUS, the Southeast showed up as a region of relatively high length scale. The reason for this discrepancy with our results is unclear (we show relatively low length scales there), but it is worth noting that their satellite-based record is dominated by C-band and X-band retrievals, which are known to be less reliable than L-band retrievals in such vegetated areas (e.g., Calvet et al. 2011; Cui et al. 2017). When Nicolai-Shaw et al. (2015) focused on in situ measurement sites, and when they used a correlation threshold of 0.4 (close to $1/e$), they found “spatial representativeness” areas of perhaps 250 000 km² in the Southern Great Plains and in the northwestern United States for April–September (top-right panel of their Fig. 3, corresponding to the soil moisture signal with the mean seasonal cycle removed). Assuming a circular area, this value corresponds to a length scale of roughly 280 km, somewhat smaller than our length scales of roughly 400–500 km for these regions. This discrepancy may simply reflect the different approaches used to estimate the length scales, which make a meaningful quantitative comparison exceedingly difficult. What can be compared sensibly is the spatial pattern of the length scales produced, and the patterns they produce from the in situ measurements are found to agree reasonably well with

ours—in both datasets, the southern Great Plains and the northwest United States host the largest length scales in CONUS.

Again, the magnitudes of the length scales from our study and the studies of Entin et al. (2000) and Nicolai-Shaw et al. (2015) show numerical differences. The question naturally arises as to the advantages of the length scales quantified here relative to those of the other studies. We argue that three features of our length scale calculations together make our set of λ_{SMAP} fields a uniquely valuable complement to existing estimates. First, they are based on soil moisture estimates that span the globe, allowing a global view of the variations of hydrological length scale, with each computed length scale itself accounting for the surrounding continental-scale statistical structure of soil moisture. Second, our length scales are derived from SMAP measurements that represent areal averages rather than from point-scale measurements, and they thus avoid the potential representativeness error of the latter. Third, and perhaps most important, the length scale calculation defined in (2) is particularly simple and straightforward. In essence, the approach provides a length scale associated with a characteristic exponential decay of correlation with distance, a first-order descriptor of the spatial variability of hydrological variables. The meaning of a plotted length scale value, we argue, is accordingly very easy to grasp.

b. Scientific relevance of computed length scales

As noted in section 1, SMAP data allow for potentially informative analyses of hydrological variability. The time dimension of this variability at a given location—for example, the drydown behavior of soil moisture following rain events—has already been addressed with SMAP data in several studies (McColl et al. 2017a,b; Koster et al. 2017; Akbar et al. 2018). The spatial dimension examined here is a distinctly different facet of the variability and deserves some discussion in the context of potential scientific relevance.

One obvious potential application of a soil moisture length scale involves the interpretation of historical (e.g., pre-SMAP) in situ soil moisture measurements. The length scale can be considered the spatial scale over which the historical measurements are relevant—it provides a direct indication of how well a given set of localized measurements represents soil moisture variations that occurred at remote, unmeasured sites at a distance. Additionally, if a new in situ soil moisture measurement network is desired to supplement SMAP information (e.g., if L-band measurements from space ever become unavailable), the length scales produced here should assist with network design. The optimal grid

resolution for such a network is a function of the operating length scale for the measured variable, since sampling at scales much finer than this would be wasteful—adjacent gauges would give redundant information. Figure 3a suggests that for a given level of accuracy in estimating large-scale warm-season near-surface soil moisture, measurement networks can be less dense, perhaps by a factor of 2, in the Southern Great Plains (Texas, Oklahoma) relative to the southeastern United States. Measurement networks would also, for example, need to be particularly dense in the Sahel and in eastern China. Furthermore, because soil moisture imposes some control on the generation of streamflow and evapotranspiration, the length scales found here for soil moisture should have some bearing on the length scales characterizing streamflow and evapotranspiration variability and thus on the measurement density requirements for these fluxes. Of course, a substantial amount of work would be needed to address properly the application of the derived λ_{SMAP} values to measurement network design.

Measurement networks aside, the length scales can have a significant impact on the character of the global hydrological cycle. Again, the length scales governing soil moisture and evapotranspiration variability are presumably connected, and thus, through energy balance considerations, soil moisture length scales are also connected to those of sensible heat flux. Various studies indicate that atmospheric variables, in both models and the real world, respond to variations in land surface energy fluxes as driven by soil moisture variations (Delworth and Manabe 1989; Koster et al. 2003, 2004; Fischer et al. 2007; Dirmeyer et al. 2013; Betts et al. 2014). This implies that the length scale of a temperature anomaly (for example) may be controlled, at least in part, by the soil moisture length scale—the large spatial extent of the heatwaves associated with the Great Plains (e.g., Namias 1982) may partly result from the high soil moisture length scales seen there in the warm season (Fig. 3a). In addition, some studies (Douville 2002; Lau and Kim 2012; Koster et al. 2014b, 2016b) suggest that land surface energy flux anomalies can affect the large-scale atmospheric circulation. If true, we can speculate that the ability of the land surface to have such an impact will depend in part on the length scale of the surface flux anomalies and thus on the soil moisture length scale itself. Presumably the overlying atmospheric circulation would be more sensitive to soil moisture anomalies acting on larger spatial scales.

Soil moisture length scale may also have an impact on the character of the streamflow produced in a hydrological basin. Consider two large basins that are identical

in every way except for the length scale of the precipitation falling therein (and thus the corresponding length scale of the soil moisture)—for basin A, the length scale is large, so that the time sequencing of rainfall and dry periods is essentially the same everywhere within the basin, whereas for basin B, the length scale is small, so that precipitation within the basin is spotty and uncorrelated in space; in basin B, there might be a small patch or two of precipitation falling somewhere within the basin at any given time. Although the two idealized basins experience the same mean precipitation, that in basin A should produce a greater range of total (basin-integrated) streamflow rates than basin B, given that all parts of basin A contribute to the total outflow of the basin during individual rainstorms and contribute little to the outflow during dry periods. Simply put, streamflow extremes (e.g., flooding) would arguably be more likely in basin A.

All of the above reasons aside, length scales of variability can be considered fundamental physical descriptors of hydrological processes in nature. Provided they can be quantified accurately from observations, length scale estimates would serve as appropriate targets for climate model validation.

5. Summary

SMAP Level-2 soil moisture retrievals have been processed to produce global maps of λ_{SMAP} —a horizontal length scale describing the distance over which the time variability of near-surface soil moisture at one location captures that at a remote location. The length scales are found to vary geographically and to differ significantly in the Northern Hemisphere warm and cold seasons, with the larger values during winter presumably reflecting the large-scale nature of the storms that dominate wintertime precipitation. Comparisons of the SMAP-based length scales against those derived from gridded precipitation data are generally consistent in areas for which the precipitation data are trustworthy, that is, in areas that contain a high density of rain gauges, and this suggests that the SMAP data may contain useful—and perhaps otherwise unattainable—information about hydrological length scales (including precipitation length scales) in poorly gauged areas.

Soil moisture length scale is relevant to the design of measurement networks and can also indicate how well historical in situ soil moisture measurements represent the historical variations of soil moisture in surrounding, unmeasured regions. The role played by λ_{SMAP} in the overall manifestation of hydrological and climatic variability—in the determination, for example, of the strength of land–atmosphere feedbacks and the

magnitude of streamflow extremes—is still largely unknown but is ripe for exploration.

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REFERENCES

- Akbar, R., D. J. S. Gianotti, K. A. McColl, E. Haghighi, G. D. Salvucci, and D. Entekhabi, 2018: Estimation of landscape soil water losses from satellite observations of soil moisture. *J. Hydrometeorol.*, **19**, 871–889, <https://doi.org/10.1175/JHM-D-17-0200.1>.
- Becker, A., P. Finger, A. Meyer-Christoffer, B. Rudolf, K. Schamm, U. Schneider, and M. Ziese, 2013: A description of the global land-surface precipitation data products of the Global Precipitation Climatology Centre with sample applications including centennial (trend) analysis from 1901–present. *Earth Syst. Sci. Data*, **5**, 71–99, <https://doi.org/10.5194/essd-5-71-2013>.
- Betts, A. K., R. Desjardins, D. Worth, and B. Beckage, 2014: Climate coupling between temperature, humidity, precipitation and cloud cover over the Canadian Prairies. *J. Geophys. Res. Atmos.*, **119**, 13 305–13 326, <https://doi.org/10.1002/2014JD022511>.
- Brocca, L., R. Morbidelli, F. Melone, and T. Moramarco, 2007: Soil moisture spatial variability in experimental areas of central Italy. *J. Hydrol.*, **333**, 356–373, <https://doi.org/10.1016/j.jhydrol.2006.09.004>.
- , and Coauthors, 2014: Soil as a natural rain gauge: Estimating global rainfall from satellite soil moisture data. *J. Geophys. Res. Atmos.*, **119**, 5128–5141, <https://doi.org/10.1002/2014JD021489>.
- Brodzik, M. J., B. Billingsley, T. Haran, B. Raup, and M. H. Savoie, 2012: EASE-Grid 2.0: Incremental but significant improvements for Earth-gridded data sets. *ISPRS Int. J. Geoinf.*, **1**, 32–45, <https://doi.org/10.3390/ijgi1010032>.
- Calvet, J.-C., J.-P. Wigneron, J. Walker, F. Karbou, A. Chanzy, and C. Albergel, 2011: Sensitivity of passive microwave observations to soil moisture and vegetation water content, L-band to W-band. *IEEE Trans. Geosci. Remote Sens.*, **49**, 1190–1199, <https://doi.org/10.1109/TGRS.2010.2050488>.
- Cayan, D. R., and K. P. Georgakakos, 1995: Hydroclimatology of continental watersheds, 2, Spatial analyses. *Water Resour. Res.*, **31**, 677–697, <https://doi.org/10.1029/94WR02376>.
- Chan, S. K., R. Bindlish, R. Hunt, T. Jackson, and J. Kimball, 2013: Ancillary data report: Vegetation water content. Tech. Rep. JPL D-53061, 18 pp., https://smap.jpl.nasa.gov/system/internal_resources/details/original/289_047_veg_water.pdf.
- , and Coauthors, 2018: Development and assessment of the SMAP enhanced passive soil moisture product. *Remote Sens. Environ.*, **204**, 931–941, <https://doi.org/10.1016/j.rse.2017.08.025>.
- Chen, M., W. Shi, P. Xie, V. B. S. Silva, V. E. Kousky, R. W. Higgins, and J. E. Janowiak, 2008: Assessing objective techniques for gauge-based analyses of global daily precipitation. *J. Geophys. Res.*, **113**, D04110, <https://doi.org/10.1029/2007JD009132>.
- Collow, A. B. M., M. G. Bosilovich, and R. D. Koster, 2016: Large-scale influences on summertime extreme precipitation in the northeastern United States. *J. Hydrometeorol.*, **17**, 3045–3061, <https://doi.org/10.1175/JHM-D-16-0091.1>.
- Cui, H., L. Jiang, J. Du, S. Zhao, G. Wang, Z. Lu, and J. Wang, 2017: Evaluation and analysis of AMSR-2, SMOS, and SMAP soil moisture products in the Genhe area of China. *J. Geophys. Res. Atmos.*, **122**, 8650–8666, <https://doi.org/10.1002/2017JD026800>.
- Dee, D. P., and Coauthors, 2011: The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quart. J. Roy. Meteor. Soc.*, **137**, 553–597, <https://doi.org/10.1002/qj.828>.
- Delworth, T. L., and S. Manabe, 1988: The influence of potential evaporation on the variabilities of simulated soil wetness and climate. *J. Climate*, **1**, 523–547, [https://doi.org/10.1175/1520-0442\(1988\)001<0523:TIOPEO>2.0.CO;2](https://doi.org/10.1175/1520-0442(1988)001<0523:TIOPEO>2.0.CO;2).
- , and —, 1989: The influence of soil wetness on near-surface atmospheric variability. *J. Climate*, **2**, 1447–1462, [https://doi.org/10.1175/1520-0442\(1989\)002<1447:TIOSWO>2.0.CO;2](https://doi.org/10.1175/1520-0442(1989)002<1447:TIOSWO>2.0.CO;2).
- Dirmeyer, P. A., Y. Jin, B. Singh, and X. Yan, 2013: Trends in land-atmosphere interactions from CMIP5 simulations. *J. Hydrometeorol.*, **14**, 829–849, <https://doi.org/10.1175/JHM-D-12-0107.1>.
- Dong, J., W. T. Crow, and R. Bindlish, 2018: The error structure of the SMAP single- and dual-channel soil moisture retrievals. *Geophys. Res. Lett.*, **45**, 758–765, <https://doi.org/10.1002/2017GL075656>.
- Dooge, J. C. I., 1988: Hydrology in perspective. *Hydrol. Sci. J.*, **33**, 61–85, <https://doi.org/10.1080/02626668809491223>.
- Douville, H., 2002: Influence of soil moisture on the Asian and African monsoons. Part II: Interannual variability. *J. Climate*, **15**, 701–720, [https://doi.org/10.1175/1520-0442\(2002\)015<0701:IOSMOT>2.0.CO;2](https://doi.org/10.1175/1520-0442(2002)015<0701:IOSMOT>2.0.CO;2).
- Entekhabi, D., and Coauthors, 2010: The Soil Moisture Active Passive (SMAP) mission. *Proc. IEEE*, **98**, 704–716, <https://doi.org/10.1109/JPROC.2010.2043918>.
- Entin, J. K., A. Robock, K. Y. Vinnikov, S. E. Hollinger, S. Liu, and A. Namkhai, 2000: Temporal and spatial scales of observed soil moisture variations in the extratropics. *J. Geophys. Res.*, **105**, 11 865–11 877, <https://doi.org/10.1029/2000JD900051>.
- Famiglietti, J. S., D. Ryu, A. A. Berg, M. Rodell, and T. J. Jackson, 2008: Field observations of soil moisture variability across scales. *Water Resour. Res.*, **44**, W01423, <https://doi.org/10.1029/2006WR005804>.
- Fischer, E. M., S. I. Seneviratne, P. L. Vidale, D. Luthi, and C. Schar, 2007: Soil moisture-atmosphere interactions during the 2003 European summer heat wave. *J. Climate*, **20**, 5081–5099, <https://doi.org/10.1175/JCLI4288.1>.
- Gelaro, R., and Coauthors, 2017: The Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2). *J. Climate*, **30**, 5419–5454, <https://doi.org/10.1175/JCLI-D-16-0758.1>.
- Gu, G., R. F. Adler, G. J. Huffman, and S. Curtis, 2007: Tropical rainfall variability on interannual-to-interdecadal and longer time scales derived from the GPCP monthly product. *J. Climate*, **20**, 4033–4046, <https://doi.org/10.1175/JCLI4227.1>.

- Helfand, H., and S. Schubert, 1995: Climatology of the simulated Great Plains low-level jet and its contribution to the continental moisture budget of the United States. *J. Climate*, **8**, 784–806, [https://doi.org/10.1175/1520-0442\(1995\)008<0784:COTSGP>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<0784:COTSGP>2.0.CO;2).
- Kerr, Y. H., and Coauthors, 2010: The SMOS mission: New tool for monitoring key elements of the global water cycle. *Proc. IEEE*, **98**, <https://doi.org/10.1109/JPROC.2010.2043032>.
- Kidd, C., A. Becker, G. J. Huffman, C. L. Muller, P. Joe, G. Skofronick-Jackson, and D. B. Kirschbaum, 2017: So, how much of the Earth's surface is covered by rain gauges? *Bull. Amer. Meteor. Soc.*, **98**, 69–78, <https://doi.org/10.1175/BAMS-D-14-00283.1>.
- Koster, R. D., M. J. Suarez, R. W. Higgins, and H. van den Dool, 2003: Observational evidence that soil moisture variations affect precipitation. *Geophys. Res. Lett.*, **30**, 1241, <https://doi.org/10.1029/2002GL016571>.
- , and Coauthors, 2004: Regions of strong coupling between soil moisture and precipitation. *Science*, **305**, 1138–1140, <https://doi.org/10.1126/science.1100217>.
- , G. K. Walker, G. J. Collatz, and P. E. Thornton, 2014a: Hydroclimatic controls on the means and variability of vegetation phenology and carbon uptake. *J. Climate*, **27**, 5632–5652, <https://doi.org/10.1175/JCLI-D-13-00477.1>.
- , Y. Chang, and S. D. Schubert, 2014b: A mechanism for land-atmosphere feedback involving planetary wave structures. *J. Climate*, **27**, 9290–9301, <https://doi.org/10.1175/JCLI-D-14-00315.1>.
- , L. Brocca, W. T. Crow, M. S. Burgin, and G. J. M. De Lannoy, 2016a: Precipitation estimation using L-band and C-band soil moisture retrievals. *Water Resour. Res.*, **52**, 7213–7225, <https://doi.org/10.1002/2016WR019024>.
- , Y. Chang, H. Wang, and S. D. Schubert, 2016b: Impacts of local soil moisture anomalies on the atmospheric circulation and on remote surface meteorological fields during boreal summer: A comprehensive analysis over North America. *J. Climate*, **29**, 7345–7364, <https://doi.org/10.1175/JCLI-D-16-0192.1>.
- , R. H. Reichle, and S. P. Mahanama, 2017: A data-driven approach for daily real-time estimates and forecasts of near-surface soil moisture. *J. Hydrometeorol.*, **18**, 837–843, <https://doi.org/10.1175/JHM-D-16-0285.1>.
- , W. T. Crow, R. H. Reichle, and S. P. Mahanama, 2018: Estimating basin-scale water budgets with SMAP soil moisture data. *Water Resour. Res.*, **54**, 4228–4244, <https://doi.org/10.1029/2018WR022669>.
- Lakhankar, T., A. S. Jones, C. L. Combs, M. Sengupta, T. H. Vonder Haar, and R. Khanbilvardi, 2010: Analysis of large scale spatial variability of soil moisture using a geostatistical method. *Sensors*, **10**, 913–932, <https://doi.org/10.3390/s100100913>.
- Lau, W. K., and K.-M. Kim, 2012: The 2010 Pakistan flood and Russian heat wave: Teleconnection of hydrometeorological extremes. *J. Hydrometeorol.*, **13**, 392–403, <https://doi.org/10.1175/JHM-D-11-016.1>.
- Lydolph, P. E., 1964: Russian Sukhovey. *Ann. Assoc. Amer. Geogr.*, **54**, 291–309, <https://doi.org/10.1111/j.1467-8306.1964.tb00490.x>.
- Maussion, F., D. Scherer, T. Molg, E. Collier, J. Curio, and R. Finkelburg, 2014: Precipitation seasonality and variability over the Tibetan Plateau as resolved by the High Asia Reanalysis. *J. Climate*, **27**, 1910–1927, <https://doi.org/10.1175/JCLI-D-13-00282.1>.
- McColl, K. A., S. H. Alemohammad, R. Akbar, A. G. Konings, S. Yueh, and D. Entekhabi, 2017a: The global distribution and dynamics of surface soil moisture. *Nat. Geosci.*, **10**, 100–104, <https://doi.org/10.1038/ngeo2868>.
- , W. Wang, B. Peng, R. Akbar, D. Gianotti, H. Lu, M. Pan, and D. Entekhabi, 2017b: Global characterization of surface soil moisture drydowns. *Geophys. Res. Lett.*, **44**, 3682–3690, <https://doi.org/10.1002/2017GL072819>.
- Mo, K. C., and D. P. Lettenmaier, 2018: Drought variability and trends over the central United States in the instrumental record. *J. Hydrometeorol.*, **19**, 1149–1166, <https://doi.org/10.1175/JHM-D-17-0225.1>.
- Mohammed, P. N., M. Aksoy, J. R. Piepmeier, J. T. Johnson, and A. Bringer, 2016: SMAP L-band microwave radiometer: RFI mitigation prelaunch analysis and first year on-orbit observations. *IEEE Trans. Geosci. Remote Sens.*, **54**, 6035–6047, <https://doi.org/10.1109/TGRS.2016.2580459>.
- Namias, J., 1982: Anatomy of Great Plains protracted heat waves (especially the 1980 U.S. summer drought). *Mon. Wea. Rev.*, **110**, 824–838, [https://doi.org/10.1175/1520-0493\(1982\)110<0824:AOGPPH>2.0.CO;2](https://doi.org/10.1175/1520-0493(1982)110<0824:AOGPPH>2.0.CO;2).
- Nicolai-Shaw, N., M. Hirschi, H. Mittelbach, and S. I. Seneviratne, 2015: Spatial representativeness of soil moisture using in situ, remote sensing, and land reanalysis data. *J. Geophys. Res. Atmos.*, **120**, 9955–9964, <https://doi.org/10.1002/2015JD023305>.
- NOAA, 1994: Natural disaster survey report, The Great Flood of 1993. NOAA Tech. Rep., 334 pp., https://www.weather.gov/media/publications/assessments/93_Flood.pdf.
- NRC, 2010: *Assessment of Intraseasonal to Interannual Climate Prediction and Predictability*. National Academies Press, 181 pp., <https://doi.org/10.17226/12878>.
- O'Neill, P. E., S. Chan, E. Njoku, T. Jackson, and R. Bindlish, 2015: Algorithm theoretical basis document level 2 & 3 soil moisture (passive) data products. Tech. Rep., JPL D-66480, 80 pp., https://smap.jpl.nasa.gov/system/internal_resources/details/original/316_L2_SM_P_ATBD_v7_Sep2015.pdf.
- , E. G. Njoku, T. Jackson, and R. Bindlish, 2016: SMAP L2 radiometer half-orbit 36 km EASE-Grid soil moisture, version 4. NASA National Snow and Ice Data Center Distributed Active Archive Center, accessed October 2018, <https://doi.org/10.5067/XPJTJT812XFY>.
- Orlowsky, B., and S. I. Seneviratne, 2014: On the spatial representativeness of temporal dynamics at European weather stations. *Int. J. Climatol.*, **34**, 3154–3160, <https://doi.org/10.1002/joc.3903>.
- Purdy, A. J., and Coauthors, 2018: SMAP soil moisture improves global evapotranspiration. *Remote Sens. Environ.*, **219**, 1–14, <https://doi.org/10.1016/j.rse.2018.09.023>.
- Reichle, R. H., and Coauthors, 2017: Global assessment of the SMAP level-4 surface and root-zone soil moisture product using assimilation diagnostics. *J. Hydrometeorol.*, **18**, 3217–3237, <https://doi.org/10.1175/JHM-D-17-0130.1>.
- Robock, A., C. A. Schlosser, K. Y. Vinnikov, N. A. Speranskaya, J. K. Entin, and S. Qiu, 1998: Evaluation of the AMIP soil moisture simulations. *Global Planet. Change*, **19**, 181–208, [https://doi.org/10.1016/S0921-8181\(98\)00047-2](https://doi.org/10.1016/S0921-8181(98)00047-2).
- Schubert, S. D., Y. Chang, M. J. Suarez, and P. J. Pegion, 2008: ENSO and wintertime extreme precipitation events over the contiguous United States. *J. Climate*, **21**, 22–39, <https://doi.org/10.1175/2007JCLI1705.1>.
- , H. Wang, R. Koster, M. Suarez, and P. Ya. Groisman, 2014: Northern Eurasian heat waves and droughts. *J. Climate*, **27**, 3169–3207, <https://doi.org/10.1175/JCLI-D-13-00360.1>.

- Seager, R., M. Hoerling, S. Schubert, H. Wang, B. Lyon, A. Kumar, J. Nakamura, and N. Henderson, 2015: Causes of the 2011–14 California drought. *J. Climate*, **28**, 6997–7024, <https://doi.org/10.1175/JCLI-D-14-00860.1>.
- Serreze, M. C., and A. J. Etringer, 2003: Precipitation characteristics of the Eurasian Arctic drainage system. *Int. J. Climatol.*, **23**, 1267–1291, <https://doi.org/10.1002/joc.941>.
- Walters, C. K., and J. A. Winkler, 2001: Airflow configurations of warm season southerly low-level wind maxima in the Great Plains. Part I: Spatial and temporal characteristics and relationship to convection. *Wea. Forecasting*, **16**, 513–530, [https://doi.org/10.1175/1520-0434\(2001\)016<0513:ACOWSS>2.0.CO;2](https://doi.org/10.1175/1520-0434(2001)016<0513:ACOWSS>2.0.CO;2).
- Xie, P., A. Yatagai, M. Chen, T. Hayasaka, Y. Fukushima, C. Liu, and S. Yang, 2007: A gauge-based analysis of daily precipitation over East Asia. *J. Hydrometeorol.*, **8**, 607–626, <https://doi.org/10.1175/JHM583.1>.
- Yang, S., and E. A. Smith, 2008: Convective-stratiform precipitation variability at seasonal scale from 8 yr of TRMM observations, Implications for multiple modes of diurnal variability. *J. Climate*, **21**, 4087–4114, <https://doi.org/10.1175/2008JCLI2096.1>.