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Using remotely sensed soil moisture for land–atmosphere coupling diagnostics: The role of surface vs. root-zone soil moisture variability

M. Hirschi [a], B. Mueller [a,1], W. Dorigo [b], S.I. Seneviratne [a]

[a] Institute for Atmospheric and Climate Science, ETH Zurich, Zurich, Switzerland
[b] Department of Geodesy and Geoinformation, Vienna University of Technology, Vienna, Austria

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ABSTRACT

Hot extremes have been shown to be induced by antecedent surface moisture deficits in several regions. While most previous studies on this topic relied on modeling results or precipitation-based surface moisture information (particularly the standardized precipitation index, SPI), we use here a new merged remote sensing soil moisture product that combines active and passive microwave sensors to investigate the relation between the number of hot days (NHD) and preceding soil moisture deficits. Along with analyses of temporal variabilities of surface vs. root-zone soil moisture, this sheds light on the role of different soil depths for soil moisture–temperature coupling. The global patterns of soil moisture–NHD correlations from remote sensing data and from SPI as used in previous studies are comparable. Nonetheless, the strength of the relationship appears underestimated with remote sensing-based soil moisture compared to SPI-based estimates, particularly in regions of strong soil moisture–temperature coupling. This is mainly due to the fact that the temporal hydrological variability is less pronounced in the remote sensing data than in the SPI estimates in these regions, and large dry/wet anomalies appear underestimated. Comparing temporal variabilities of surface and root-zone soil moisture in in-situ observations reveals a drop of surface-layer variability below that of root-zone when dry conditions are considered. This feature is a plausible explanation for the observed weaker relationship of remote sensing-based soil moisture (representing the surface layer) with NHD as it leads to a gradual decoupling of the surface layer from temperature under dry conditions, while root-zone soil moisture sustains more of its temporal variability.

1. Introduction

The role of soil moisture anomalies for the occurrence of hot days and the evolution of heatwaves in transitional climate regions has received increasing attention during the recent years. Soil moisture deficits affect hot extremes through the energy balance: Low soil moisture availability reduces evaporative cooling and increases atmospheric heating from sensible heat flux (Alexander, 2011; Seneviratne et al., 2010). In addition, indirect feedbacks with cloud cover and dry air advection (Fischer, Seneviratne, Vidale, Lüthi, & Schär, 2007; Haarsma, Selten, van den Hurk, Hazeleger, & Wang, 2009), as well as the dominance of specific weather regimes may play a role (Quesada, Vautard, Yiou, Hirschi, & Seneviratne, 2012).

Apart from modeling studies (e.g., Fischer et al., 2007; Jaeger & Seneviratne, 2011; Lorenz, Jaeger, & Seneviratne, 2010; Seneviratne, Lüthi, Litschi, & Schär, 2006; Vautard et al., 2007), the relationship between soil moisture deficits and the frequency and duration of hot extremes was also demonstrated using observational data at the regional scale (Hirschi et al., 2011). Recently, Mueller & Seneviratne, (2012, hereafter referred to as MS12) extended this analysis to the global scale. Their analysis uses reanalyses-based number of hot days (NHD) and the observations-based standardized precipitation index (SPI) as a proxy for soil moisture deficit, and focuses at each location on the respective hottest month of each year, allowing a global coverage of soil moisture–temperature coupling diagnostics over the 1979–2010 time period. By using correlation as coupling diagnostic and repeating the analysis with NHD calculated from different reanalysis products and SPI from different observational precipitation datasets, MS12 derived robust *hot spots* of strong soil moisture–temperature coupling. These *hot spots* partly agree with identified soil moisture–temperature coupling regions from other studies (Dirmeyer, 2011; Koster et al., 2006; Miralles, van den Berg, Teuling, & de Jeu, 2012), but also highlight several additional regions (see Supplementary Fig. S2 of MS12).

While the study of MS12 relies on the precipitation-based SPI as an indirect proxy for soil moisture, the purpose of the present paper is to investigate the suitability of a new long-term remote sensing (RS) soil moisture product (Liu et al., 2011, 2012) for the analysis of soil moisture–temperature coupling. The addressed questions are whether this new RS dataset can strengthen the evidence of the soil moisture–temperature coupling *hot spots* from MS12, and whether the strength and location of

E-mail addresses: martin.hirschi@env.ethz.ch (M. Hirschi), sonia.seneviratne@env.ethz.ch (S.I. Seneviratne).
[1] Now at: Environment Canada, Climate Research Division, Toronto, Canada.

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the coupling are comparable, and if not, what could be reasons for identified differences. In this context, the coupling and temporal variabilities of surface vs. root-zone soil moisture are investigated using in-situ soil moisture measurements, shedding light on the role of different soil depths for soil moisture–temperature coupling.

2. Data and methods

Our analysis is based on a new remote sensing (RS) soil moisture product merging active and passive microwave sensors by combining scatterometer- and radiometer-based products (Liu et al., 2011, 2012, available from http://www.esa-soilmoisture-cci.org). The products are merged based on their relative sensitivity to vegetation density. Microwave RS soil moisture represents the top ~2 cm of the soil (i.e., surface soil moisture, SSM; Owe & Van de Griend, 1998). The availability of the RS SSM data is variable over time and space, depending on the number of sensors used for respective time periods and their specifications (W. Dorigo et al., in press). Data availability is better for areas of low vegetation cover, and in general the observation frequency for all areas increases over time (Fig. 1b).

From the monthly aggregated RS SSM values, we consider the anomalies with respect to the mean seasonal cycle for the analyses as we are mainly interested in the potential of anomalously dry soil conditions to trigger and increase the number of hot days. In addition, the RS SSM data was standardized into a standard normal distribution using the same methodology as Vidal et al. (2010). This also allows us to quantify anomalies in soil moisture with respect to a chosen averaging time scale (3-month in this case to be consistent with the applied time scale of the standardized precipitation index, SPI; see below), and to express the soil moisture anomalies in units of standard deviation from normal conditions.

Number of hot days (NHD) are defined as days with maximum 2-m air temperature above the 90th-percentile of the 1979–2010 reference period, where temperature is from the ERA-Interim reanalysis (Dee et al., 2011). Moreover, the 3-month SPI (McKee, Doesken, & Kleist, 1993) is applied for comparison with MS12. It characterizes the observed precipitation deficits accumulated in the three months before the hottest month, where precipitation is taken from CRU (Mitchell & Jones, 2005).

For comparative analyses, we also use soil moisture from observation-driven land-surface models from the Global Land Data Assimilation System (GLDAS, Rodell et al., 2004; Rui, 2011). Moreover, we employ in-situ soil moisture observations from the International Soil Moisture Network (ISMN, Dorigo et al., 2011, see Supplementary Table S1 for considered networks) and from the Swiss Soil Moisture Experiment (SwissSMEX, http://www.iac.ethz.ch/url/research/SwissSMEX, see also Mittelbach & Seneviratne, 2012). For the distinction between surface and root-zone soil moisture, the in-situ measurements of volumetric soil moisture (in m^3/m^3) from various depths have been integrated down to depths of 5 cm (for surface layer) and maximal 0.9 m (for root zone) respectively using the trapezoidal method (e.g., Mittelbach, Lehner, &

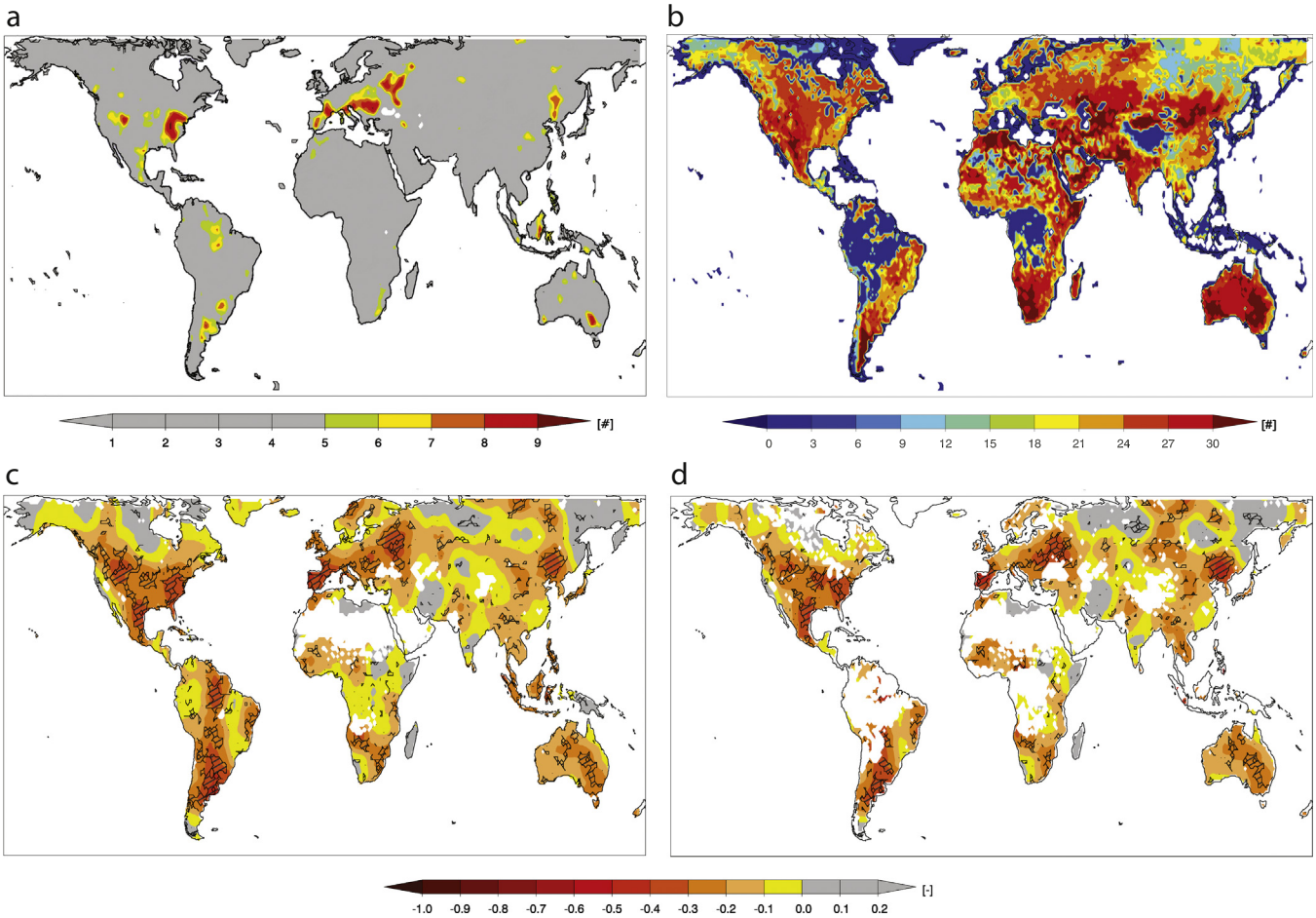

Fig. 1. (a) *Hot spots* regions of soil moisture–temperature coupling based on the number of dataset combinations from MS12 (adapted from their Supplementary Fig. S2), which show significant anti-correlations (10% significance level) between NHD and preceding 3-month SPI. Here, regions where more than half of the nine dataset combinations from MS12 agree on significant anti-correlations are considered (regions with lower agreement have been masked for better visibility). (b) Number of years with available RS SSM at the month preceding the hottest month. (c) Correlations between NHD (at the hottest month of each year) and preceding 3-month SPI (cf. Fig. 1b from MS12, hatched areas show significantly negative correlations at the 10% significance level); (d) SPI–NHD correlations when only years with RS data are considered (see panel b).

Seneviratne, 2012). The applied in-situ data from ISMN undergo automatic harmonization and quality checking for outliers and implausible values (Dorigo et al., 2011, 2013). In the case of SwissSMEX, site-specific calibrated sensors are used that were previously evaluated regarding climate research applications (Mittelbach, Casini, Lehner, Teuling, & Seneviratne, 2011). Also, the fact that we are focusing on anomalies rather than absolute soil moisture values reduces the effect of local influences (e.g., differing soil textures) in the in-situ data and may provide a more stable spatial signal of the measured soil moisture variations (Mittelbach & Seneviratne, 2012).

As a measure of soil moisture–temperature coupling, we analyze correlations between NHD at the hottest month of each year and preceding drought conditions (expressed in soil moisture or cumulated precipitation deficits at the month preceding the hottest month, see above). Besides investigating global patterns of the correlations, the strength of the coupling is analyzed in the *hot spot* regions from MS12 (their Supplementary Fig. S2). Here, these regions are defined as areas where more than half of the nine dataset combinations from MS12 show significantly negative correlations between NHD and preceding drought conditions (10% significance level, non-masked regions in Fig. 1a). Note that statistical relationships as e.g., based on correlations do not necessarily imply causality. However they can be used to evaluate the coupling between two variables given the existence of plausible underlying mechanisms (Seneviratne et al., 2010).

3. Results

3.1. Comparison between RS SSM–temperature and SPI–temperature coupling diagnostics

Fig. 1c displays the correlations between NHD and the preceding 3-month SPI (cf. Fig. 1b from MS12). Significantly negative correlations (10% significance level, hatched) show regions of strong coupling between moisture availability and hot days. Fig. 2a displays the same analysis, but using RS SSM anomalies instead of the SPI. While the global patterns of correlations are comparable, there is a tendency for less strongly negative correlations when using the RS-based soil moisture product, in particular in the MS12 *hot spot* regions. This is confirmed by the analysis in Fig. 2b, which shows the correlations from Figs. 1c and 2a, with the colored shading displaying the 2-dimensional density estimation of the correlations globally, and black points representing correlations in *hot spot* regions only (regions in Fig. 1a). In these regions, almost all points of the SPI–NHD correlations are negative as expected (i.e., 98% of the grid boxes show correlations < 0). However, the RS SSM–NHD correlations show a tendency for less strongly negative values (or even positive correlations in some cases, with 82% of the grid boxes showing correlations < 0). Thus we see a weaker soil moisture–temperature coupling in RS data compared to SPI. Also, when using standardized RS SSM (Fig. 2c,d), a very similar picture

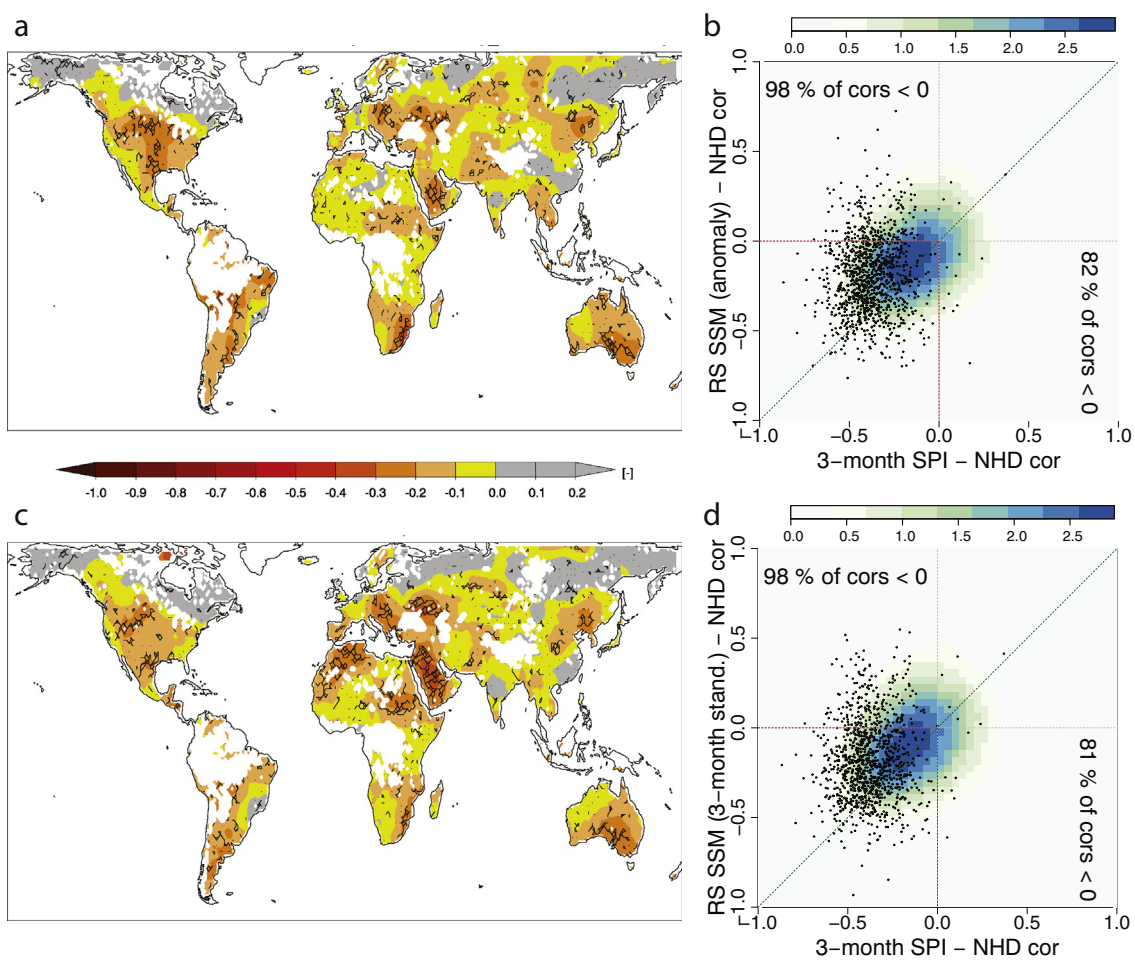

Fig. 2. As Fig. 1c but using (a) RS SSM anomalies (instead of SPI) and (c) standardized 3-month RS SSM. (b) and (d) show the correlations from SPI (Fig. 1c) on the x-axes vs. the correlations from the corresponding RS soil moisture on the y-axes: the colored shading displays the 2-dimensional density estimation of the global correlations (i.e., all grid boxes), black points represent the *hot spot* regions only (see Fig. 1a). In case of the latter, points are expected to be located in the lower left square indicated with red dashed lines (i.e., negative correlations).

emerges both in terms of the global pattern, as well as in terms of the strength of the coupling (with 81% of the grid boxes showing correlations < 0). Note that using Spearman instead of Pearson correlation does not alter these results (not shown).

As pointed out in Section 2 (Fig. 1b), the RS soil moisture product has a reduced data availability in some regions. To investigate the influence of the reduced RS data availability, the data availability for SPI was artificially reduced, and only years where RS data is available at the month preceding the hottest month were considered in Fig. 1d. Although the strength of the SPI–NHD relationship is slightly reduced, it is still visibly stronger for SPI than for the RS data.

Also using the absolute values of RS SSM (instead of anomalies), as well as using the RS profile soil water index (SWI), which is derived by extrapolating RS SSM to root zone with an exponential filter (see e.g., Wagner, Lemoine, & Rott, 1999), does not lead to comparable coupling strength as for SPI (see Supplementary Fig. S1). Thus we see a generally weaker relationship in the RS soil moisture data with subsequent NHD compared to SPI in previously identified *hot spot* regions of soil moisture–temperature coupling, while the global pattern of the relationship is comparable.

To investigate the possible impact of using soil moisture vs. SPI on the observed relationship, the same analysis was repeated using soil moisture anomalies from the observation-driven GLDAS land-surface model NOAH (GLDAS-2, Rui, 2011), which is driven with the climatologically consistent Princeton forcing dataset (Sheffield, Goteti, & Wood, 2006). Soil moisture–NHD correlations from the layer down to one meter show similar coupling strength as compared to SPI (Fig. 3a,b). The same picture (Supplementary Fig. S2) also emerges when using the GLDAS-1 CLM and NOAH models (which are driven with a temporally non-consistent forcing, see Rui, 2011). Hence, the GLDAS-based results do not suggest that the comparison between precipitation- and soil moisture-based dataset is the main reason underlying the weaker coupling in the RS SSM–temperature coupling diagnostics.

3.2. Temporal variability of RS SSM data and decoupling of surface vs. root-zone soil moisture

The temporal evolution of the SPI, standardized RS SSM and GLDAS NOAH surface-layer soil moisture is displayed in Fig. 4a,c,e. The data is averaged over the MS12 *hot spot* regions (Fig. 1a) of North America, Europe and South America (i.e., the Argentinean Pampa) and taken at the month before the hottest month of each year (consistent with the data used for the correlations of Figs. 1–3). Also shown are the corresponding scatter plots of standardized RS and GLDAS NOAH soil moisture vs. SPI (Fig. 4b,d,f). In general the temporal evolution is comparable between the three datasets. However, RS SSM shows less temporal variability and misses some pronounced anomalies (e.g., 1988 or 2007 in North America, 1989 in the Pampa, and the 2003 heatwave in Europe). Consequently, SPI shows higher correlations with GLDAS NOAH than with RS SSM (Fig. 4b,d,f), particularly for North America. The linear regression between SPI and GLDAS NOAH shows an almost one-to-one relation, while there is an indication that RS SSM underestimates the more pronounced anomalies. This is partly due to data gaps in the RS SSM data (e.g., in case of 2003 in Europe, see also Fig. 1b), although this behavior is also seen when RS SSM data is available.

As microwave RS only sees the top ~2 cm of the soil, the question arises if this penetration depth is deep enough to capture the mechanisms relevant for soil moisture–temperature coupling as identified when using SPI or GLDAS soil moisture. This means is the reduced surface-layer variability in RS data (Fig. 4) a general feature of surface soil moisture when compared to root-zone soil moisture, and under what conditions does such a reduced variability manifest itself? We hypothesize in the following that the different behavior in the analyzed datasets is due to the small storage of the surface layer, leading it to reach dry levels more quickly and thus to show little variability between medium and extensively dry climate conditions (see schematic in Fig. 5a). This implies that very dry conditions could lead there to reduced soil moisture variability while root-zone soil moisture is still able to dry further (and thus show higher relative soil moisture anomalies). In order to assess if this diverging behavior is indeed found in observations, we compare the temporal variability of integrated surface and root-zone in-situ soil moisture (see Section 2) by constraining the selection of data on the surface-layer quantiles (i.e., going from a data selection representing all conditions towards dry conditions). This is done for in-situ stations of the ISMN and SwissSMEX networks (see Supplementary Fig. S3 for their spatial distribution). We consider only stations with at least 40 temporally coincident data points in the two soil layers and results are summarized in the box plots of Fig. 5b for monthly anomalies. For all conditions (i.e., surface-layer quantiles ≤ 1), the variability in surface-layer soil moisture is larger than for root-zone soil moisture (in agreement with e.g., Albergel et al., 2013; Paris Anguela, Zribi, Hasenauer, Habets, & Loumagne, 2008). For dry conditions however (i.e., surface-layer quantiles ≤ 0.1;0.05), the relative responses switch and surface-layer soil moisture variability drops below that of root-zone soil moisture. In addition, Supplementary Fig. S4 shows the differences between surface and root-zone soil moisture variability (i.e., surface minus root-zone) at the individual stations and color coded by the networks. The surface-layer variability decreases

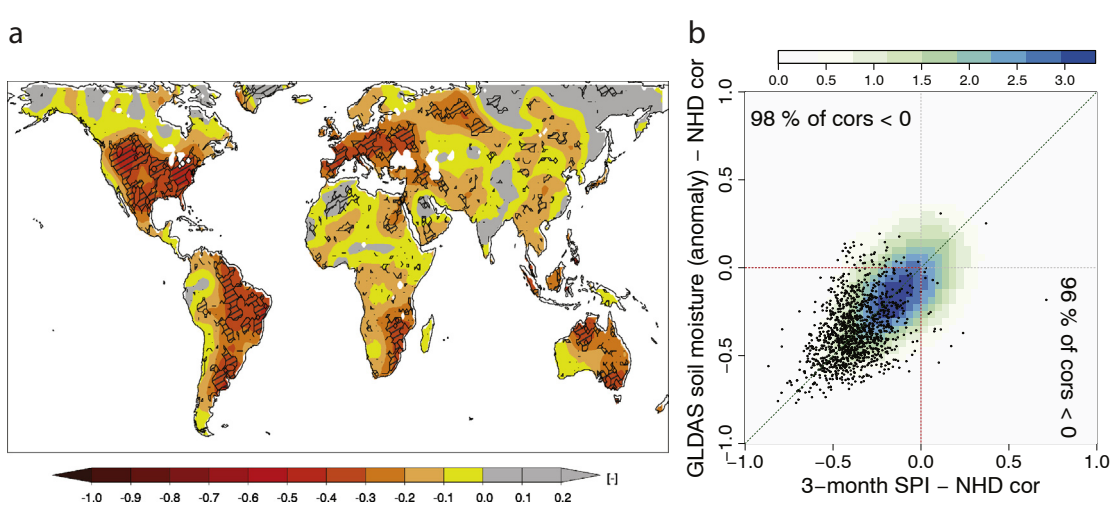

Fig. 3. As Fig. 2 but for GLDAS NOAH instead of RS soil moisture: (a) top three layers (1 m depth) soil moisture anomalies correlated with subsequent NHD, (b) corresponding correlations from SPI (Fig. 1c) vs. correlations from GLDAS.

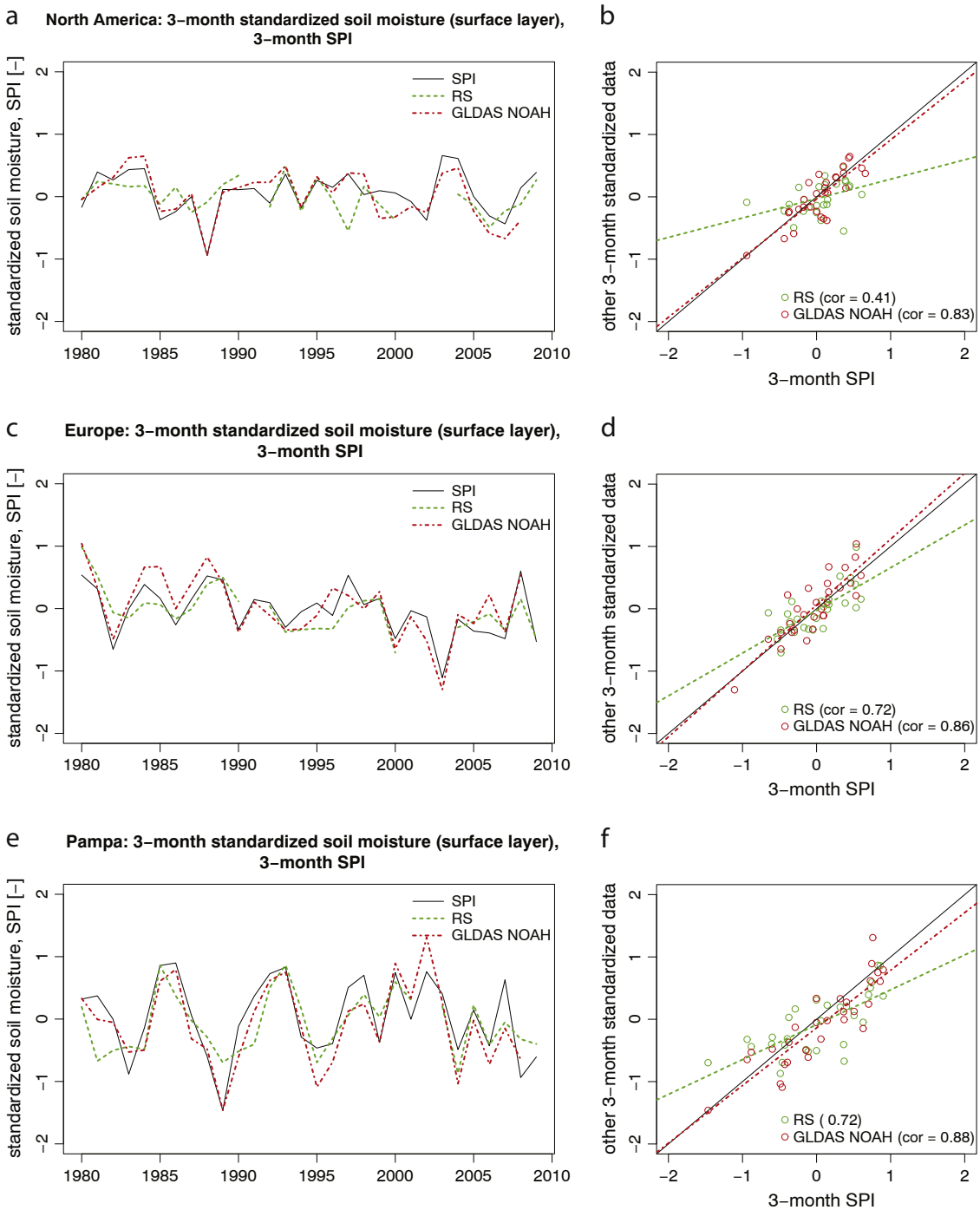

Fig. 4. (a,c,e) Time series in selected *hot spot* regions (North America, Europe and Pampa) and (b,d,f) corresponding scatters of the 3-month standardized soil moisture (RS SSM and GLDAS NOAH surface layer) and 3-month SPI (at the months preceding the hottest month of each year). Numbers in brackets in (b,d,f) show the correlation between SPI and the respective RS and GLDAS data, dashed lines the corresponding linear regression.

for the majority the stations when going to dry conditions, rather independently of the network. This reduced surface-layer variability for dry conditions is a plausible explanation for the observed weaker coupling of RS SSM with NHD, as such a behavior of surface-layer soil moisture leads to a gradual decoupling (in a statistical sense) from root-zone soil moisture and from atmospheric conditions. On the other hand, root-zone soil moisture (as rather represented by SPI in the context of this analysis) sustains more of its temporal variability also when going to dry conditions.

For GLDAS grid boxes located at the in-situ stations (Fig. 5c) the same but less pronounced behavior in surface vs. root-zone soil moisture variabilities is visible when going from all conditions towards dry conditions. The variabilities and the difference between surface and root-zone soil moisture variabilities appear smaller for all conditions compared to the in-situ stations, which is likely due to the deeper first layer, i.e., 0.1 m for GLDAS vs. 0.05 m for the in-situ stations, but may possibly also indicate a shortcoming of the GLDAS model. Furthermore, the spread between the locations is smaller. The RS SSM variabilities show comparable decrease when going to dry conditions (Supplementary Fig. S5).

It is interesting to note that the observed decoupling of surface and root-zone soil moisture during dry conditions is not necessarily

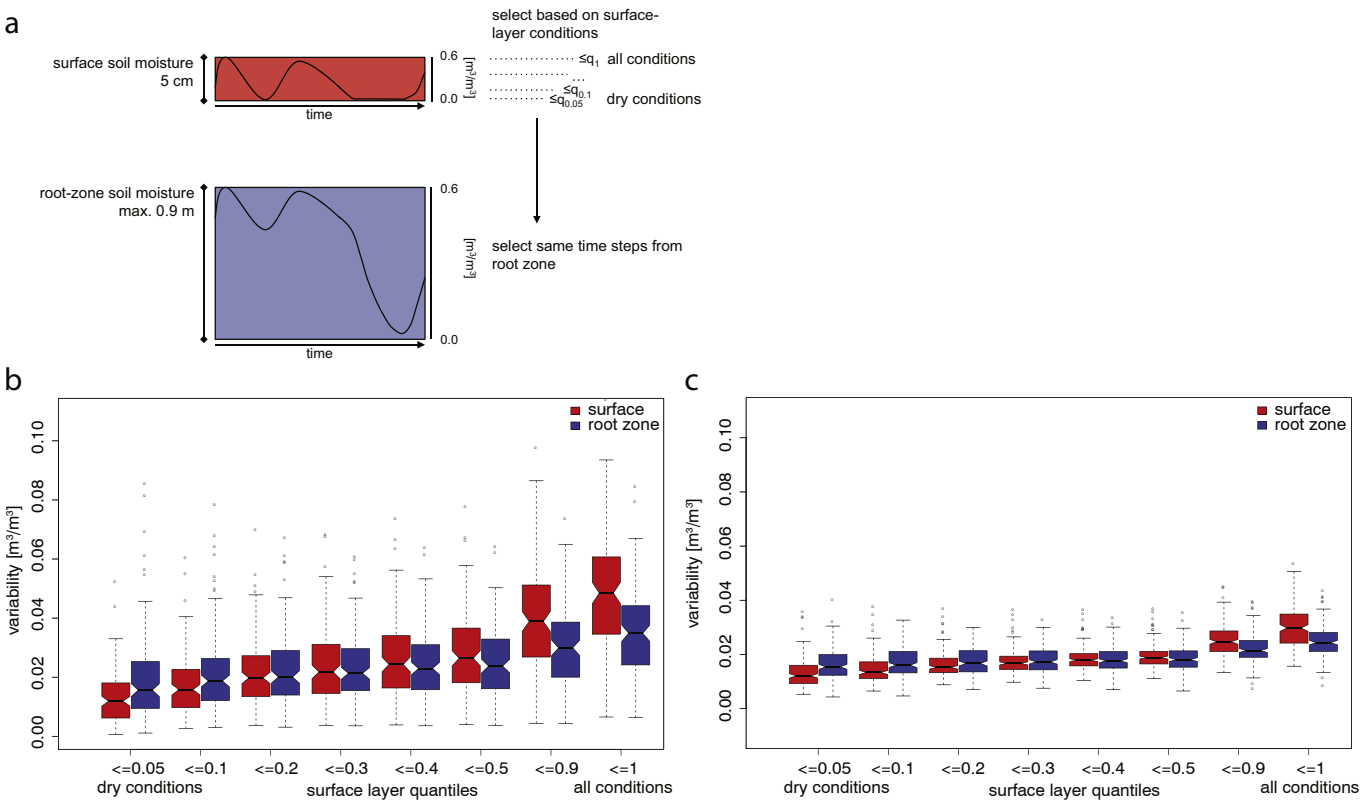

Fig. 5. (a) Schematic of a hypothetical temporal surface and root-zone soil moisture evolution. The indicated depths denote the depths over which the in-situ measurements of volumetric soil moisture (in m^3/m^3) have been integrated for the analyses. For the comparison of temporal variabilities in surface and root-zone soil moisture under different conditions, the data is selected based on the surface-layer quantiles, i.e., going from a data selection representing all conditions (surface-layer quantiles ≤ 1) towards dry conditions (surface-layer quantiles $\leq 0.1;0.05$). (b) Variabilities of in-situ surface vs. root-zone soil moisture (monthly anomalies), conditioned by surface soil moisture conditions going from all conditions to dry conditions. (c) As (b), but for GLDAS (0.1 m vs. 1 m depths, same locations as for the in-situ analyses).

apparent when looking at overall correlations between soil moisture in the two layers (see Supplementary Fig. S3). This explains why we find this behavior, despite previous analyses suggesting a strong correlation of surface and root-zone soil moisture in in-situ data (e.g., Albergel et al., 2008; Ford, Harris, & Quiring, 2014).

4. Conclusions

We analyzed soil moisture–temperature coupling with a new merged active/passive microwave RS SSM product in order to investigate the suitability of such data for diagnosing soil moisture–temperature coupling on climatological monthly time scales. Together with analyses of temporal variabilities of in-situ surface vs. root-zone soil moisture, this shed light on the role of different soil depths for soil moisture–temperature coupling. Overall, the global patterns of soil moisture–NHD correlations from RS data and from SPI as used in previous studies are comparable, suggesting that these patterns are partly independent of the chosen dataset. Nonetheless, the strength of the relationship appears underestimated with RS SSM compared to those derived with SPI-based estimates, in particular in previously identified hot spots regions of soil moisture–temperature coupling. This is mainly due to the fact that the temporal variability in these regions is less pronounced in the RS data, and that pronounced dry anomalies are underestimated.

Observation-driven GLDAS land-surface model soil moisture displays a comparable coupling strength with NHD as the SPI-based analyses, independently of the soil depth taken into account (not shown). Hence, this suggests that the differences between the RS SSM–NHD analyses and those based on SPI–NHD estimates are not primarily due to the use of soil moisture instead of SPI. However, it should be noted that the GLDAS estimates are more strongly constrained by meteorological data than the RS-based estimates, which could partly explain why the former is closer to the precipitation-based SPI. On the other hand, microwave-based RS soil moisture data is known to perform more poorly in some locations, especially in regions with dense vegetation cover or at low soil moisture levels (e.g., de Jeu et al., 2008). Also, the merged product uses sensors with differences in the temporal and spatial resolution, spatial coverage, observation principle, sensor calibration etc. (Dorigo et al., 2012), which could influence the coupling diagnostics.

Despite the often documented long-term correlation between surface and root-zone soil moisture at in-situ stations (e.g., Albergel et al., 2008; Ford et al., 2014), our results reveal a reduced surface-layer variability when only extreme dry conditions are considered. This behavior is a plausible explanation for the observed weaker coupling of RS SSM with NHD, especially given the very shallow soil depth captured by RS SSM. It leads to a gradual decoupling (in a statistical sense) of the surface layer from temperature under dry conditions, while root-zone soil moisture sustains more of its temporal variability.

For climate applications and soil moisture–temperature coupling diagnostics, our results suggest that future developments of a RS-based soil moisture product would preferably include the assimilation of RS SSM in a land surface model (e.g., Reichle, 2008). This could yield a better representativity of more pronounced soil moisture anomalies and more realistic root-zone soil moisture beyond simple extrapolation of RS SSM to root zone as done for the profile SWI. Our results further highlight the need for a clear distinction between SSM and total column soil moisture, and for the consideration of the decoupling between the two variables under dry conditions in future related studies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.rse.2014.08.030.

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