Calculating Crop Water Requirement Satisfaction in the West Africa Sahel with Remotely Sensed Soil Moisture

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ABSTRACT

The Soil Moisture Active Passive (SMAP) mission (https://smap.jpl.nasa.gov/) aims to provide high-quality soil moisture data and enhance predictive models for many applications. However, new tools need to be developed that can leverage these higher-resolution data for specific applications. The objective of this study is to evaluate the possibility and efficiency of replacing the rainfall-derived soil moisture component of a crop water stress index with SMAP data. The approach is demonstrated with 0.1°-resolution, ~10-day microwave soil moisture from the European Space Agency and simulated soil moisture from the Famine Early Warning Systems Network Land Data Assimilation System. Over a West Africa domain, the approach is evaluated by comparing the different soil moisture estimates and their resulting Water Requirement Satisfaction Index values from 2000 to 2010. This study highlights how the ensemble of indices performs during wet versus dry years, over different land-cover types, and the correlation with national-level millet yields. The new approach is feasible and useful way to quantitatively assess how satellite-derived rainfall and soil moisture track agricultural water deficits. Given the importance of soil moisture in many applications, ranging from agriculture to public health to fire, this study should inspire other modeling communities to reformulate existing tools to take advantage of SMAP data.

1. Introduction

Soil moisture is a critical variable for weather and climate forecasting and early warning for natural disasters like drought, floods, landslides, and fire. Soil moisture also plays an important role in the early warning of human health concerns like hunger and malaria. The Soil Moisture Active Passive (SMAP) mission (https://smap.jpl.nasa.gov/) aims to provide high-quality soil moisture data and enhance predictive models for many applications. However, new tools need to be developed that can leverage these higher-resolution data for specific applications.
Drought, crop monitoring, and yield forecasting are a particularly important application set for the new SMAP data (Kumar et al. 2014; Champagne et al. 2015; Das et al. 2014, manuscript submitted to J. Hydrometeor.; El Sharif et al. 2014, manuscript submitted to J. Hydrometeor.). The impacts of agricultural drought (i.e., soil moisture deficit) on crop production are not only of interest to farmers but also to businesses and policy makers involved in commodity markets and organizations that provide emergency assistance before food crises arise.

SMAP data will be especially useful in regions around the world that have sparse hydrologic and meteorological monitoring networks. In these places, analysts rely on models and remotely sensed data as the primary tools for monitoring and predicting the impact of drought on crop production (Verdin et al. 2005). Currently, the Standardized Precipitation Index (SPI) is the standard dry-spell monitoring tool used by the World Meteorological Organization (Hayes et al. 2011; Svoboda 2009) and has been used in drought vulnerability models, for example, for yield loss in maize (Jayanthi et al. 2013). It is important to note, however, that SPI tracks meteorological drought, while agricultural drought is characterized by soil moisture deficits and low ratios of evapotranspiration (ET) to potential evapotranspiration (PET; Mishra and Singh 2010; NDMC 2014). Thus, a more process-based agricultural drought analysis requires the spatial and temporal characterization of supply (precipitation), demand (ET), and storage (soil moisture) in order to make the connection with crop yields.

Hydrologic models with precipitation inputs can provide the necessary water balance information for agricultural drought applications. One way is via crop productivity models that simulate crop growth in a process-based manner (for citations see, e.g., Boegh et al. 2004; Moulin et al. 1998). Another approach is to use hydrologic model outputs to calculate indices of agricultural drought stress [reviewed in Keyantash and Dracup (2002)]. Particularly relevant for SMAp applications are the soil moisture–based indices [e.g., the Palmer drought severity index (PDSI) and the soil moisture deficit index (SMDI; Narasimhan and Srinivasan 2005)]. We use the water requirement satisfaction index (WRSI; Senay and Verdin 2003; Verdin and Klaver 2002) because it is used operationally by the Famine Early Warning Systems Network (FEWS NET) to inform food security monitoring and ultimately contributes to relief decisions. Specifically, the WRSI (Popov and Frere 1986) is based on a soil moisture accounting scheme that uses satellite rainfall and modeled PET as inputs. Unlike the PDSI, WRSI can be parameterized with crop and soil characteristics. It has been shown to correspond well with maize and sorghum yields in water-limited regions in Ethiopia (Senay and Verdin 2003) and maize in Zimbabwe (Verdin and Klaver 2002).

Hydrologic models driven with satellite rainfall, and resulting drought metrics, will be sensitive to the errors in satellite rainfall inputs (e.g., Ramarohetra et al. 2013). However, ancillary land measurements can help reduce forcing and parameter uncertainty. Assimilating microwave data has already been shown to improve errors associated with satellite rainfall estimates (Crow et al. 2011; Ines et al. 2013; Pellarin et al. 2008) and to improve modeled estimates of ET and surface and root-zone soil moisture (e.g., Peters-Lidard et al. 2011). Soil moisture data from SMAP is expected to further improve the quality of regional soil moisture estimates, especially in places like West Africa (Bolten et al. 2010; Pellarin et al. 2009, 2013) and other data-sparse regions across the globe (Crow et al. 2012).

This study examines one way that SMAP Level 4 soil moisture data (7-day, 9-km resolution) can complement existing agricultural drought and yield monitoring tools, with a focus on data-sparse and food-insecure regions. Specifically, we develop a method for deriving a crop water stress index, the WRSI, from SMAP data. Because it explicitly includes soil moisture as a variable, the WRSI allows us to demonstrate a new way that remotely sensed soil moisture could replace remotely sensed rainfall inputs to calculate the crop water stress index. By showing how SMAP data can be readily incorporated into an existing convergence-of-evidence-based agricultural drought monitoring framework, we aim to maximize its utility for real-world applications.

Our study is organized as follows. In section 2, we describe our study domain, the satellite estimated inputs to the hydrologic models, the remotely sensed and modeled soil moisture inputs that we used to replace the rainfall driven soil moisture accounting scheme, and the calculation of the WRSI. The results in section 3 include a comparison of different SMAP-like soil moisture estimates and their derived WRSIs, an evaluation of how error propagates from different moisture sources to the end-of-season WRSI values, and the correlation between the WRSI and millet yields in West Africa. In section 4 we conclude with a discussion and summary of how our new approach will enable the use of SMAP data in agricultural drought monitoring and yield forecasting.

1 The SMAP Level 4 soil moisture product is a gap-filled estimate of root-zone soil moisture obtained from combining SMAP observations and land surface model estimates of soil moisture (i.e., via data assimilation; Entekhabi et al. 2010).
2. Methods

We focused our analysis on the west-central African Sudano-Sahel, which spans from Senegal in the west to Chad in the east and is the wooded grassland transition zone between the Sahara desert in the north and the Guinean woodland to the south (Fig. 1). The main crops grown in the region are rain-fed millet, sorghum, maize, cotton, and groundnuts. Rice is grown along the Senegal and Niger Rivers where natural flooding and large-scale irrigation projects meet this crop’s high water demand (UNEP 2012). More widespread irrigation is also present in Chad (FEWSNET 2013). The topography is mainly flat and the region has a unimodal rainfall regime dominated by the migration of the intertropical convergence zone (ITCZ) and at the southern extent of the domain, the West African monsoon.

Because of its low vegetation density, lack of rainfall gauges, and widespread food insecurity (UNEP 2012), this is an appropriate domain to test our new approach. Moreover, other studies have already found that microwave soil moisture retrievals have improved hydrologic monitoring in this region (Bolten et al. 2010; Pellarin et al. 2009, 2013).

For this study, we used three different estimates of soil moisture: 1) the soil water accounting scheme described in the WRSI literature (Verdin and Klaver 2002; Senay and Verdin 2003), 2) estimates from an instance of the Noah land surface model (LSM), and 3) microwave-derived soil moisture estimates from the European Space Agency (ESA) Essential Climate Variable (ECV) project. We standardized the Noah and ECV soil moisture estimates and then used them to replace the soil moisture values in the original WRSI calculation. This section describes in detail the meteorological inputs for the Noah LSM and the soil water accounting scheme; the different soil moisture products; the calculation of the WRSI values; and finally, the method of analysis used to compare the different WRSI estimates.

a. Meteorological forcing data description

Across our Sudano-Sahel domain, we used the bias-corrected African Rainfall Estimation, version 2.0 (RFE2), rainfall product from the National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center (CPC). RFE2 is derived from rain gauge data merged with satellite (infrared and microwave) observations (Xie and Arkin 1997) and is available from 2000 to the present at 0.1° latitude–longitude (~10 km²). These data perform well over West Africa (Guichard et al. 2010) in terms of the bias of cumulative rainfall amount compared to gauges and krigged station data (Pierre et al. 2011). However, Ramarohetra et al. (2013) found that RFE2 has too many rainy days with relatively small daily rain amounts, resulting in poor crop yield estimates. To remove false detection of rainfall in the dry season, we used a bias correction procedure that scales the rainfall time series to long term (1960–89) monthly mean fields (Funk et al. 2012).

In addition to RFE2 rainfall, the WRSI formulation described in Verdin and Klaver (2002) and Senay and Verdin (2003) relies on a modeled Reference ET (RefET) product. RefET is calculated globally on a cell-by-cell basis according to the Penman–Monteith equation. A detailed explanation of this formulation of RefET can be found in Senay et al. (2008). These data are produced operationally at the U.S. Geological Survey’s (USGS) Earth Resources Observation and Science Data Center. The meteorological data (solar radiation, air temperature, wind, humidity, and atmospheric pressure) come from the NOAA Global Data Assimilation System (GDAS) dataset on a 1° × 1° grid. Also, the GDAS data (at varying resolutions) are used as meteorological inputs to the Noah model described below.
b. Soil moisture estimates

1) SOIL WATER ACCOUNTING SCHEME

The standard WRSI formulation uses a rainfall-driven water balance accounting scheme to estimate soil moisture (SM) for each growing season:

\[ SM_i = SM_{i-1} + P_i - ET_i \]

and

\[ SM_i = WHC \quad \text{if} \quad SM > WHC. \]

Equation (1) is used to calculate each time step’s SM, by adding the current dekad’s precipitation \((P_i)\) to SM\(_{i-1}\), minus ET\(_i\) (Verdin and Klaver 2002; Senay and Verdin 2003). The total volume of SM (mm) varies from a minimum of 0 to a maximum equal to the water holding capacity [WHC; Eq. (2)]. We use WHC from the Food and Agriculture Organization of the United Nations (FAO) World Soil Map. Soil water accounting begins 2 months (6 dekads) before the start of season (SOS) to initialize soil moisture conditions. Antecedent soil moisture beyond these two previous months is not accounted for. For these experiments, we used the climatological SOS, defined as the first dekad with at least 25 mm of total rainfall followed by at least a combined total of 20 mm in the following two dekads (AGRHYMET 1996). Hereafter, we also refer to this as the “bucket” model.

2) MICROWAVE SOIL MOISTURE

We used merged active and passive soil moisture data from the ESA Climate Change Initiative (CCI) ECV (Liu et al. 2011, 2012). The dataset merges soil moisture estimates from different microwave sensors over a 32-yr period from 1978 to 2010 at 0.25° resolution over the entire globe. We refer to this dataset as “ECV soil moisture.” More information is available at the product website (www.esa-soilmoisture-cci.org/).

To fill gaps in the data, we aggregated daily values to monthly averages. The WRSI is calculated on an approximately 10-day time step (dekad) requiring us to subsample these data. We used the monthly average value for each of the three dekads in a given month. Using nearest-neighbor interpolation (in IDL) we regridded these data to 0.1°. These steps matched the ECV data to the spatiotemporal resolution of the RFE2 rainfall and approximate the SMAP level 4 data.

3) NOAH LSM

The FEWS NET Land Data Assimilation System (FLDAS) is a custom instance of the NASA Land Information System (LIS; Kumar et al. 2008) adapted to work with data and models commonly used by FEWS NET, like the Africa RFE2 rainfall. The Noah LSM (Chen et al. 1996) is one of several land surface models included in the FLDAS. For this study we used Noah version 3.2. To compute Earth’s energy and water balance, Noah requires meteorological variables (precipitation, solar radiation, air temperature, wind, humidity, and atmospheric pressure), vegetation (land cover) type, soil texture, and slope as inputs.

The surface water budget is computed as

\[ dSM = P - R - ET, \]

where dSM is change in soil moisture, \(P\) is precipitation, and \(R\) is runoff. To compute ET, Noah requires vegetation parameters associated with a land-cover type. For this study, we specified a uniform land-cover type, “crop,” with associated parameters (e.g., 1-m rooting depth, stomatal resistance) from the University of Maryland (UMD) Global Land Cover Classification (Hansen et al. 2000). The vegetation phenology is represented by a monthly varying green vegetation fraction derived from a composite of a 5-yr (1985–89) dataset using the AVHRR satellite (Gutman and Ignatov 1998) available from the National Centers for Environmental Prediction (NCEP).

The soil profile is represented by four soil layers (0–10, 10–40, 40–100, and 100–200 cm). Flow between layers is calculated using Richard’s equation, a function of diffusivity \(D\) and hydraulic conductivity \(K\). Values for \(D\) and \(K\) are a function of the soil moisture [Eq. (3)] and soil texture defined by the FAO maps of global sand, silt, and clay percentages (Reynolds et al. 2000). All processes are vertically integrated (no horizontal flow between grid cells), a reasonable assumption for the Sahel at 10-km scale given that the topography is relatively flat. We averaged the top two layers (0–40 cm) for comparison with other soil moisture estimates and millet yields.

For this study, both the soil water accounting scheme and Noah use RFE2 precipitation, GDAS meteorological forcings, and soil parameters from FAO. However, unlike the soil water accounting scheme, Noah has diffusion between multiple layers and an explicit runoff scheme. We expect these differences to yield differences between their respective soil moisture estimates.

c. Soil moisture rescaling

Koster et al. (2009) discuss how the variable “soil moisture” is highly model dependent in ways beyond user-defined layer thickness and soil texture. However, if the different SM estimates are normalized (mean zero and unit variance), they showed that different models tend to produce similar information on SM temporal
variability. In this study, SM values in the WRSI [Eqs. (5) and (6)] are estimated in three different ways: the original rainfall-driven water balance accounting scheme (bucket), the Noah LSM, and the ECV soil moisture. Given that each different estimate has a unique distribution, and ECV is in units of percent volumetric water content (%VWC), we transformed the soil moisture moments [Eq. (4)] as recommended by Koster et al. (2009) for model interoperability:

\[
\text{SM}(A^*) = \left\{ \frac{[\text{SM}(A) - \text{SM}_{\text{mean}}(A)]}{\sigma_{\text{SM}}(A)} \right\} \sigma_{\text{SM}}(B) + \text{SM}_{\text{mean}}(B),
\]

where soil moisture SM(A) is either Noah or ECV soil moisture [and SM(A*) indicates an estimate] and SM(B) is from the original soil water accounting scheme. In other words, we retain the standardized anomalies of Noah and ECV and force their magnitudes to match the 10-yr bucket mean and standard deviation.

d. Water requirement satisfaction index

WRSI is the ratio of cumulative actual ET to cumulative PET over the course of a growing season [Eq. (5)]. The spatially distributed formulation (Verdin and Klaver 2002; Senay and Verdin 2003) is an ideal test bed for integrating SMAP data because, compared to other fully dynamic crop models [e.g., EPIC and Decision Support System for Agrotechnology Transfer (DSSAT)], its underlying soil water accounting and ET schemes have relatively few parameters, and it operates on an approximately 10-day time step. In addition to ease of manipulation, the WRSI is designed to work with remotely sensed inputs for applications in data-sparse regions (Verdin and Klaver 2002) and is a commonly used early warning monitoring tool (Verdin et al. 2005):

\[
\text{WRSI} = \frac{\sum_{t}^{\text{ET}_t}}{\sum_{t}^{\text{PET}_t}} \times 100
\]

and

\[
\text{PET}_t = K_c \times \text{RefET}_t.
\]

In Eqs. (5) and (6), PET\(_t\) represents the water requirement of a specific crop during a particular time step and is equivalent to RefET adjusted by K\(_c\), the FAO crop coefficient (Allen et al. 1998). K\(_c\) indicates the growing stage of the crop and the associated water demand of the crop at that stage. The growing season begins with the SOS (described earlier) and continues for the length of growing period (LGP). The LGP parameter is the period of time when average precipitation is greater than half of the average PET.

Depending on the amount of SM (mm), ET is determined by the following rules:

\[
\text{ET} = \text{PET} \quad \text{when} \quad \text{SM} \geq \text{SWC}
\]

and

\[
\text{ET} = \frac{\text{SM}}{\text{SWC}} \times \text{PET} \quad \text{when} \quad \text{SM} \leq \text{SWC}
\]

where SWC (mm) is the critical soil water threshold parameter below which ET < PET and is a function of a crop transpiration stress value defined by Allen et al. (1998).

If, at the end of the season, crop water requirements were met at each time step, recorded WRSI equals 100. A rule of thumb is that a seasonal WRSI value less than 50 corresponds to crop failure (Popov and Frere 1986). However, the actual relationship between crop yields and WRSI values varies by crop and location (Jayanthi et al. 2013, 2014).

e. Correlation analysis

To determine how well SM products agreed in identifying wet versus dry growing seasons, we used correlation analysis. We defined the growing season at each 0.1° pixel by the climatological SOS plus the LGP, parameters previously described for the WRSI calculation. We then computed seasonal totals and mapped the rank correlation between the rainfall-driven bucket model, Noah (average of top two layers), and the ECV microwave SM estimates. The comparisons with bucket SM estimates serve as a control, since it is the original derivation of the WRSI. We expected Noah SM estimates to be similar to bucket-modeled SM since they both use GDAS-derived meteorological inputs and RFE2 rainfall, as well as soil information from FAO.

f. Uncertainty analysis

The SMAP mission is set to launch in January 2015; hence data are not yet available. Despite lack of real data at this time, we investigated how measurement errors propagate to the WRSI values. In the original WRSI formulation, variability associated with the rainfall inputs is constrained by the WHC parameter in the soil water accounting scheme. In our new method we bypass the water balance model; thus, we expect that errors in input data will be more directly propagated to WRSI output values.

To test if our new approach was introducing any changes to the sensitivity of WRSI values to SM estimates, we performed a sensitivity analysis. We regressed
seasonal soil moisture totals against WRSI for all three products and evaluated the regression coefficients (i.e., slope).

Next, we evaluated error propagation by perturbing the satellite inputs. We assume that satellite-derived rainfall has \( \sim 20\% \) error in estimating dekadal rainfall totals (Laws et al. 2003). The SMAP L4 will be validated to an RMSE threshold of \( \pm 4\% \) volumetric accuracy in the top 5 cm of soil for locations with low vegetation water content \( (\leq 5 \text{ kg m}^{-2}; \text{Reichle et al. 2012}) \). To be conservative and consistent with the rainfall errors, we perturbed the Noah and ECV SM by \( \pm 20\% \). To limit computational costs we generated synthetic time series \( (n = 100) \) of rainfall and soil moisture (Noah and ECV) based on 2002 and 2005, which were anomalously dry and anomalously wet years, respectively. We then used these synthetic time series to calculate the WRSI across the West Africa domain. We evaluated the coefficient of variation (CV) of the simulated end-of-season WRSI values. The CV for the perturbed inputs was 0.12; hence, where WRSI CV > 0.12, uncertainty is amplified and where WRSI CV < 0.12, uncertainty is damped. Our end-of-season WRSI is expected to maintain some of the variability, but reduced with respect to the magnitude of the perturbations in both the rainfall and soil moisture inputs. We also expected reduced variability during wet years given that WRSI has an upper threshold of 100.

3. Results

g. Correlation analysis with yields

To demonstrate how WRSI values correspond to reported crop yields, we calculated and plotted the rank correlations between the end-of-season WRSI and millet production anomalies reported by FAO for Chad, Burkina Faso, Mali, Niger, and Senegal. We assumed that crops were exclusively produced in the areas mapped as cropping zones (Fig. 5; B. Siwela 2008, personal communication) and therefore spatially averaged WRSI values over these zones. We expected that the Noah modeled soil moisture would best correlate with millet production since it represents the root zone in greater detail than the bucket or ECV microwave soil moisture.

ECV tend to have higher and more spatially coherent correlation values than the bucket–ECV correlations (Fig. 2c). With the exception of Senegal, the bucket model estimates and the ECV SM correlations are comparatively low in the northern half of our domain \( R < 0.5 \) (Fig. 2c). Neither rainfall driven model corresponds well with ECV SM in central Nigeria or southern Chad (Figs. 2b,c).

Next, we qualitatively evaluated the resulting end-of-season WRSI values (Fig. 3). We found general agreement between the spatial patterns of WRSI anomalies (departure from the 2001–10 mean). However, some regions’ anomalies disagreed in sign. For example, we show maps of WRSI anomalies in 2002 where all three products show crop water deficits in Senegal and the northern edge of our study domain in Mali and Burkina Faso. The two water balance approaches agree that conditions were anomalously wet in Niger; however, WRSI values derived from ECV SM are anomalously dry. Inspecting the time series for that region (Fig. 4) shows that time series agree well when there were the “irregular and insufficient rains” in 2004 (www.fao.org/docrep/007/j3969e/j3969e00.htm) and 2009 (www.wfp.org/content/niger-nigeria-low-rains-high-risks). We found similar results, in other regions in other years, where products agreed on severe agricultural droughts and diverged under more moderate conditions.
b. Uncertainty analysis

First, we regressed seasonal soil moisture totals against WRSI and confirmed that the sensitivity of WRSI to soil moisture did not change with our new method. For the uncertainty analysis, we perturbed the rainfall and SM inputs for 2002 and 2005 and mapped the CV of the resulting 100 end-of-season WRSI values (not shown).

We found that, in locations marked by higher average annual rainfall totals, as well as seasons marked by higher rainfall totals, wetter conditions result in lower CV values. Specifically, CV across the entire domain was lower in 2005 (wet year), when WRSI values were more often at the maximum value of 100. CVs were comparatively higher during the drier year of 2002, where WRSI values were not approaching the upper threshold. Similarly, we find that the CV is consistently lower at the southern extent of the domain, where rainfall totals are greater. Similarly, the sensitivity analysis showed that WRSI is less sensitive (smaller regression coefficient) to SM in wetter conditions compared to drier conditions.

With respect to the different ways of computing WRSI, the bucket model had a CV < 0.12 (CV$_{\text{max}}$ = 0.08), indicating that variability in the outputs is damped with respect to the satellite rainfall inputs. When using the Noah or ECV inputs, however, the northern extent of the domain (more arid) had a CV > 0.12 (CV$_{\text{max}}$ = 0.6 and 0.8 for Noah and ECV, respectively). These results show that perturbations in the soil moisture (Noah and ECV) inputs are more readily propagated to values of WRSI compared to rainfall inputs.

c. Correlation with yields

We correlated the crop-zone-averaged WRSI outputs with FAO-reported national millet production (2001–10; Table 1, Fig. 5) for five countries. Burkina Faso and Mali yield data show the highest ($R > 0.6$) correlations with the different WRSIs. Yields in Chad, Niger, and Senegal showed poor correlations with rainfall-derived (bucket and Noah) WRSI but good ($R > 0.6$) correlation with ECV WRSI. This result is promising for the use of SMAP data, as the ECV data (the closest of our tested products to anticipated SMAP data) show the highest correlation in all countries.

Given that crop production can be reduced by factors other than drought, we qualitatively evaluate production versus WRSI anomaly plots (Fig. 5). Ideally, WRSI predicts yield anomalies during poor yield years (lower-left quadrant) and good yield years (upper-right quadrant). However, we also expect there will be events when production may be low because of wet conditions when floods or locusts may damage crops (lower-right quadrant). In Burkina Faso, Mali, and Chad, a majority

<table>
<thead>
<tr>
<th>Moisture source for</th>
<th>Burkina Faso</th>
<th>Chad</th>
<th>Mali</th>
<th>Niger</th>
<th>Senegal</th>
</tr>
</thead>
<tbody>
<tr>
<td>WRSI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RFE</td>
<td>0.75</td>
<td>0.43</td>
<td>0.67</td>
<td>0.13</td>
<td>0.27</td>
</tr>
<tr>
<td>Microwave</td>
<td>0.78</td>
<td>0.73</td>
<td>0.62</td>
<td>0.72</td>
<td>0.56</td>
</tr>
<tr>
<td>Noah (0–40 cm)</td>
<td>0.79</td>
<td>0.35</td>
<td>0.71</td>
<td>0.44</td>
<td>0.15</td>
</tr>
</tbody>
</table>
of events fall into one of these three categories. In Niger and Senegal, however, three events fall in the upper-left quadrant, indicating that there were positive yield anomalies during anomalously dry years. Potential reasons include errors in the yield data, technological advances (irrigation, fertilizers), or market forces that encourage farmers to plant millet varieties that do well in dry conditions. These types of events are more difficult to screen for than wet years and require additional investigation.

4. Discussion and conclusions

First and foremost, this study demonstrates how SMAP can be used to replace the water balance accounting scheme used to compute an index that is already used in agricultural drought monitoring and yield estimation. We showed broad agreement between different remotely sensed and modeled soil moisture estimates, demonstrating that our rescaling of the different SM products produces sound results. While the goal of this paper was not necessarily to improve WRSI performance, it is promising that the ECV WRSI is well correlated with millet yields, and, in the cases of Senegal and Niger, superior to water-balance-driven WRSI estimates (Table 1). This finding supports expectations of SMAP’s ability to contribute to agricultural drought early warning.

While we will not be able to assess the quality of SMAP data until they are publicly available, we did find that, compared to the traditional method of computing WRSI with satellite rainfall, proportionally more uncertainty will be propagated from SMAP inputs to the derived WRSI values. The difference is that satellite

FIG. 5. The map shows crop zones within the five countries of interest (from left to right: Senegal, Mali, Burkina Faso, Niger, and Chad). We used this map to constrain the spatial average of WRSI anomalies for comparison with standardized national production anomalies. The different colored dots in the scatterplots indicate WRSI derived from different moisture sources. Rank correlation values for each product and FAO millet yields in each country are listed in Table 1.
rainfall is first routed though the soil water accounting scheme, while SMAP inputs will bypass constraints imposed by the bucket model. The bucket model’s initialization procedure (2 months prior to SOS) and the upper threshold on WHC limit soil moisture memory of rainfall event. Without these constraints, the variability in the Noah and ECV soil moisture inputs readily propagated to the WRSI values, resulting in higher CVs.

Given that there will be differences between SMAP and rainfall-derived WRSI, it is important for analysts to know which combination of moisture inputs and models are most reliable at a given location. Our comparisons of soil moisture estimates, WRSIs, and yields can help generate hypotheses for attribution of errors (model and input) that covary with factors like rainfall regime, rainfall station density (used in satellite bias correction), land-cover type, and irrigation. In Mali and Burkina Faso, for example, all three soil moisture estimates are positively correlated with each other (Figs. 2a–c). Burkina Faso has high correlations between all three WRSI estimates and yields, while Mali’s are more moderate (Table 1). Potential sources of error may be where cropping zones coincide with woodland vegetation (Fig. 1), where higher vegetation water content can interfere with microwave retrievals, and errors in satellite rainfall, particularly in Mali (Pierre et al. 2011). In locations where only Noah and ECV SM are well correlated, the difference between Noah and bucket’s soil moisture parameterizations should be investigated as a source of error. In Chad, all three SM products are positively correlated over the central cropping region (Fig. 2c); however, Chad’s microwave soil moisture estimates had a much higher correlation with yields than water-balance-based estimates (Table 1). Here, errors in RFE rainfall errors (Pierre et al. 2011) and irrigated agriculture (Salmon 2013) contribute to the mismatch between rainfall-driven WRSI and yield anomalies.

Less clear, however, are the results in Senegal and Niger. In Senegal, for example, bucket, Noah and ECV are well correlated (Figs. 2a–c), but all of the products’ associated WRSI values were poorly correlated \( (R < 0.3) \) with millet yield anomalies (Table 1). This, in conjunction with low WRSI values during years with high yields (upper-left quadrant, Fig. 5), suggest the need for further investigation in the quality of yield data and our assumptions about the area under cultivation. In Niger, along the northern margin of agriculturally viable land, low correlation between WRSI and yield and variable soil moisture correlations may be caused by highly variable rainfall and crop extent (and hence production) that can change dramatically from year to year.

In general, the poor correlations between WRSI and yields (Table 1) highlight the need for better understanding of the relationship between drought indices and crop productivity. Work by Jayanthi et al. (2014) addresses the regional relationships between yields and WRSI, and future work will be needed to further refine this relationship where a suite of factors (e.g., low-quality yield data, model uncertainty, and model input uncertainty) contribute to low correlations. In addition to intermodel comparisons and the use of ancillary land-cover and irrigation data, the Hydrologic Atmospheric Pilot Experiment in the Sahel (HAPEX-Sahel; Goutorbe et al. 1994) and Africa Monsoon Multidisciplinary Assessment (Lebel et al. 2009) field campaigns could provide data (e.g., in situ and remotely sensed rainfall and soil moisture) to quantitatively attribute sources of model and input error for sites in Niger, Benin, and Mali.

A major contribution of this work is that we have shown that remotely sensed soil moisture, like SMAP, and rainfall can be compared vis-à-vis the WRSI values, for a more apples-to-apples comparison. While the spatial pattern of WRSI anomalies, from different moisture inputs, generally agreed over our study period (2001–10), we showed that exploring points of divergence can help analysts more quantitatively characterize the severity of drought events. Currently, drought analysts rely on qualitative comparisons between vegetation indices, like the normalized difference vegetation index (NDVI) and various rainfall statistics (e.g., Funk and Brown 2006). Our results suggested that conditions in 2002, where WRSI values diverged between products, were not as severe as the 2004 and 2009 droughts in Niger, when all of the products agreed and the World Food Program provided food assistance. We are developing a similar approach for computing WRSI with NDVI values, preliminarily described in McNally et al. (2013). Overall, the ability to replace the current, operational WRSI soil moisture estimates with SMAP and other soil moisture estimates will be especially valuable for agricultural monitoring applications in data-sparse regions, where multiple independent methods are needed to identify and address limitations and generate consensus among drought indices (Anderson et al. 2012).

The early warning community looks forward to the SMAP Level 4 data as a readily available source of soil moisture observations. Currently, there are no datasets produced at near–real time that are widely available and postprocessed for ease of the applications community [e.g., SMOS and Soil Moisture Operational Products System (SMOPS)]. Given the potential improvement in many other data products downstream of such a real-time, high-quality soil moisture product, we think that production of such a dataset—whether SMAP or other soil moisture products—should be a priority of the hydrologic community.
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