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# Estimating Sahelian and East African soil moisture using the Normalized Difference Vegetation Index

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## Abstract

Rainfall gauge networks in Sub-Saharan Africa are inadequate for assessing Sahelian agricultural drought, hence satellite-based estimates of precipitation and vegetation indices such as the Normalized Difference Vegetation Index (NDVI) provide the main source of information for early warning systems. While it is common practice to translate precipitation into estimates of soil moisture, it is difficult to quantitatively compare precipitation and soil moisture estimates with variations in NDVI. In the context of agricultural drought early warning, this study quantitatively compares rainfall, soil moisture and NDVI using a simple statistical model to translate NDVI values into estimates of soil moisture. The model was calibrated using in-situ soil moisture observations from southwest Niger, and then used to estimate root zone soil moisture across the African Sahel from 2001–2012. We then used these NDVI-soil moisture estimates (NSM) to quantify agricultural drought, and compared our results with a precipitation-based estimate of soil moisture (the Antecedent Precipitation Index, API), calibrated to the same in-situ soil moisture observations. We also used in-situ soil moisture observations in Mali and Kenya to assess performance in other water-limited locations in sub Saharan Africa.

The separate estimates of soil moisture were highly correlated across the semi-arid, West and Central African Sahel, where annual rainfall exhibits a uni-modal regime. We also found that seasonal API and NDVI-soil moisture showed high rank correlation with a crop water balance model, capturing known agricultural drought years in Niger, indicating that this new estimate of soil moisture can contribute to operational drought monitoring. In-situ soil moisture observations from Kenya highlighted how the rainfall-driven API needs to be recalibrated in locations with multiple rainy seasons (e.g., Ethiopia, Kenya, and Somalia). Our soil moisture estimates from NDVI, on the other hand, performed well in Niger, Mali and Kenya. This suggests that the NDVI-soil moisture relationship may be more robust across rainfall regimes than the API because the relationship between NDVI and plant available water is less reliant on local charac-

teristics (e.g., infiltration, runoff, evaporation) than the relationship between rainfall and soil moisture.

## 1 Introduction

The US Agency for International Development's (USAID) Famine Early Warning Systems Network (FEWS NET) aims to mitigate the political and societal impacts of food shortages by identifying appropriate food, health, and market-related interventions. Satellite estimates of precipitation, vegetation, and soil moisture can contribute substantially to both the contingency planning and disaster response planning phases of FEWS NET, supporting decisions that reduce the impacts of drought and save lives (Funk and Verdin, 2009). To detect agricultural drought, FEWS NET currently relies on qualitative, spatio-temporal comparisons between precipitation and NDVI, as well as precipitation indices (e.g., Standardized Precipitation Index) and modeled soil water and evapotranspiration indices. This convergence-of-evidence approach recognizes that there is a no single optimum product for assessing the different dimensions of agricultural drought (Rowland et al., 2005).

A key component in monitoring and studying agricultural drought with remotely sensed inputs in semi-arid regions is that there is a direct relationship between moisture available to plants, from rainfall and soil moisture storage, and the "greenness" of vegetation (Srivastava et al., 1997). An extensive body of literature shows how vegetation indices, like the Normalized Difference Vegetation Index (NDVI), and precipitation are related, especially in semi-arid regions of Africa (e.g., Hielkema et al., 1986; Nicholson et al., 1990; Liu and Kogan, 1996; Richard and Poccard, 1998; Anyamba and Tucker, 2005; Zhang et al., 2005; Chamaille-Jammes and Fritz, 2009). Other studies have explored using NDVI for computing drought indices (Gu et al., 2008; Karnieli et al., 2010), estimating crop production (Funk and Brown, 2009; Funk and Budde, 2009), estimating cultivated area (Husak et al., 2008; Marshall et al., 2011), estimating start of growing





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season (Brown and de Buers 2008), and validating estimates of maize yields (Rojas, 2007).

There are few accurate estimates of regional soil moisture, the intermediary between rainfall and vegetation greenness. Point observations of soil moisture are sparse in their spatial extent, which limits their ability to represent regional soil moisture patterns. For regional estimates, microwave remote sensing data can detect wetness in the upper five centimeters of soil, but are compromised if thick vegetation is present. The most common alternative is to use precipitation-based estimates of soil moisture. However, errors in rainfall data propagate into the soil moisture estimates, as do the errors inherent in the assumptions of the model (e.g., how precipitation is partitioned into soil moisture storage, runoff and drainage). In contrast to these approaches, the present study asks: can we estimate soil moisture directly from NDVI to produce a product with errors independent from those in satellite rainfall products? And how do these estimates compare to precipitation derived soil moisture estimates?

There are two reasons why it is useful to explicitly model soil moisture as an intermediary between rainfall and vegetation greenness. First, it is a more process-based representation of the relationship between rainfall and vegetation greenness. Studies have attributed variation in the rainfall-NDVI relationship to rainfall regime (Liu and Kogan, 1996; Zhang et al., 2005), vegetation type (Davenport and Nicholson, 1993), rooting depth (Lozano-Garcia et al., 2002), soil type (Farrar et al., 1994; Nicholson and Farrar, 1994), and topography (Svoray and Karnieli, 2011). However, these studies have not explicitly modeled the soil processes that are assumed to mediate the relationship between rainfall and vegetation greenness. A more mechanistic understanding of rainfall–soil moisture-plant interactions would contribute to both land surface modeling research and operational drought monitoring, as well as help bridge the gap between these fields (Crow et al., 2012).

Second, transforming satellite-derived NDVI and precipitation observations, whose seasonal signatures are out of phase, into an estimate of soil moisture converts both variables into the same units and phase. In this study we used two separate models to



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formalize the lagged relationships between precipitation and soil moisture and between soil moisture and NDVI. Other studies that have investigated the relationship between precipitation and vegetation address how lags differ between locations, hence we expect that there will be some locations where our model assumptions will not hold, likely due to differences in soil and vegetation from our calibration site. The transformation into soil moisture (units and timing), however, makes it easier to compare and contrast the rainfall and NDVI products for FEWS NET's convergence of evidence approach.

NDVI-derived soil moisture estimates can contribute to agricultural drought monitoring by improving estimates of evapotranspiration (ET) and quantifying errors in gridded rainfall estimates, as has been shown with microwave soil moisture estimates (Crow and Bolten, 2007; Crow et al., 2009, 2012; Bolten and Crow, 2012). However, NDVI's spatial resolution and data latency provides an advantage over, for example, the AMSR-E surface soil moisture estimates (Owe et al., 2008) available at 0.25° ($\sim$ 25 km) from 2002–2011. NDVI's higher spatial resolution is able to resolve convective scale processes (1–10 km) (Hartmann, 1994), which are important drivers of drought in places like sub-Saharan Africa, and is reasonable for comparisons with subnational administrative units that report crop yields.

With these needs in mind we developed a new approach to estimate soil moisture with current and lagged NDVI using multiple linear regression, with parameters estimated by least squares fit of the output to in-situ soil moisture observations from Niger. First, for comparison with our new model, we fit parameters for the Antecedent Precipitation Index (API) to the same in-situ soil moisture observations and compute the API using satellite-derived rainfall. We then analyzed the temporal correlation of our NDVI and rainfall-derived soil moisture estimates to assess the coherency between estimates. Additionally, we compared the estimates to soil moisture observations in Mali and Kenya. Finally, we compared our soil moisture estimates to an agricultural drought indicator in Niger to evaluate the potential of this new data set to contribute to agricultural drought monitoring in areas with sparse in-situ data.





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## 2 Study region, sites and data

We focused our analysis on the Africa Sahel and East Africa, which present different climatic and topographic conditions. The Sahel spans the northern part of Africa from Senegal in the west to Eritrea in the east, and is the grassland savanna transition zone between the Sahara desert to the north and the Sudanian woodland savanna to the south. The topography is mainly flat and the region has a unimodal rainfall regime that is dominated by the northward migration of the intertropical convergence zone (ITCZ) in summer. In situ observations for this region are from Niger and Mali. East Africa has semi-arid highland and lowland regions with a multimodal rainfall regime that is dominated by the seasonal passage of the ITCZ in spring and fall. In-situ observations for this region are from Kenya.

In southwest Niger in-situ soil moisture measurements are from the Wankama (WK1: 13.6456° N, 2.632° E, elevation 238 m; WK2: 13.6448° N, 2.63° E, elevation 244 m) and Tondi Kiboro (13.5483° N, 2.6966° E, elevation 250 m) endorheic catchments (Cappelaere et al., 2009; Ramier et al., 2009). The sites are part of the AMMA-CATCH network (www.amma-catch.org), which monitors sites intended to represent conditions across the West African eco-climate gradient (Lebel et al., 2009). The observations are from fallow agricultural fields with loamy sand soils (Pellarin et al., 2009), and vegetation is primarily *Guiera senealensis* (10–50 % cover) shrubs and annual grasses (25–75 % cover) (d'Herbes and Valentin, 1997). Mean annual rainfall in Niamey, 60 km to the west, is 560 mm. Details about the Niger field sites can be found in Cappelaere et al. (2009). The in-situ measurements from Mali are located at the Agoufou site (15.3367° N, 1.479° W, elevation 308 m), also part of the AMMA-CATCH network. There is sparse tree and shrub cover with a grassy understory on sandy dunes (Baup et al., 2007; Gruhier et al., 2008).

In addition to these sites there are two soil moisture observation sites located in Kenya rangelands administered by the COSMOS project (http://cosmos.hwr.arizona.edu/). The Mpala, Kenya (0.4856° N, 36.8701° E, elevation 1619 m) site has mixed Acacia savanna vegetation (*A. mellifera* and *A. tortilis* with grass and succulent understory) and sandy clay loam soils with 5–7 % slopes. The Kenya Long-term Exclosure Experiment (KLEE) (0.2825° N, 36.8669° E, elevation 1824 m) site is a flat savanna composed of *Acacia drepanolobium* with grass understory and clay soils. Mean annual rainfall at KLEE, about 20 km south of Mpala, is 614 mm.

### In-situ soil moisture measurements

Soil moisture at the Wankama (WK) and Tondi Kiboro (TK) sites in Niger and Agoufou (AG), Mali is measured every half hour with water content reflectometer probes (model CS616, Campbell Scientific Inc., Logan, UT) from 2006–2011 at Niger sites and 2005–2008 in Mali. The Niger data was measured at 40–70 and 70–100 cm in fallow fields, and the Mali data at 60 cm on grassy dunes. The probe output is a period, measured in µs, and needs to be transformed to percent volumetric water content (% VWC) which could be a source of error (e.g., Pellarin et al., 2009). The data in % VWC for the WK, TK and AG sites are available from the International Soil Moisture Network from 2005–2011 (Dorigo et al., 2011). We aggregated the calibrated data to 8–11 day (dekadal) increments. The dekad is a standard time step for agricultural monitoring and NDVI that aligns with calendar months: the first and second dekads being 10 days each and the third being the remainder of the month (8–11 days).

Soil moisture (and daily rainfall) is highly variable in space and so it is not surprising that data reveal differences in the mean and variance between the two Niger sites, despite being defined as having similar (but not identical) amounts of rainfall, and similar soil texture and vegetation characteristics (Fig. 2). Given our interest in the regional relationships between precipitation, soil moisture, and vegetation (rather than the landscape characteristics such as topography and soil type) we averaged the 40–70 cm observations across all sites, and all years to remove site-specific noise. We then used this annual dekadal mean (36 dekads year$^{-1}$) for comparison with annual dekadal mean NDVI. We also used rainfall station data at the Wankama and Agoufou sites to evaluate satellite precipitation based estimates of soil moisture discussed in Sect. 4.

Soil moisture measurements at the site in Kenya are available for September 2011–present and October 2011–present for the Mpala and KLEE sites, respectively. The sites are part of COSMOS, which uses cosmic-ray moisture probe instrumentation with a footprint of 34 ha and depths up to 50 cm. The cosmic-ray moisture probe measures low energy cosmic-ray neutrons whose intensity is inversely correlated with soil water content (Zreda et al., 2012). We used the hourly data, which has been quality controlled, corrected for local effects, and converted to a soil moisture measurement in units of % volume. As with the AMMA soil moisture data, we averaged each station's data to dekadal time steps. We also used rainfall station data at the KLEE site to evaluate satellite precipitation-based estimates of soil moisture discussed in Sect. 4.

## 3 Soil moisture estimated from NDVI

To reconstruct a soil moisture time series from the NDVI data we assume a linear system where NDVI is the input and soil moisture is the output. We used the eMODIS NDVI (data and documentation available from http://earlywarning.usgs.gov/fews/Africa) based on the National Aeronautics and Space Administration's (NASA) Earth Observing System (EOS) Moderate Resolution Imaging Spectroradiometer (MODIS) and produced at the US Geological Survey's Earth Resources Observation and Science (USGS-EROS) Center. Specifically, NDVI is calculated using MODIS L1B Terra surface reflectance. The index is defined as (NIR – RED)/(NIR + RED), where NIR is the near-infrared reflectance and RED is the visible-red reflectance. The eMODIS NDVI is a 10 day maximum-value composite, originally at 250 m resolution. We compared individual sites to NDVI aggregated to 750 m in order to match the reported positional accuracy of the AMMA CATCH station locations. We also aggregated NDVI to 0.1° ($\sim$ 10 km), matching the resolution of the bias corrected RFE2 satellite rainfall estimates (described below).

For the six years of soil moisture data available at the Wankama and Tondi Kiboro sites, peak NDVI lags peak soil moisture by one dekad. Figure 3 shows dekadal NDVI and soil moisture averaged over these sites across six years. We are able to estimate the previous dekad's soil moisture as a weighted sum of the current and previous dekad's NDVI. Thus, the soil moisture is determined by filtering (convolving) the NDVI input time series (Chatfield, 2004, Chap. 9). In this case we used current and one dekad lag NDVI, classifying this as a finite impulse response filter.

$$\widehat{\mathrm{NSM}_{t-1}} = \beta_0 + \beta_1 \mathrm{NDVI}_{t-1} + \beta_2 \mathrm{NDVI}_t \quad (1)$$

We restricted our model to current and one dekad lag to maintain near real-time estimation capabilities. The model, fit to annual mean soil moisture, improved when we included an additional lag. However incorporating the additional lag delayed soil moisture estimates by an additional dekad ($\mathrm{SM}_{t-2}$) and did not substantially improve the NDVI-derived soil moisture estimate (hereafter referred to as NSM), fit to observed soil moisture time series. The short lag (1–2 dekads) between soil moisture and NDVI is consistent with estimates from Farrar et al. (1994) that found the highest correlations between concurrent monthly modeled soil moisture and average monthly NDVI.

We solved for the NSM coefficients using a least squares fit to the average dekadal in-situ soil moisture observations. The filter coefficients were 0.003, −0.113, 0.392 for $\beta_o$, $\beta_1$, and $\beta_2$, and standard errors of 0.07 for both $\beta_1$, and $\beta_2$.

As a multiple regression model, the independent variables are the current ($t$) and lag one NDVI ($t-1$) and dependent variable is the observed negative lag one ($t-1$) soil moisture. The signs and magnitudes of the two NDVI coefficients indicate that soil moisture is related to the change in NDVI from dekad $t-1$ to $t$ plus the actual NDVI value at dekad $t$. Figure 3 shows the NSM (NDVI estimated soil moisture, dashed line), the NDVI time series (black), and the observed soil moisture (grey).

We applied this same filter to the observed dekadal NDVI from 2006–2011 (36 dekads · 6 yr) which results in the dekadal NSM (dashed line) in Fig. 4. Later we use these same model parameters to estimate soil moisture across the Sahel for the 2001–2012 NDVI record (Fig. 5).





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## 4 Soil moisture estimated with antecedent precipitation index

For comparison, we estimated a separate time series of soil moisture derived from precipitation. We use multi-satellite rainfall estimates (RFE2) at 0.1° from NOAA CPC (Xie and Arkin, 1997). RFE2 is a merged satellite (infrared and microwave) and rainfall gauge product available from 2000–present. RFE2 was found to be an acceptable product over West Africa when compared to other merged satellite-gauge products (Guichard et al., 2010), and offers the best match with validation estimates in terms of distribution and bias (Jobard et al., 2011). With respect to East Africa, Funk and Verdin (2003) found high correlations between RFE2 rainfall and station data in Kenya. In Ethiopia, however, Dinku et al. (2008) found that the complex topography and associated orographic rainfall events contributed to RFE2's poor performance. Beyene and Meissner (2010) found that most of the errors in the rainfall estimates over Ethiopia occurred during the winter months, while the important crop growing season of spring and summer showed good correlation with gauge observations.

To remove false detection of rainfall in the dry season we used a bias correction procedure that scales the rainfall time series to a long term mean field (FEWS NET Climatology or FCLIM). The method used to generate the FCLIM long term mean rainfall fields incorporates climate, satellite, and physiographic data using a local regression technique (Funk et al., 2012). These monthly mean fields can be used in near real time to parsimoniously remove substantial bias from satellite RFE, producing unbiased rainfall estimates (Funk et al., 2007).

Using the bias-corrected RFE2 rainfall estimates across the Sahel we calculated the Antecedent Precipitation Index (API) at each pixel as an indicator of root zone soil moisture. The API is a moving average of precipitation with weights that decay exponentially toward zero for past rainfall events or totals. In the current study, we estimated the API (mm), solving for the necessary parameters by fitting to the Niger soil moisture observations (averaged 40–70 cm) using non-linear least squares (Fig. 4). For a given dekad ($t$) API was calculated based on all dekadal precipitation ($P$) values



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that occur during dekad $t$ and the previous 6 dekads (∼ 61 days). This also roughly corresponds to the work of Nicholson et al. (1990) that finds monthly NDVI has the highest correlation with the current and two previous months of rainfall.

$$\mathrm{API}_t = \beta_0 + \beta_1 \sum_{n=0}^{6} P_{t-n} e^{-\beta_2 n} \tag{2}$$

where $n$ is time in dekads. The parameters were estimated as 0.0401, 0.0002, and 0.7905 ($\beta_0, \beta_1, \beta_2$, respectively). Yamaguchi and Shinoda (2002) explain that in this formulation of the API, parameter $\beta_1$ is the effective rainfall or rate of initial input of precipitation ($P$) into the root-zone soil (the rest is lost through surface runoff and infiltration) and $\beta_2$ represents the drying rate of the soil moisture lost between time steps or stored in the upper 40 cm of soil. Here, $\beta_0$ corresponds to the wilting point, the proportional volume of water where plants can no longer extract water from the soil. FAO (2009) estimates the wilting points of loamy sands and sandy loams, soils characteritic of Niger, as 0.027 and 0.047, respectively (FAO, 2009). Our modeled $\beta_0$ falls within that range.

## 5 API and NSM model evaluation

We evaluated the fit of the NSM and API to observations based on how well we captured the timing of the seasonal cycle and the magnitude and rank of the annual peak soil moisture values. We use correlation ($R$) and root mean square error (RMSE) of the observed and predicted values of soil moisture to assess the accuracy of the timing and magnitude of our estimates. We also use rank correlation ($\rho$) of peak annual soil moisture to assess the ability of the models to capture the inter-annual variability.

Compared to the soil moisture observations in Niger (also used to calibrate the models), the NSM accurately captures the timing of the wet season ($R = 0.71$, $p = 0.06$, RMSE = 1.2), but does not accurately capture the magnitude of the peaks, i.e.,





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the inter-annual variability ($\rho = 0.6$, $p > 0.2$). Similarly, the API ($R = 0.72$, $p = 0.07$, RMSE = 1.2) did capture the seasonal cycle but was unable to represent the inter-annual variability ($\rho = 0.1$). In-situ soil moisture observations in Mali and Kenya allowed us to assess our model and calibrated parameters at specific sites with different soil textures, and vegetation types, and rainfall regimes, and will be described in the discussion section.

## 6 API and NSM across the Sahel

We then calculated the API across the Sahel using dekadal RFE2 data from 2001–2012, and compared these time series with the dekadal NSM estimates computed using NDVI data from 2001–2012. Correlation analysis (Fig. 5) allows us to see where the temporal pattern generally agrees, even if the magnitudes differ (the amplitude of API estimates tend to be less than that of the NSM). These two independent models agree well ($R > 0.9$) in the semi-arid west and central Sahel where annual rainfall ranges between 200–1200 mm. This spatial pattern is consistent where monthly NDVI has been shown to be highly correlated with concurrent and 2 previous months precipitation (Nicholson et al., 1990; Funk and Brown, 2006). The short lag between NDVI and soil moisture is also consistent with other studies of vegetation response to modeled soil moisture in southern Africa (Farrar et al., 1994).

Correlations are low in regions with little vegetation (e.g., the Sahara) and in higher rainfall/dense vegetation regions where NDVI saturates (e.g., Congo). We see low correlation in places where vegetation has access to water other than rainfall (e.g., Sudd Swamp and Niger Delta). We next used available soil moisture data from other sites to investigate the accuracy of both the NSM and API, and provide insight into potential reasons for low correlations in Kenya.



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# 7 In-situ comparisons

The soil moisture observations from Agoufou, Mali and Mpala, Kenya, not used in calibrating Eqs. (1) and (2), were useful in further evaluating the performance of the NSM estimates. In Mali, the NSM captures the timing of the wet season ($R = 0.65$, $p = 0.07$, RMSE = 1.55), but the peak soil moisture is estimated a dekad late. In addition to the shift, the NSM does not capture the magnitude of the peaks nor the inter-annual variability at this particular station ($\rho = -0.8$, $p = 0.2$). By these metrics the API better captured the timing of the seasonal cycle ($R = 0.68$, $p = 0.03$) but predicted the reverse wet-to-dry rank in seasons ($\rho = -1.0$).

Initially, we found that the magnitude of the minimum (wilting point) for the NSM and API estimates calibrated to the Niger sites was higher than observations at Agoufou, Mali. We adjusted for differences in soil type between sites by adding the difference between the Mali and Niger sites wilting points (WP). The Niger site is a loamy sand with a wilting point of $\sim 4\,\%$ as estimated by the API, while the Agoufou site in Mali is a coarse sand (WP = 1 %; FAO et al., 2009). This means that for the same volume of soil moisture, there is less water available to plants at the loamy sand Niger site, relative to the sandy Mali sites during dry conditions. This assumption allows us to subtract the difference in wilting point between the Niger and Mali, which appropriately adjusts the seasonal minima of our estimates.

At the Mpala, Kenya site the NSM accurately captures the timing of the wet season ($R = 0.76$, RMSE = 2.78). The time series is too short to assess inter-annual variability, but qualitatively the NSM seems to capture the May 2012 peaks, but is late in 2011 and misses the July–August 2012 peak. Similarly, the API did capture the seasonal cycle ($R = 0.72$, RMSE = 5.8). The NSM outperformed API in terms of RMSE. Notably, the API has a very late start in October 2011 compared to the NSM or soil moisture observations, which will be discussed later.





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## 8 Discussion

A challenge when using in-situ soil moisture observations is appropriately leveraging sparse measurements to analyze broad scale patterns over space and time. Our approach was to use in-situ measurements to calibrate soil moisture models driven satellite rainfall and vegetation and analyze resulting patterns over space and time. We find that the NSM and API are well correlated in the same locations where NDVI is well correlated with the two previous and concurrent month's rainfall (Nicholson et al., 1990). Our API and NSM models essentially split this relationship into two, with API representing the relationship between soil moisture and previous 6 dekads (∼ 61 days) of rainfall and the NSM representing the relationship between soil moisture and two dekads (∼ 20 days) of NDVI. These model formulations agreed with the API in Yamaguchi and Shinoda's (2002) study of soil moisture in southwest Niger and the finding that NDVI is best correlated with the concurrent month's modeled soil moisture in southern Africa (Farrar et al., 1994). Farrar et al. (1994) also found soil texture to be an important determinant in the relationship between rainfall and NDVI, supported by our finding that neither API nor NSM parameters calibrated at the loamy-sand Niger site fit soil moisture observations from clay soils at the KLEE, Kenya site (not shown). Given the importance of soil texture we restricted our model evaluation to sites with high sand content: sand, loamy sand, and sandy clay loam sites in Agoufou, Mali; Wankama and Tondi Kiboro, Niger; and Mpala, Kenya, respectively.

Both the API and NSM are providing coarse scale estimates of soil moisture, and we do not expect that they will match with the point soil moisture observations. We do know, however, that API calculated with a co-located rain gauge does show very high agreement with observed soil moisture, giving us confidence in the model structure (e.g., Yamaguchi and Shinoda, 2002). With respect to the NSM model structure, the NSM under predicted the peak and over predicted the thickness of the moisture recession tail (Fig. 3). This shortcoming is evident at the Niger sites where comparisons between observed soil moisture and NSM time series showed that the fat tails in the





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NSM distribution did not reflect observed soil moisture recession (Fig. 4). This pattern of seasonal bias suggests that looking at integrated NSM and integrated soil moisture might yield a closer match in this location.

The results from Mpala, Kenya highlighted how correlation between the NSM and API, as shown in Fig. 5, does not tell the full story of model performance. The correlation between API and NSM at Mpala, Kenya was high (Fig. 5, $R = 0.9$, $p = 0.03$), while correlation of the models and the observed data was considerably lower and similar for both models (Fig. 7, $R = 0.76$ and $R = 0.72$, NSM and API, respectively). However, the lower RMSE of the NSM suggest that the NSM parameters are more robust than the API parameters when making prediction in different rainfall regimes. Because the NSM estimates are derived from NDVI, they may be a more direct reflection of available water, while the API makes assumptions about how much precipitation is retained in the soil after runoff, drainage and evaporation. This was an encouraging result, but will need to be investigated further when there is a longer time series of data and, ideally, with more observations on soils with high sand content.

In addition to the NSM and API correlation analysis we also evaluated the quality of the rainfall forcing in both Niger and Kenya. With respect to West Africa, other studies vouch for RFE2's performance (Guichard et al., 2010; Jobard et al., 2011). We also looked at 0.25° (∼ 25 km) interpolated rainfall fields generated from AMMA-CATCH high density rain gauges (Vischel et al., 2011). These rainfall fields agreed well with RFE2 satellite rainfall estimates, aggregated to 0.25°, in terms of daily min, max, mean, standard deviation and number of rain days.

We also evaluated in-situ rainfall observations from the KLEE site to help explain why the RFE2-driven API detected a notably late start to the 2011 season compared to the NSM and soil moisture observations (Fig. 7). Given that Mpala and KLEE are 20 km apart, day-to-day rainfall may not match. However, it is the closest gage available to Mpala and data is aggregated to dekads, which we feel makes for a reasonable comparison. With these caveats in mind, the rain gauge at KLEE showed that the RFE had under-predicted (or completely missed) rain events during the previous four dekads,





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hence underestimating antecedent soil moisture conditions (API). The RFE2 rainfall estimates also under-predicted station rainfall in October and November 2012, but to a lesser degree than observed in 2011. The literature suggests that in general RFE2 performs very well ($R > 0.9$) compared to station data in the Rift Valley and Western Kenya but does not perform as well in central, northeastern, eastern and coastal Kenya, likely a result of low station density and difficulty of retrievals along coasts (Funk and Verdin, 2010). Across the broader Horn of Africa the RFE2 has difficulty predicting rainfall in Ethiopia due to complex topography (Dinku et al., 2008; Beyene and Meissner, 2010). These patterns somewhat correspond to the API-NSM correlation map (Fig. 5) and suggest that poor RFE2 performance may limit the ability of the API to track seasonal changes in soil moisture and vegetation. However, confirmation of this hypothesis would require more investigation of in-situ rainfall, soil moisture and vegetation data, or other ancillary sources of data. For example, Nicholson et al. (1990) described how the annual rainfall-NDVI relationship is not as strong in Kenya as it is in West Africa – potentially limiting the ability of NSM (or NDVI) to be evaluated in conjunction with RFE2.

## 9 Comparison with WRSI and yields

NDVI has shown high correlation with drought indices (Peled et al., 2009; Crow et al., 2012), suggesting that the NSM may as well. Moreover, the NDVI and RFE2 are operational drought monitoring products, thus we expect that their derived soil moisture estimates (NSM and API) will have some utility for agricultural drought monitoring. To test this hypothesis we compared annual July-August-September NSM and API totals to an index of crop water satisfaction, and FAO reported millet yields (FAOSTAT, 2013). We limited our analysis to areas designated as crop (millet) growing zone (Siwela, 2008) and took the spatial average over this cropped area for each year (Fig. 8). The index that FEWS NET uses for operational drought monitoring, called the Water Requirement Satisfaction Index (WRSI) (Senay and Verdin, 2002; Verdin and Klaver,





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2002), is calculated using a simple soil water balance model driven with potential evapotranspiration (PET) (USGS-EROS) and the same RFE2 precipitation estimates that we used to calculate the API. The crop water requirement for millet, the most common crop in Niger, is calculated by multiplying potential evapotranspiration (PET) by the FAO crop coefficient. The index then, is the ratio of AET to PET, where AET < PET when the soil water balance is below a critical threshold specified by the FAO for millet. The WRSI is a simple metric for water stress and has been shown to be well correlated with crop yields. We expected that the total soil moisture for the growing season would be below average during years when the WRSI is low.

In particular, we were most interested in how well each of these metrics (API, NSM, WRSI, and yields) indicated the known agricultural drought years of 2004, 2009, and 2011. The NSM estimates are completely independent from WRSI, while the WRSI and API are not entirely independent because they are both driven with the same RFE2 rainfall data. These dry years showed a coherent pattern between the four metrics, as all were below their ten year average (Fig. 8). Such convergence of evidence can help motivate timely and effective humanitarian relief efforts.

The rank correlations between the metrics are shown in Table 1. Both the API and NSM are significantly correlated with WRSI ($p < 0.01$), and NSM has the highest correlation of all of the metrics with yields, which we assume represent true agricultural drought conditions in the field. In general the high correspondence between yields and NSM give us confidence in our new approach to estimating soil moisture across the Sahel.

## 10 Conclusions

This work provides a novel way to estimate soil moisture from NDVI, using the NSM multiple regression model that predicts the previous dekad's soil moisture using current and negative lag one NDVI. To compensate for the small number of soil moisture observations in the Sahel and East Africa we compared our modeled results to a rainfall





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based estimate of soil moisture, the API. Our approach effectively deconstructed the relationship between NDVI and rainfall that has been studied over the Sahel. The API represented the relationship between soil moisture and the two previous month's rainfall whereas the NSM represented the relationship between soil moisture and NDVI in the concurrent month (two dekads). Finally, by developing a way to reasonably estimate soil moisture with NDVI we increase the potential utility of NDVI data by transforming it into a variable commonly used in land surface and water balance models.

In addition to showing where the NSM and API estimates both capture the seasonal distribution of soil moisture, our specific examples in Niger, Mali and Kenya offered insight into the relationship between soil moisture and satellite derived estimates of rainfall and NDVI. Occurrences where NSM and API are in high agreement, both in terms of seasonal distribution and interannual variability, as was the case in Mali, suggest that both estimates are accurately representing pixel scale soil moisture. This is important because we need soil moisture estimates at the regional scale ($\sim$ 10 km) to address questions regarding land-atmosphere interactions. The Mali example also highlighted that among soils with high sand content adjusting for wilting point of the soil may help improve both rainfall and NDVI derived estimates away from calibration sites. Instances where the timing of the NSM and soil moisture agree but do not match the API, as in the case of Kenya, may be useful in pointing out deficiencies in satellite derived rainfall estimates. The Kenya example, where NSM better fit soil moisture observations (lower RMSE) than API, also highlighted that the calibrated parameters in the NSM may be more robust that parameters in the rainfall driven API across different rainfall regimes.

One of the major limitations in this study, and in other studies that aim to model the relationship between NDVI and soil moisture, is that we were unable to capture the interannual variability as measured at specific sites. This is similar to problems that plagued studies of point based correlations between in-situ soil moisture observations and satellite derived vegetation indices across the US (Adegoke and Carleton, 2002; Wang et al., 2007; Gu et al., 2008; Schnur et al., 2010). In these studies soil moisture-





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NDVI correlations tend to be low because soil texture, vegetation type, and climate are thought to control the relationship. In our study, these additional controlling factors likely contribute to the high spatial heterogeneity of soil moisture observations, making them a noisy basis for anchoring regional scale models of soil moisture. We found that at 750–10 000 m NDVI is insensitive to these fine scale variations, confounded by low soil water contents. Still the NSM seems to be able to resolve differences in wet-dry years in Niger, but, when integrated over the season showed higher correlation with millet yields than the two satellite rainfall derived indices (WRSI, API).

Moving forward, the NSM soil moisture estimates can more readily interface with water balance and land surface models than NDVI. This greatly expands the utility of NDVI, which was previously limited to being a qualitative comparison for model outputs (e.g., soil moisture and ET). Having an estimate of soil moisture independent from rainfall is particularly useful in the Sahel and East Africa where the high spatial heterogeneity in rainfall limits a rainfall driven models' ability to make accurate fine scale estimates of soil moisture. The NSM can help us explore these and other sources of error (e.g., due to model assumptions). Mapping these errors may more clearly reveal where soil moisture estimates from either NDVI or satellite rainfall may be preferred. Finally, NSM estimates can be available at a 10 day delay, allowing us to reconstruct soil moisture time series at near real-time. This is important if these estimates are to be considered as one of the environmental variables in operational USAID food security assessments. Recently, Bolten et al. (2012) showed how remotely sensed estimates of soil moisture using microwave sensors have added value to crop monitoring models, especially in regions with poor rainfall data. Future work will see if our NDVI-based estimates could offer similar benefits, while being available at near-real time.

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(LTREB BSR 08-16453) to T. P. Young, C. Riginos, K. Veblen, and K. Caylor. The COSMOS (soil moisture) project is funded by the Atmospheric Science, Hydrology, and Ecology Programs of the US National Science Foundation (grant ATM-0838491). The authors would also like to thank Tom Dunne helpful comments on the manuscript.

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**Table 1.** Rank correlations between annual drought metrics in cropping zones of Niger.

| | Yields | WRSI | NSM | API |
|---|---|---|---|---|
| Yields | 1 | 0.42 | 0.50[a] | 0.38 |
| WRSI | | 1 | 0.51[a] | 0.78[b] |
| NSM | | | 1 | 0.77[b] |
| API | | | | 1 |

[a] $p \leq 0.1$, [b] $p \leq 0.01$.





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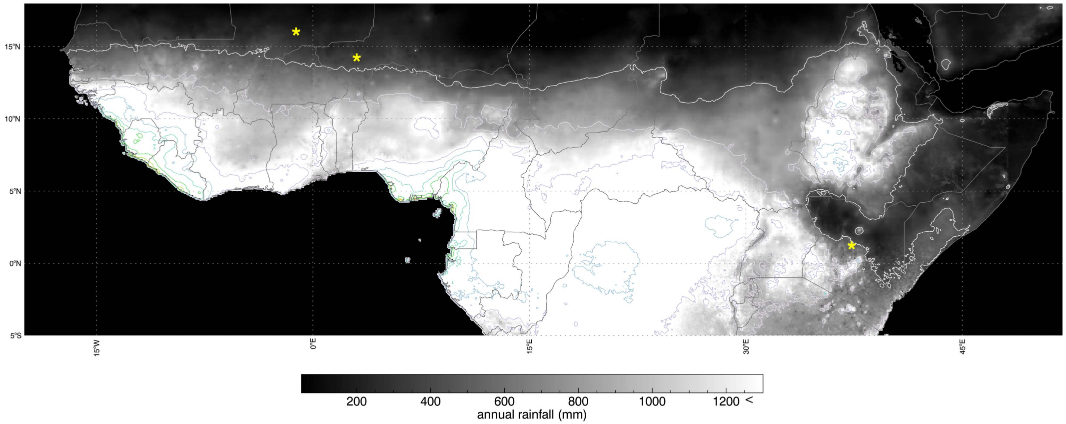


**Fig. 1.** Yellow stars indicate location of study sites in Agoufou, Mali (15.35400° N, 1.47900° W, elevation 308 m), Wankama, Niger (WK: 13.6456° N, 2.632° E, elevation 238 m), Tondi Kiboro, Niger (13.5483° N, 2.6966° E, elevation 250 m), Mpala, Kenya (0.4856° N, 36.8701° E, elevation 1619 m), The Kenya Long-term Exclosure Experiment (KLEE), Kenya (0.2825° N, 36.8669° E, elevation 1824 m). Annual rainfall (mm) from FEWS-NET climatology (FCLIM).

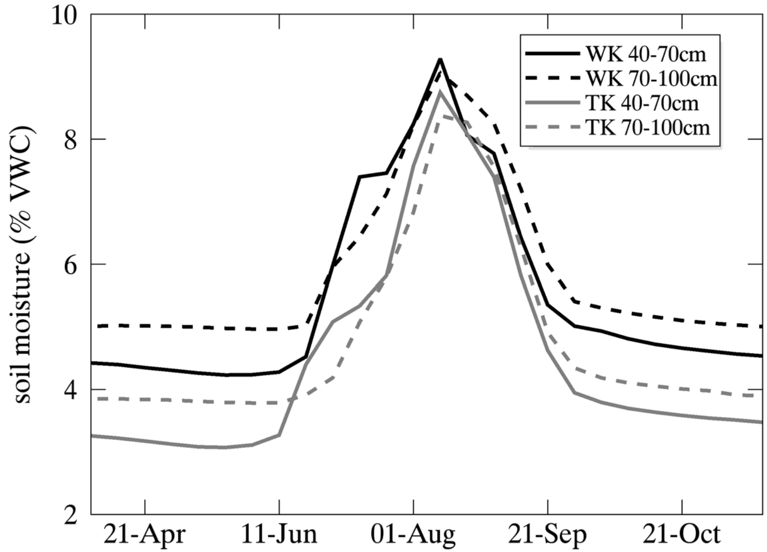


**Fig. 2.** Average dekadal volumetric soil moisture (% VWC) at the two Wankama sites and Tondi Kiboro, Niger (2006–2011).





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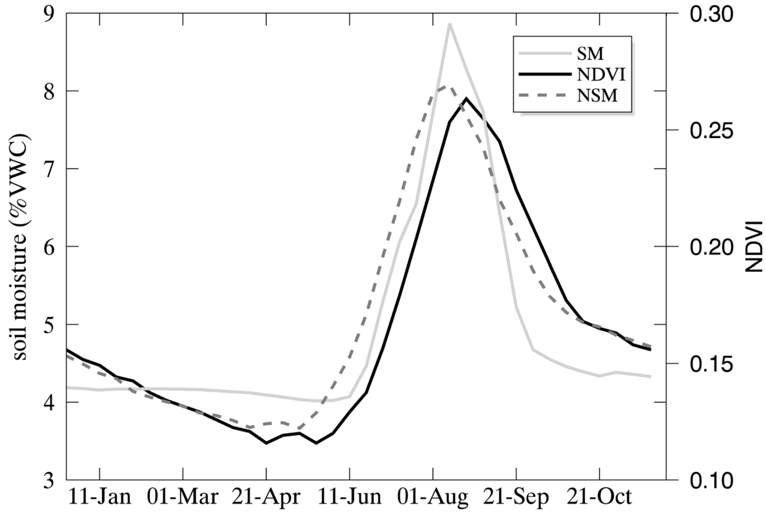


**Fig. 3.** Average 2006–2011 dekadal NDVI input to the soil moisture model, fit to observed dekadal soil moisture in Niger. NSM (dashed line) is the NDVI-derived soil moisture estimate. $NSM_{t-1}$. Is estimated with $NDVI_{t-1}$ and $NDVI_t$ ($R = 0.93$, RMSE = 0.005).





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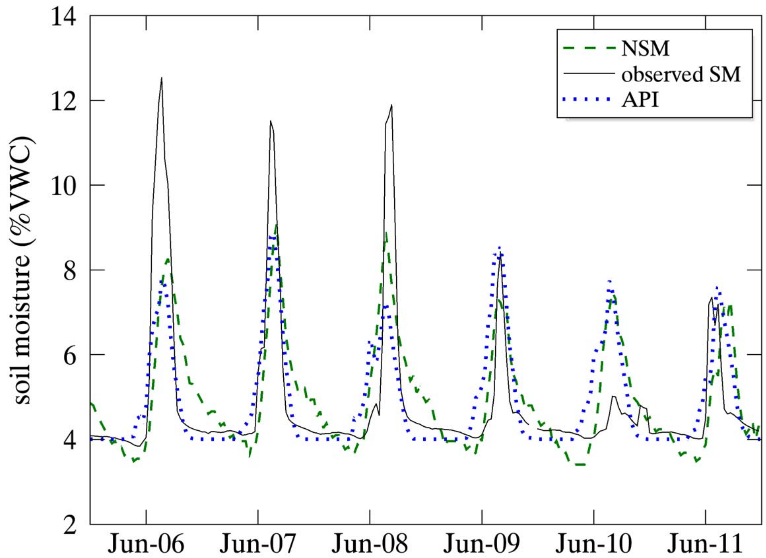


**Fig. 4.** NSM ($R = 0.71$, $p = 0.06$, RMSE = 1.2) and API-estimated soil moisture ($R = 0.72$, $p = 0.07$, RMSE = 1.2) and average observed soil moisture, Niger sites. Correlation between NSM and API is $R = 0.78$, $p = 0.04$.

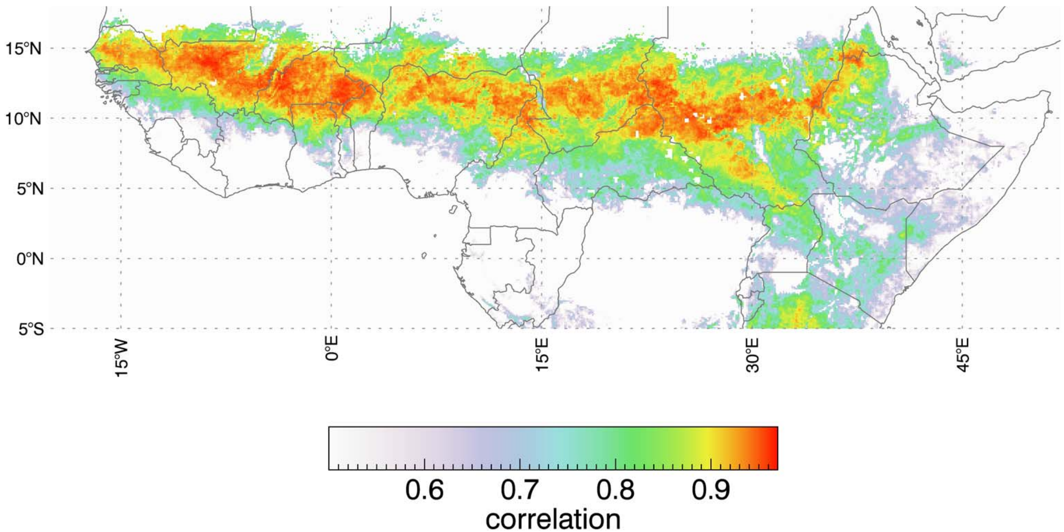


**Fig. 5.** Correlation between the API and NSM soil moisture estimates.





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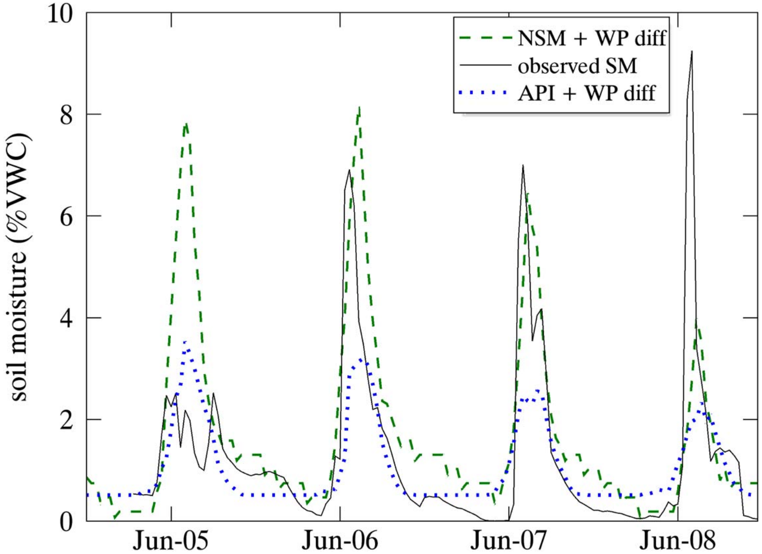


**Fig. 6.** NSM ($R = 0.65$, $p = 0.07$, RMSE = 1.55) and API-estimated soil moisture ($R = 0.68$, $p = 0.03$, RMSE = 1.33) compared to average observed soil moisture, Mali sites. Correlation between NSM and API, $R = 0.9$, $p = 0.02$.

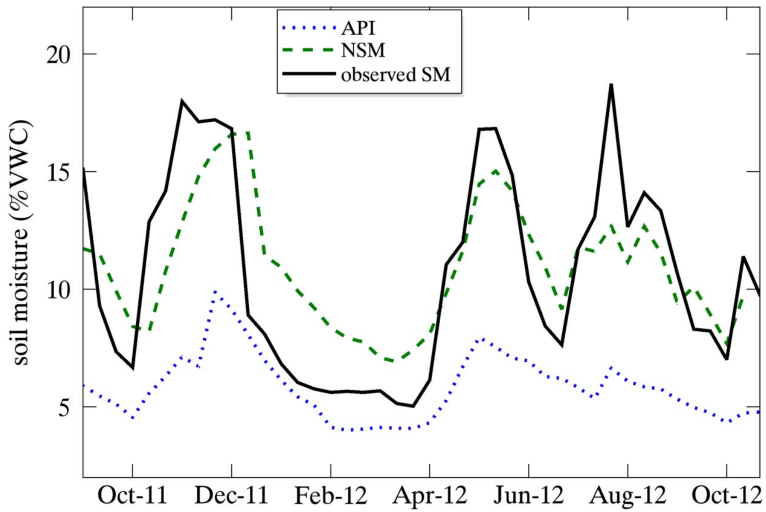


**Fig. 7.** Observed soil moisture (black), NSM ($R$ = 0.76, RMSE = 2.78), API ($R$ = 0.72, RMSE = 5.8) estimated soil moisture driven RFE rainfall and NDVI at Mpala, Kenya – using the parameters fit to the Niger observed soil.





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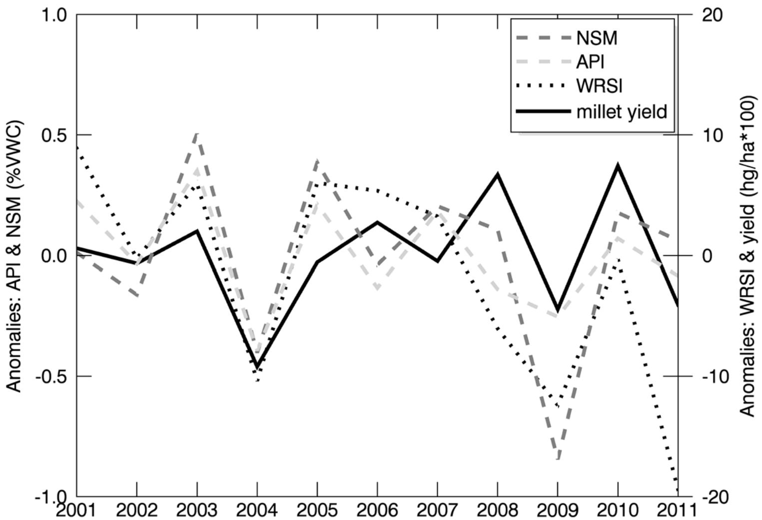


**Fig. 8.** NSM, API, WRSI anomalies averaged over the crop zones in Niger, and national yield anomalies.





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