Assessing Multi-satellite Remote Sensing, Reanalysis, and Land Surface Models’ Products in Characterizing Agricultural Drought in East Africa

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Abstract

Heavy reliance of East Africa (EA) on rain-fed agriculture makes it vulnerable to drought-induced famine. Yet, most research on EA drought focuses on meteorological aspects with little attention paid on agricultural drought impacts. The inadequacy of in-situ rainfall data across EA has also hampered detailed agricultural drought impact analysis. Recently, however, there has been increased data availability from remote sensing (rainfall, vegetation condition index – VCI, terrestrial water storage – TWS), reanalysis (soil moisture and TWS), and land surface models (soil moisture). Here, these products were employed to characterise EA droughts between 1983 and 2013 in terms of severity, duration, and spatial extent. Furthermore, the capability of these products to capture agricultural drought impacts was assessed using maize and wheat production data. Our results show that while all products were similar in drought characterisation in dry areas, the similarity of CHIRPS and GPCC extended over the whole EA. CHIRPS and GPCC also identified the highest proportion of areas under drought followed closely by soil moisture products whereas VCI had the least coverage. Drought onset was marked first by a decline/lack of rainfall, followed by VCI/soil moisture, and then TWS. VCI indicated drought lag at 0-4 months following rainfall while soil moisture and TWS products had variable lags vis-à-vis rainfall. GLDAS mischaracterized the 2005-2006 drought vis-à-vis other soil moisture products. Based on the annual crop production variabilities explained, we identified CHIRPS, GPCC, FLDAS, and VCI as suitable for agricultural drought monitoring/characterization in the region for the study period. Finally, GLDAS explained
the lowest percentages of the Kenyan and Ugandan annual crop production variances. These findings are important for the gauge data deficient EA region as they provide alternatives for monitoring agricultural drought.

Keywords: Agricultural drought, East Africa, Partial least squares regression, Rotated principal component analysis, Rainfall, Standardised Anomalies, Standardised Index, SPI, Soil moisture, TWS, VCI.

1. Introduction

East Africa (EA, defined as Kenya, Uganda, Tanzania, Rwanda, and Burundi) relies heavily on rain-fed subsistence agriculture, which is increasingly becoming vulnerable to frequent drought events (see, e.g., Rojas et al., 2011; Loewenberg, 2011; Stampoulis et al., 2016). Furthermore, the impacts of drought are compounded by high levels of poverty, conflicts, population migration, and lack of social infrastructure across the region, triggering famine cycles every time an episode occurs (Nicholson, 2014; Kurnik et al., 2011; Loewenberg, 2011; IFRC, 2011; OEA, 2011a,b). As drought is in part a naturally recurrent feature in EA, there is a need for comprehensive and reliable monitoring in order to aid planning and mitigation of drought impacts. Since frequency and severity of droughts are likely to intensify with climate change (e.g., Williams and Funk, 2011), the need to characterize droughts in terms of duration, severity, frequency and spatial extent is critical.

Comprehensive characterization of drought in EA, like in many other places around the world, faces a number of challenges with respect to use of in-situ precipitation data. For instance, often spatial variability in precipitation cannot be adequately captured due to sparse and uneven spatial distribution of rain gauges. Furthermore, gaps in individual rainfall records, and at times lack of consistency due to poor handling complicate the use of precipitation data (Nicholson, 2014; Rojas et al., 2011; Naumann et al., 2014). In many studies, this led to the replacement or augmentation of in-situ rainfall data with remotely sensed precipitation, reanalysis, and model outputs, providing consistent and homogeneous data with global coverage at various spatial scales that are suitable for drought monitoring (Damberg and AghaKouchak, 2014). However, these products can have considerable discrepancies and
limitations in representing rainfall at local and regional scales (Rojas et al., 2011; Naumann et al., 2014; Damberg and AghaKouchak, 2014; Hong et al., 2006; AghaKouchak et al., 2009).

In addition to satellite and model-based precipitation products, normalised difference vegetation index (NDVI, Rousel et al., 1974; Tucker, 1979) and Gravity Recovery and Climate Experiment (GRACE) total water storage (TWS, Tapley et al., 2004) have been used to monitor drought. NDVI has been used directly or in its derivative form to monitor impacts of drought on vegetation health (e.g., Kogan, 1995; Rhee et al., 2010; Bayarjargal et al., 2006). In EA, it has been used by Anyamba and Tucker (2005), Anderson et al. (2012), and Nicholson (2014), while the use of GRACE satellite temporal gravity measurements (see, e.g., Wouters et al., 2014; Tapley et al., 2004) in EA has been limited to monitoring changes in total water storage (e.g., Swenson and Wahr, 2009; Awange et al., 2008; Becker et al., 2010; Awange et al., 2013), and recently drought analysis (Awange et al., 2016).

Currently, drought studies carried out in the EA region range from purely precipitation based (e.g., Naumann et al., 2014; Kurnik et al., 2011; Clark et al., 2003), a combination of precipitation and climate models (e.g., Yang et al., 2014a; Dutra et al., 2013), to precipitation in combination with soil moisture and/or NDVI (e.g., Anderson et al., 2012; Nicholson, 2014; AghaKouchak, 2015). Some of the aforementioned studies and few others (see, e.g., Shukla et al., 2014; Mwangi et al., 2014; Anderson et al., 2012; Rojas et al., 2011) have examined agricultural drought using standardised precipitation index (SPI), NDVI, and/or soil moisture. However, for a region like EA, where the majority of the population depends on subsistence rain-fed agriculture, additional studies focusing on agricultural drought impacts, e.g., related to crop production, would be more relevant and beneficial to the population. Therefore, this study focuses on both the characterization of drought behavior in general and agricultural drought in particular using various indicators (precipitation, soil moisture, and total water storage) derived from multi-satellite remote sensing, reanalysis, and model products. Further, this study evaluates the utility of these products using annual crop production, which has so far not been done by the aforementioned studies.

To support agricultural drought monitoring from diverse indicators, it is imperative to identify and provide information on the most effective agricultural drought indicator or a
combination of indicators for the EA region. Therefore, the objectives of this study are: (i) to characterise agricultural drought in terms of severity, duration, and spatial (areal) extent using satellite remote sensing, reanalysis, and modelled soil moisture data, and (ii) evaluate how well these products capture agricultural drought in the region as reflected by national crop production data (wheat and maize) during the study period.

To the best of our knowledge, this is the first comprehensive study to assess the potential of these remotely sensed products, reanalysis data, and land surface model outputs to monitor agricultural drought in the EA region. Moreover, this contribution proposes for the first time the possibility of using GRACE satellite products for agricultural drought monitoring in EA thus providing a link between TWS and crop production.

2. Study area and data

2.1. Study area

The EA region (Fig. 1) has a bimodal rainfall regime, the March-April-May (MAM; long rains) and the October-November-December (OND; short rains) with the MAM contributing over 70% of the annual rainfall while the OND contributing less than 20% (Michael, 2006). The rainfall regime is controlled by the inter-tropical convergence zone, effects of El Niño Southern Oscillation (ENSO), and sea surface temperature variations in the Indian and Pacific oceans (EACS, 2014; Pricope et al., 2013; Williams et al., 2012; Lyon and DeWitt, 2012; Tierney et al., 2013; Clark et al., 2003).

The amount of the MAM rainfall has been declining in the region since 1999, with the recent (1990’s to 2000’s) mean being below the 1980’s mean (Williams et al., 2012; Lyon and DeWitt, 2012), whilst the frequency and duration of drought episodes have increased since 1998 (Nicholson, 2014; Lyon, 2014). Drought events have been observed in 2000–2001, 2005–2006, 2008–2009, and 2010–2011, with the latter being the worst in 60 years due to failure of short rains in 2010 and long rains in 2011. This particular drought affected over 12 million people bringing untold sufferings to the region (IFRC, 2011; Loewenberg, 2011).
2.2. Data

The following data sets were used (see Table 1 for a summary): precipitation products from the Global Precipitation Climatology Centre (GPCC) and Climate Hazard Group (Climate Hazard Group InfraRed Precipitation with Stations (CHIRPS)); soil moisture products from the Global Land Data Assimilation System (GLDAS), Climate Prediction Center (CPC), the European Centre for Medium-Range Weather Forecasts Interim Re-Analysis (ERA-Interim),
the second Modern-Era Retrospective analysis for Research and Applications (MERRA-2), and Famine Early Warning System Network (FEWS NET) Land Data Assimilation System (FLDAS); Global Inventory Monitoring and Modelling Studies (GIMMS) NDVI; and terrestrial water storage (TWS) from MERRA-2 and GRACE.

2.2.1. Precipitation

1. CHIRPS is a quasi-global (50°S - 50°N) high resolution, 0.05°, daily, pentad, and monthly precipitation data set produced from a combination of in-situ station observations and satellite precipitation estimates based on Cold Cloud Duration (CCD) observations to represent sparsely gauged regions. It has been developed to primarily support agricultural drought monitoring (see Funk et al. (2015) for a detailed description). Monthly precipitation data, version 2.0, from 1982 to 2013 was downloaded from ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/. CHIRPS precipitation was found to have correlation of greater than 0.75 with GPCC over EA region (see, e.g., Funk et al., 2015) and has subsequently been used in a number of drought and hydrology related studies in the region (see, e.g., Priscope et al., 2013; Shukla et al., 2014; McNally et al., 2016).

2. GPCC (Schneider et al., 2014) full data reanalysis version 7, 0.5° spatial resolution, monthly land surface precipitation from 1982 to 2013 downloaded from ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata_v7_doi_download.html was used in addition to CHIRPS for drought analysis. It is a purely gauge gridded product based on 75,000 rain gauge stations worldwide, that feature record durations of 10 years or longer (see, Schneider et al., 2014). It has been used in several drought related studies both globally and in EA region (see, e.g., Kurnik et al., 2011; Funk et al., 2014; Ziese et al., 2014; Dutra et al., 2014).

2.2.2. Soil moisture

Soil moisture nominal depths considered in the study were root zone for MERRA-2; aggregation of 0 - 1 meter depth layers for ERA-Interim, GLDAS, and FLDAS; and whole column depth (≈ 0.76 meters) for CPC since its a single bucket layer product.
1. MERRA-2 is a NASA atmospheric re-analysis from 1980 that replaces the original MERRA reanalysis (Decker et al., 2012; Rienecker et al., 2011) using upgraded version of the Goddard Earth Observing System Model, version 5.12.4 (GEOS 5.12.4) data assimilation system (Bosilovich et al., 2016). Monthly 0.625° by 0.5° root zone soil moisture from 1982 to 2013 was downloaded from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/. Because of the improved assimilation system (updates to the treatment of canopy interception) and better forcing data (use of observation-corrected precipitation), MERRA-2 has improved soil moisture estimates over MERRA (Bosilovich et al., 2015).

2. ERA-Interim (Decker et al., 2012; Dee et al., 2011) monthly (monthly means of daily means) soil moisture, from 1982 to 2013, at 0.25° spatial resolution was downloaded from http://apps.ecmwf.int/datasets/data/interim-full-moda/levtype=sfc/. The three layers of soil moisture from 0 to 1 meter were aggregated into one soil moisture product before application to drought analysis. ERA-Interim has been found to have a good skill in capturing surface soil moisture variability, though it tends to overestimate soil moisture, especially over dry lands (Albergel et al., 2012). In addition, it has been used in a number of studies globally and in EA region (see, e.g., Balsamo et al., 2009; Dee et al., 2011; Decker et al., 2012; Dutra et al., 2013; Viste et al., 2013; Mwangi et al., 2014).

3. GLDAS (Rodell et al., 2004) version 2, Noah, monthly 1° spatial resolution soil moisture product from 1982 to 2010 was downloaded from http://disc.sci.gsfc.nasa.gov/services/grads-gds/gldas. Like ERA-Interim, the three layers of soil moisture from 0 to 1 meter depth were aggregated into one soil moisture product before further processing.

4. FLDAS is a custom instance of NASA Land information System (LIS), adapted to work with domains, data streams and monitoring, and forecast systems associated with food security assessment in data sparse, developing country settings (Rui and McNally, 2016). FLDAS is driven by Noah and VIC land surface models. FLDAS Noah 0.1° spatial resolution, monthly soil moisture from 1982 to 2013 downloaded from ftp://hydro1.sci.gsfc.nasa.gov/data/s4pa/FLDAS/FLDAS_NOAH01_C_EA_M.001/ was
used. This soil moisture resulted from simulation run forced by a combination of MERRA-2 and CHIRPS dataset. Noah model (GLDAS and FLDAS) was chosen due to its wide use by atmospheric and land modelling communities hence model parameters are well tested (McNally et al., 2016). In addition, various studies have used it (Noah) over EA region e.g., Anderson et al. (2012); Yilmaz et al. (2014); McNally et al. (2016).

5. CPC (van den Dool et al., 2003; Fan and van den Dool, 2004) global monthly mean 0.5° spatial resolution soil moisture, version 2, for the duration 1982 – 2013 downloaded from the National Oceanic & Atmospheric Administration’s (NOAA) Earth System Research Laboratory database (http://www.esrl.noaa.gov/psd/data/gridded/data.cpcsoil.html) was used. It is used in the present study because it incorporates in-situ rainfall as one of its inputs, hence likely to be closer to real soil moisture. CPC soil moisture simulates the seasonal and inter-seasonal annual variability reasonably well over EA region (see, Dirmeyer et al., 2004).

2.2.3. Terrestrial water storage (TWS)

1. GRACE satellite mission has been in operation from 2002 providing global monthly temporal gravity variations (see, e.g., Tapley et al., 2004; Wouters et al., 2014). These gravity variations are provided in terms of spherical harmonic coefficients. The Centre for Space Research’s (CSR) release five (RL05) monthly spherical harmonic coefficients for the duration 2003 - 2013 downloaded from International Centre for Global Earth Models (ICGEM, http://icgem.gfz-potsdam.de/ICGEM/shms/monthly/csr-rl05/) were processed following the approach of Wahr et al. (1998) and used in this study. During the processing, the coefficients were filtered using a decorrelation and non-isotropic filter (see, e.g., Kusche, 2007; Kusche et al., 2009) in order to remove stripes and spurious patterns. This was followed by the application of a scaling factor, derived using GLDAS TWS following the approach of Landerer and Swenson (2012), onto the synthesised GRACE TWS to remove the leakage effect due to filtering. The synthesised GRACE-derived TWS over EA comprises changes from accumulated soil moisture, groundwater, surface water, and biomass/canopy water content. It is referred to as GTWS in the remainder of the manuscript. GRACE measurements agree with Earth rotation-derived
changes and geophysical model estimates (Chen et al., 2004), and has a global root mean square error of 2 cm to degree and order 70, uniformly over land and ocean (Tapley et al., 2004). It has been used in a number of drought related studies both globally and in EA region (see, e.g., Chen et al., 2009; Long et al., 2013; Awange et al., 2016).

2. MERRA-2 total land water storage from 1982 to 2013, at 0.5° latitude by 0.625° longitude downloaded from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/ was used in addition to GTWS. It does not include canopy water content and groundwater. It is referred to as MTWS in the remainder of the manuscript.

2.2.4. Vegetation Condition Index (VCI)

Long term series of NOAA Advanced Very High Resolution Radiometer (AVHRR) NDVI dataset 1982–2013, from NASA’s Global Inventory and Modelling Systems (GIMMS) downloaded from http://ecocast.arc.nasa.gov/data/pub/gimms/3g.v0/ was used to compute VCI (Kogan, 1995). The data comprised of 15 days maximum composites at 5-arc-minute spatial resolution (for a detailed description see Tucker et al. (2005); Pinzon and Tucker (2014)).

VCI is advantageous as it is able to isolate weather related vegetation stress (Kogan, 1995; Quiring and Ganesh, 2010; Rojas et al., 2011), which within the study area, would correspond to water availability. It is computed as (Kogan, 1995)

\[
VCI_i = 100 \times \frac{NDVI_i - NDVI_{min}}{NDVI_{max} - NDVI_{min}},
\]

where \(NDVI_i\) is the monthly NDVI, \(NDVI_{max}\) and \(NDVI_{min}\) are multi-year maximum and minimum NDVI, respectively.

AVHRR NDVI has been used extensively globally and over Africa for drought and other related studies (see, e.g., Verdin et al., 2005; Rojas et al., 2011; Dorigo et al., 2012; Guan et al., 2012; Chen et al., 2014).

2.2.5. National annual Crop Production

National annual maize and wheat production data for Kenya, Uganda, and Tanzania downloaded from Food and Agriculture Organization (FAO) data portal (http://www.fao.org/faostat/en/#data/QC) was used to evaluate the effectiveness of various satellite/model drought indices in
capturing agricultural droughts. Even though this data set undergoes several quality checks along the processing chain (see, e.g., Kasnakoglu and Mayo, 2004), lack of direct production/yield reporting from farmers to government agencies in developing countries (e.g., EA region) means there is some level of uncertainty in the production data used. Even with the uncertainties, this data is still the most credible, readily available production data.

Table 1: A summary of the dataset used in this study

<table>
<thead>
<tr>
<th>Data</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
<th>Period used</th>
<th>Primary references/ Studies where used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Precipitation</td>
<td>GPCC Monthly</td>
<td>0.5°× 0.5°</td>
<td>1982 - 2013</td>
<td><em>Schneider et al.</em> (2014); <em>Kurnik et al.</em> (2011); <em>Funk et al.</em> (2014); <em>Ziese et al.</em> (2014); <em>Dutra et al.</em> (2014).</td>
</tr>
<tr>
<td></td>
<td>CHIRPS Monthly</td>
<td>0.05°× 0.05°</td>
<td>1982 - 2013</td>
<td><em>Funk et al.</em> (2015); <em>Pricope et al.</em> (2013); <em>Shukla et al.</em> (2014); <em>McNally et al.</em> (2016).</td>
</tr>
<tr>
<td>Soil moisture</td>
<td>MERRA-2 Monthly</td>
<td>0.625°× 0.5°</td>
<td>1982-2013</td>
<td><em>Bosilovich et al.</em> (2016, 2015).</td>
</tr>
<tr>
<td></td>
<td>ERA-Interim Monthly</td>
<td>0.25°× 0.25°</td>
<td>1982 - 2013</td>
<td><em>Albergel et al.</em> (2012); <em>Balsamo et al.</em> (2009); <em>Dee et al.</em> (2011); <em>Decker et al.</em> (2012); <em>Dutra et al.</em> (2013); <em>Viste et al.</em> (2013); <em>Mwangi et al.</em> (2014).</td>
</tr>
<tr>
<td></td>
<td>FLDAS Monthly</td>
<td>0.1°× 0.1°</td>
<td>1982 - 2013</td>
<td><em>Rui and McNally</em> (2016); <em>Anderson et al.</em> (2012); <em>Yilmaz et al.</em> (2014); <em>McNally et al.</em> (2016).</td>
</tr>
<tr>
<td></td>
<td>CPC Monthly</td>
<td>0.5°× 0.5°</td>
<td>1982 - 2013</td>
<td><em>van den Dool et al.</em> (2003); <em>Fan and van den Dool</em> (2004); <em>Dirmeyer et al.</em> (2004).</td>
</tr>
<tr>
<td></td>
<td>MERRA-2 Monthly</td>
<td>0.625°× 0.5°</td>
<td>1982 - 2013</td>
<td><em>Bosilovich et al.</em> (2016, 2015).</td>
</tr>
<tr>
<td></td>
<td>VCI NDVI 15 days</td>
<td>0.083°× 0.083°</td>
<td>1982 - 2013</td>
<td><em>Tucker et al.</em> (2005); <em>Pinzon and Tucker</em> (2014); <em>Verdin et al.</em> (2005); <em>Rojas et al.</em> (2011); <em>Dorigo et al.</em> (2012); <em>Guan et al.</em> (2012); <em>Chen et al.</em> (2014).</td>
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</table>

3. Methodology

Due to the existence of a link between agricultural drought and 1 to 6 months precipitation anomalies (e.g., Kurnik et al., 2011; Elagib, 2013; Svoboda et al., 2012; Rouault and
Standardised Indices (SI) (e.g., SPI, McKee et al. (1993)) were derived to characterize agricultural drought using precipitation, VCI, TWS, and soil moisture products. Similarly, Standardized Anomalies (SA)/Z-scores (Wu et al., 2001) were computed to characterize drought from GTWS due to its short duration. The resulting SI and SA indices were then subjected to rotated principal component analysis to obtain their most dominant spatial and temporal drought variabilities. Finally, the temporal variabilities were subjected to partial least-squares regression analysis to determine how well they captured drought variability. Other than GRACE and GLDAS, all the other data sets were spatially aggregated to 1° by 1° before standardization for consistency. For all products, the unstandardised data were tested using w-statistics (Shapiro et al., 1968) and found to be normally distributed.

Given the differences in the variables used in this study, comparison of drought information was primarily carried out between various products of the same variables, e.g., between precipitation products, or soil moisture products, or TWS. Notwithstanding the differences between the variables, links/relations in drought information across the various products were explored since drought progresses from deficiencies in rainfall followed by moisture through to TWS.

### 3.1. Standardized Precipitation Index (SPI)

SPI (McKee et al., 1993), one of the most commonly used drought indices due to its numerous advantages (Svoboda et al., 2012), expresses precipitation anomalies with respect to its long term average. Its computation involves fitting a gamma probability distribution function to precipitation time series followed by the transformation of the accumulated gamma probability distribution to the cumulative distribution function of the standard normal distribution (see, e.g., Naresh Kumar et al., 2009; Farahmand and AghaKouchak, 2015). Due to the sensitivity of the computed SPI values to the fitted parametric distributions, especially at the tail ends of the distribution (see, Quiring, 2009), a non-parametric SPI fitting method was adopted in this study (see, e.g., Farahmand and AghaKouchak (2015) and the references therein for the formulation). This approach was implemented using the Standardized Drought Analysis Toolbox (SDAT, Farahmand and AghaKouchak (2015)) and the SPI drought limit categories (intensities) proposed by Agnew (2000) (Table 2) were used. For this study, a
drought episode begins any time SPI is continuously less than $-0.84$ for a period of at least three months, and ends when SPI value exceeds $-0.84$. The various drought intensities (moderate, severe, and extreme) are then said to occur when the values in Table 2 are attained. The resulting standardized indices in this study were SPI, standardised soil moisture index (SSI), standardised vegetation condition index (SVCI), and standardised terrestrial water storage index (STWSI).

Table 2: Drought Categories According to SPI Values (Agnew, 2000)

<table>
<thead>
<tr>
<th>SPI</th>
<th>Drought Category</th>
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<tbody>
<tr>
<td>$&gt;1.65$</td>
<td>extremely wet</td>
</tr>
<tr>
<td>$&gt;1.28$</td>
<td>severely wet</td>
</tr>
<tr>
<td>$&gt;0.84$</td>
<td>moderately wet</td>
</tr>
<tr>
<td>$&gt;-0.84$ and $&lt;0.84$</td>
<td>normal</td>
</tr>
<tr>
<td>$&lt;-0.84$</td>
<td>moderate drought</td>
</tr>
<tr>
<td>$&lt;-1.28$</td>
<td>severe drought</td>
</tr>
<tr>
<td>$&lt;-1.65$</td>
<td>extreme drought</td>
</tr>
</tbody>
</table>

3.2. Standardized Anomalies (SA)

As already pointed out, due to the short time frame of the GRACE product, SA instead of SI was computed for characterizing agricultural drought. Here, the 3 and 6 months GTWS time series cumulations were obtained in a manner similar to those of the Standardized Precipitation Index (McKee et al., 1993). Due to seasonality in precipitation, soil moisture, TWS, and NDVI dataset (Yang et al., 2014b), GTWS anomalies were calculated by removing the monthly mean from the 1, 3, and 6 month time series. The anomalies were then divided by the standard deviation for the duration of the data (e.g., Peters et al., 2002), i.e.,

$$XS_{ijk} = \frac{X_{ijk} - \frac{1}{n} \sum_{k=1}^{n} X_{ijk}}{\sigma_{ij}},$$  (2)
where $XS_{ijk}$ is the monthly standardized GTWS anomaly for location $i$, month $j$, and year $k$; $X_{ijk}$ is the monthly GTWS for location $i$, month $j$, and year $k$; $n$ is the length of GTWS in years; and $\sigma_{ij}$ is the multi-year standard deviation for location $i$, month $j$. The resulting standardized anomalies (z-scores), express the deviation of the GTWS above or below the mean value and has been used to monitor drought in various studies (e.g., Wu et al., 2001; Agnew and Chappell, 1999; Lough, 1997; Katz and Glantz, 1986). Positive values indicate wet conditions, 0 indicate normal (average) conditions while negative values indicate drought conditions (Wu et al., 2001).

In order to demonstrate the consistency between SPI and SA in characterizing drought over the region, the study compared the spatio-temporal decompositions of CHIRPS-derived SPI and CHIRPS-derived SA over the study region. This comparison showed similar spatio-temporal drought patterns (See Figs. 2 and 4 for CHIRP-derived SPI spatio-temporal drought patterns). Further, Pearson correlations between the SI and SA temporal patterns were greater than 0.95 over the region. Due to the close association between SA and SI (see, Wu et al., 2001), the SPI drought limit categories (Table 2) were used to differentiate the various SA drought intensities.

### 3.3. Principal Component Analysis

Principal component analysis (PCA, Hannachi et al., 2007; Jolliffe, 2002; Preisendorfer, 1988; Wilks, 2006; Lorenz, 1956) is one of the most widely used methods in atmospheric sciences for pattern extraction and dimensionality reduction among. It has been used in drought studies (e.g., Santos et al., 2010; Raziei et al., 2009; Sigdel and Ikeda, 2010) to decompose spatial-temporal fields such as SPI, SSI, SVCI, STWSI, etc., into spatial patterns and their corresponding temporal evolutions.

In this contribution, PCA was applied to the 1, 3, 6-month time scales of SI and SA. Log-eigenvalue (LEV) diagrams (Jolliffe, 2002) were used to determine and retain the significant components that were then rotated through Varimix rotation (Kaiser, 1958; Forina et al., 1988; Jolliffe, 1995) for better localization (for more information on rotated PCA, see, e.g., Schönemann (1958); Richman (1986); von Storch and Zwiers (1999); Hannachi et al. (2007)). The resulting spatial patterns, normalised by multiplying with the standard deviation of their
corresponding rotated principal components (RPC) series, represent the correlation between the original data (in our case 1, 3, 6 month SI or SA at single grid point) and the corresponding RPC. Normalised RPC (divided by its standard deviation) represent SI/SA in each case (see Bordi et al. (2006)).

3.4. Partial least squares regression (PLSR)

PLSR is a regression technique in which the response variables are regressed on the predictor scores. The scores (few new variables) are linear combinations of the original predictor variables (Wold et al., 2001; Geladi and Kowalski, 1986). The generation of the scores takes into account the variability in the dependent variable ensuring that only those components of the independent variables that are related to the dependent variables are used in the regression (Geladi and Kowalski, 1986). It is a generalization of the multiple linear regression (MLR), but unlike MLR, it can analyze data with collinearity (correlated), noisy, and with numerous predictor variables (Wold et al., 2001) hence its use in the current study. Detailed description and formulation can be found in Helland (2004); van Huffel (1997).

For each country, SI/SA values for each month of the year over the entire duration were extracted from the rotated principal components. For example, considering Kenya with four GRACE SA rotated principal components, each component comprising of 120 values/months (2004 to 2013), corresponding to January, February, ..., December were extracted resulting in four 10 by 12 matrices, i.e., 10 years of data for every month of the year. The resulting four matrices were concatenated to a 10 by 48 matrix, which served as the predictor variable in the PLSR against national annual production data (maize/wheat) as the response variable. This was done for 1, 3, and 6 month SA time scales for all the variables across Kenya, Uganda, and Tanzania.

4. Results and Discussion

4.1. Spatio-temporal drought Patterns

The PCA decomposition of SI/SA showed spatial and temporal patterns, which became very distinct upon applying varimax rotation as compared to unrotated components (data not
Table 3: Geographical coverage of SI/SA spatial patterns.

<table>
<thead>
<tr>
<th>Region</th>
<th>Countries/Areas</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Lake Victoria, Uganda, and western Kenya</td>
</tr>
<tr>
<td>2</td>
<td>Western Tanzania, Rwanda, and Burundi</td>
</tr>
<tr>
<td>3</td>
<td>Eastern Kenya</td>
</tr>
<tr>
<td>4</td>
<td>Eastern and southern Tanzania</td>
</tr>
</tbody>
</table>

shown). Integrating the spatial and temporal patterns of the SIs/SAs, and using the drought category definitions in Table 2, percentage of areas under various drought intensities were evaluated. The results presented and discussed here are for the 3-month time scale only, as this was representative of the results for the 1 and 6-month time scales.

4.1.1. Spatial Variability

The four most significant components in terms of explaining the total variability from RPCA of SI/SA revealed four distinct spatial patterns across all products (Figs. 2 and 3). The geographical coverage of these spatial patterns is summarized in Table 3. The spatial patterns of ERA-Interim and to some extent of GLDAS in region 2 were different from those of other products.

The four RPCs explained between 38% (SVCI) and 96% (GTWS SA) of the total variance of the respective original SI/SA variables (Table 4). Most of the products had the highest and the lowest variabilities explained in regions 3 and 4, respectively (Table 4). This could be attributed to the fact that region 3 covering almost the entire region of Kenya (in those indicators showing it highest) is wet and dry on the western and eastern parts of the country, respectively, hence has high variability due to the presence of wet and dry extremes. On the other hand, region 4 is relatively wet and receives consistent rainfall resulting in a smaller variation in SI/SA.

4.1.2. Temporal Patterns

The temporal evolutions of the spatial patterns in regions 1 to 4 (Figs. 2 and 3) from the rotated PCA are shown in Figs. 4 and 5. In general, the temporal evolutions (interpreted
Figure 2: Rotated principal component spatial patterns of standardized index/anomalies (SI/SA). Rows denote products while columns denote regions (also see Table 3). The spatial patterns have been scaled to ±1, thus the temporal evolutions shown in Fig. 4 indicate the actual magnitude of SA/SA for regions where the spatial patterns have values close to ±1. The spatial patterns are interpreted in conjunction with temporal evolutions in Fig. 4 and represent drought spatial patterns any time the temporal evolutions falls below −0.84, as in Table 2. The white rectangular area in all the images except CHIRPS and GTWS is Lake Victoria.

in conjunction with Figs. 2, 3, and Table 2) show most of the regions suffering from severe to extreme drought in 1984/1985, 1999, 2000, 2005/2006, and 2010/2011. These and other
Figure 3: Rotated principal component spatial patterns of standardized soil moisture indices (SSI). Rows denote products while columns denote regions (also see Table 3). The spatial patterns have been scaled to ±1, thus the temporal evolutions shown in Fig. 5 indicate the actual magnitude of SSI for regions where the spatial patterns have values close to ±1. The spatial patterns are interpreted in conjunction with temporal evolutions in Fig. 5 and represent drought spatial patterns any time the temporal evolutions falls below −0.84, as in Table 2. Patterns are consistent with those in Fig. 2 except for ERA-Interim and to some extent GLDAS in region 2. The white rectangular area in all the images except MERRA-2 is Lake Victoria.

Drought episodes captured in these figures are consistent with documented drought episodes in the EA region (e.g., Masih et al., 2014; Nicholson, 2014; IFRC, 2011).
Table 4: Proportion of variances explained by various spatial patterns across the four regions (see, Figs. 2 and 3, and Table 3 for the regions). Many of the products explain highest and lowest variabilities in regions 3 and 4, respectively. In addition, MERRA-2 and MTWS appear very close.

<table>
<thead>
<tr>
<th>Region</th>
<th>CHIRPS</th>
<th>GPCC</th>
<th>VCI</th>
<th>MTWS</th>
<th>GTWS</th>
<th>ERA-Interim</th>
<th>GLDAS</th>
<th>CPC</th>
<th>MERRA-2</th>
<th>FLDAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region 1</td>
<td>15.26</td>
<td>12.07</td>
<td>8.24</td>
<td>13.86</td>
<td>29.88</td>
<td>18.91</td>
<td>11.79</td>
<td>10.29</td>
<td>13.61</td>
<td>14.86</td>
</tr>
<tr>
<td>Region 2</td>
<td>14.62</td>
<td>13.15</td>
<td>10.01</td>
<td>24.58</td>
<td>10.78</td>
<td>15.75</td>
<td>17.72</td>
<td>16.46</td>
<td>17.21</td>
<td>15.77</td>
</tr>
<tr>
<td>Region 3</td>
<td>15.26</td>
<td>13.67</td>
<td>12.57</td>
<td>21.44</td>
<td>14.32</td>
<td>14.22</td>
<td>20.05</td>
<td>13.27</td>
<td>14.64</td>
<td>12.64</td>
</tr>
<tr>
<td>Region 4</td>
<td>10.60</td>
<td>11.64</td>
<td>6.94</td>
<td>13.67</td>
<td>19.77</td>
<td>21.80</td>
<td>16.72</td>
<td>13.27</td>
<td>14.64</td>
<td>12.64</td>
</tr>
<tr>
<td>Total</td>
<td>55.53</td>
<td>50.53</td>
<td>37.77</td>
<td>67.10</td>
<td>95.81</td>
<td>64.06</td>
<td>58.48</td>
<td>61.83</td>
<td>67.95</td>
<td>61.48</td>
</tr>
</tbody>
</table>

All products had similar performance in region 3 (Figs. 4c and 5c), which may be attributed to the relatively flat terrain (Fig. 1a) coupled with relatively less rainfall hence good performance by the models and rainfall products. The performance of the rainfall products (CHIRPS and GPCC) were almost identical over the entire study region as a result of both containing in-situ rainfall (CHIRPS has satellite-derived precipitation estimates in addition to in-situ data while GPCC is purely gridded in-situ product, see e.g., Schneider et al., 2014; Funk et al., 2015). In relation to the rainfall products, the remaining products (VCI, soil moisture, and TWS) showed delayed (lagged) response in the temporal evolution. This is clearly visible in Fig. 4a in which MTWS appears like a low pass filtered version of the CHIRPS/GPCC signals. This behavior could be due to a delayed response of terrestrial water storage changes to rainfall and soil moisture changes. Finally, the soil moisture products seemed to be from largely two classes/categories of models with ERA-Interim, FLDAS, and GLDAS in one category and CPC and MERRA-2 on the other, especially considering region 1 (Fig. 5).

Further, correlation analysis between the drought indices revealed close relationships between various products e.g., CHIRPS and GPCC, MERRA-2, MTWS, and CPC, etc., across the regions (Table 5). The close relationship between MTWS and MERRA-2 is similar to that between CHIRPS and GPCC, since MTWS include aspects of soil moisture captured by MERRA-2 in addition to greater depth of soil water content. Furthermore, the significant and high correlations between the drought indices in region 3 support the similar performance
Figure 4: Temporal evolutions of SA/SI spatial patterns in Fig. 2. The temporal evolutions are interpreted in conjunction with Table 2, to classify drought and/or wet conditions. Rainfall products (CHIRPS and GPCC) exhibit similar consistent performance across the region. Also, all the products exhibit consistent performance in region 3, while VCI and GTWS show some lag in relation to rainfall.

VCI had weak negative correlation trends with the following products: MTWS, MERRA-2 and CPC in region 1 due to these products showing a predominantly wet pre-1993 and dry post-1999 that was opposite to the general VCI trend.
Figure 5: Temporal evolutions of SSI spatial patterns in Fig. 3. The temporal evolutions are interpreted in conjunction with Table 2, to classify drought and/or wet conditions. All the moisture products have consistent performance in region 3 while in the rest of the regions, CPC is similar to MERRA-2 and similarly, ERA-Interim is closer to GLDAS.

4.1.3. Drought Intensity Area Analyses

In order to gain further insight into the spatial extent of the drought events and their intensities, the spatial and temporal patterns (Figs. 2, 3, 4, and 5) were integrated and using
Table 5: Relationship between the drought indices by regions: (i) Region-1 upper table, upper triangle (red), (ii) Region-2 upper table, lower triangle (blue), (iii) Region-3 lower table, upper triangle (green), and (iv) Region-4 lower table, lower triangle (brown). Regions are as in Fig. 2. Non-significant correlations are in italics ($p < 0.05$). Region 3 has the strongest relationships with all values being significant. Also, note the high correlations between the following products across the regions: GPCC and CHIRPS; and MTWS, MERRA-2, and CPC. (MTWS - MERRA-2 TWS, GTWS - GRACE TWS).

<table>
<thead>
<tr>
<th></th>
<th>CHIRPS</th>
<th>GPCC</th>
<th>VCI</th>
<th>MTWS</th>
<th>ERA</th>
<th>CPC</th>
<th>MERRA2</th>
<th>FLDAS</th>
<th>GLDAS</th>
<th>GTWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CHIRPS</td>
<td>1</td>
<td><strong>0.8991</strong></td>
<td>0.4907</td>
<td>0.1203</td>
<td>0.4255</td>
<td>0.1073</td>
<td>0.2052</td>
<td>0.7300</td>
<td>0.5106</td>
<td>0.3196</td>
</tr>
<tr>
<td>GPCC</td>
<td><strong>0.8619</strong></td>
<td>1</td>
<td>0.4250</td>
<td>0.1288</td>
<td>0.4505</td>
<td>0.1266</td>
<td>0.2161</td>
<td>0.6120</td>
<td>0.5454</td>
<td>0.2433</td>
</tr>
<tr>
<td>VCI</td>
<td>0.2832</td>
<td>0.1918</td>
<td>1</td>
<td>-0.1082</td>
<td>0.4366</td>
<td>-0.1091</td>
<td>-0.0690</td>
<td>0.6737</td>
<td>0.527</td>
<td>0.3658</td>
</tr>
<tr>
<td>MTWS</td>
<td>0.3922</td>
<td>0.4683</td>
<td>0.2152</td>
<td>1</td>
<td><strong>0.0526</strong></td>
<td><strong>0.8437</strong></td>
<td><strong>0.9910</strong></td>
<td>0.1888</td>
<td>0.0359</td>
<td>0.7939</td>
</tr>
<tr>
<td>ERA</td>
<td><strong>0.0947</strong></td>
<td>0.2525</td>
<td><strong>-0.1041</strong></td>
<td><strong>0.3628</strong></td>
<td>1</td>
<td>0.1788</td>
<td>0.1138</td>
<td>0.5229</td>
<td>0.6664</td>
<td><strong>-0.1708</strong></td>
</tr>
<tr>
<td>CPC</td>
<td>0.2970</td>
<td>0.3962</td>
<td>0.2410</td>
<td>0.8714</td>
<td>0.4240</td>
<td>1</td>
<td><strong>0.8482</strong></td>
<td>0.1370</td>
<td>0.0976</td>
<td>0.5036</td>
</tr>
<tr>
<td>MERRA2</td>
<td>0.4546</td>
<td>0.5310</td>
<td>0.1889</td>
<td><strong>0.9864</strong></td>
<td>0.3791</td>
<td><strong>0.8513</strong></td>
<td>1</td>
<td>0.2431</td>
<td><strong>0.0810</strong></td>
<td>0.7352</td>
</tr>
<tr>
<td>FLDAS</td>
<td>0.6324</td>
<td>0.6352</td>
<td>0.4079</td>
<td>0.7372</td>
<td>0.2704</td>
<td>0.6844</td>
<td>0.7212</td>
<td>1</td>
<td>0.6365</td>
<td>0.7047</td>
</tr>
<tr>
<td>GLDAS</td>
<td>0.4141</td>
<td>0.4499</td>
<td>0.4494</td>
<td>0.5911</td>
<td>0.3352</td>
<td>0.6274</td>
<td>0.5583</td>
<td>0.6940</td>
<td>1</td>
<td><strong>0.0643</strong></td>
</tr>
<tr>
<td>GTWS</td>
<td>0.1101</td>
<td>0.0776</td>
<td>0.1863</td>
<td>0.7310</td>
<td>0.5553</td>
<td>0.6465</td>
<td>0.651</td>
<td>0.4429</td>
<td>0.4505</td>
<td>1</td>
</tr>
</tbody>
</table>

**drought limit (intensity) categories in Table 2, percentage of areas under drought (by intensity) were evaluated and results presented in Fig. 6. Overall, the rainfall products (CHIRPS and GPCC) and the soil moisture products had higher estimate of percentage areas under drought whereas VCI had the lower estimates (average means of 13.09%, 11.90%, and 5.5%, respectively at $F(2,2212) = 19.7220$, $p = 3.2384 \times 10^{-9}$). One reason for the rainfall prod-**
ucts showing more areas as being under drought may be that meteorological drought is a binary event (present or absent) which is not affected by modulating factors unlike the other drought indicators e.g., VCI. VCI-based drought, unlike meteorological drought, is modulated by soil characteristics (water holding capacity) and/or plant (vegetation) type. Thus, for example, there could be meteorological drought over an area but due to soil water retention capacity and/or vegetation with deep roots capable of drawing water from deep soils (underground), VCI indicates no drought condition, hence the smaller area under drought. Since the soil moisture products and MTWS are modelled from rainfall and other additional inputs, their estimates of percentage areas under drought are likely to follow closely those of rainfall. However, the soil moisture products had statistically significantly different percent of areas under drought amongst themselves as was determined by one way ANOVA ($F(4, 1250) = 3.5410, p = 0.0070$).

The observed differences in percentage of drought areas between the various soil moisture products arise from differences in; (i) forcing precipitation, (ii) the ways in which the individual hydrological models partition precipitation into run-off and evapotranspiration, and (iii) water holding capacities, the last two of which impacts on the modelled soil moisture sensitivities to precipitation variability (Shukla et al., 2014). The contribution of forcing precipitation on the differences in percentage of areas is highlighted by the differences in areas presented by GLDAS and FLDAS, products of the same model (Noah) but different forcing precipitation, hence different drought spatial extents and cycles. Of all the model forcing parameters, precipitation is the key factor determining the characteristics of the resulting soil moisture (see, e.g., Entin et al., 1999; Dirmeyer et al., 1999, 2004; Mo et al., 2012), hence the areal extents under drought.

The MERRA-2 products show similar patterns and are closer to CPC (Fig. 6d, e, and h) while GLDAS is closer to ERA-interim as had been observed from the correlations (Table 5) and in the temporal evolutions (Figs. 4 and 5). FLDAS appear to be in between the two groups. Also, the lag in drought detection (already noted in Figs. 4 and 5) becomes more evident with the rainfall products detecting drought onset and duration first, followed by VCI/soil moisture products, and finally the TWS products. This would be attributed to time...
Figure 6: Percentage of area affected by various drought intensities during the period 1983 – 2013. Percentage areas are computed by integrating the regional spatial and temporal patterns (Figs. 2, 3, 4, and 5) then determining percentage of pixels under each drought category as per Table 2. The rainfall products have the highest percentage areas under drought followed closely by soil moisture products and finally the lowest percentage areas are by VCI. In addition to the soil moisture products having different percentage areas under drought, CPC is consistent with MERRA-2, GLDAS is consistent with ERA-Interim while FLDAS is in between.

delayed response in moisture accumulation from rainfall through soil moisture, vegetation, and finally to changes in TWS during both the start and cessation of rainfall. Generally, the results also indicate the post-1999 period as having more drought events with higher intensity
than the pre-1999 period except for ERA-Interim and GLDAS indicators. This is in line with other drought and climate studies that observed a decline in rainfall since 1999 and increased drought frequencies (see, Lyon and DeWitt, 2012; Lyon, 2014; Yang et al., 2014a). Also, GLDAS seems to have underestimated the 2005 - 2006 drought in terms of both duration and intensity as compared to the rest of the soil moisture products.

Figure 7: Comparison of performance between GTWS and MTWS in terms of percentage of areas affected by various drought categories. Percentage areas are computed as in Fig. 6. They have consistent performance, with GTWS having a lag in drought detection probably due to groundwater that is lacking in MTWS.

Further, GTWS returned higher percentage of areas under drought on average than MTWS as confirmed by one way ANOVA (25.307 vs 9.8147 at \( F(1,138) = 16.1064, \ p = 0.0001 \)) though with almost equal percentage of areas at drought peaks, at which GTWS lagged MTWS by 0 – 3 months in the detection of drought onset and cessation (Fig. 7a and b). Since MTWS is modelled on precipitation and other input without groundwater while GTWS
is observed, the lack of groundwater in MTWS probably explains why it does not properly account for the buffer effect, hence possible lag by GRACE in detecting the onset and cessation of drought. In addition, GTWS shows drought episodes in the post 2012 period while MTWS does not (see, Fig. 7).

Figure 8: Percentage of areas affected by various drought intensities during the 1983 – 1984, 2005 – 2006, and 2010 – 2011 drought episodes. Each bar has up to 3 colour grades (gradients) representing from bottom moderate, severe, and extreme droughts at the top. Percentage areas are computed as in Fig. 6 but only for the duration of drought. VCI has a lag of about 2 – 3 months in identifying the drought cycle in relation to CHIRPS. The rest of the products have inconsistent lags in relation to rainfall across the three drought episodes.

The drought severity is well captured by all the products as evidenced by the majority
of the areas being under moderate drought followed by severe drought and then extreme
according to the definition of SPI (see, e.g., Figs. 6 and 7; McKee et al., 1993). All the
products captured different severity levels except MTWS and MERRA-2, which had similar
severity levels as a result of overlapping formulation. The differences in severity levels among
the other products could be attributed to the different formulation of the products and to the
fact that they represent droughts in different environments with different impacting factors,
e.g., soil properties influence the severity of drought as captured by the soil moisture products
while rainfall characteristics (amount, intensity and duration) influence the drought severity
as captured by rainfall products.

Table 6: Drought lags (in months) by various products in relation to CHIRPS drought cycle (onset, peak,
and cessation). Negative values indicate the respective product had drought cycle before CHIRPS while dash
indicate products not available during that particular drought. The lags were quantified from selected droughts
of 1983 - 1984, 2005 - 2006, and 2010 - 2011, see Fig. 8.

<table>
<thead>
<tr>
<th>Year/Drought cycle</th>
<th>VCI</th>
<th>CPC</th>
<th>ERA</th>
<th>GLDAS</th>
<th>FLDAS</th>
<th>MTWS/ MERRA2</th>
<th>GTWS</th>
</tr>
</thead>
<tbody>
<tr>
<td>1983 - 1984/ Onset</td>
<td>1</td>
<td>1</td>
<td>6</td>
<td>-1</td>
<td>0</td>
<td>0</td>
<td>-</td>
</tr>
<tr>
<td>1983 - 1984/ Peak</td>
<td>3</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>-6</td>
<td>-</td>
</tr>
<tr>
<td>1983 - 1984/ Cessation</td>
<td>2</td>
<td>4</td>
<td>5</td>
<td>4</td>
<td>5</td>
<td>3</td>
<td>-</td>
</tr>
<tr>
<td>2005 - 2006/ Onset</td>
<td>1</td>
<td>5</td>
<td>4</td>
<td>7</td>
<td>5</td>
<td>-1</td>
<td>6</td>
</tr>
<tr>
<td>2005 - 2006/ Peak</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>2005 - 2006/ Cessation</td>
<td>2</td>
<td>&gt;5</td>
<td>5</td>
<td>1</td>
<td>2</td>
<td>&gt;5</td>
<td>&gt;5</td>
</tr>
<tr>
<td>2010 - 2011/ Onset</td>
<td>3</td>
<td>1</td>
<td>2</td>
<td>-</td>
<td>3</td>
<td>2</td>
<td>4</td>
</tr>
<tr>
<td>2010 - 2011/ Peak</td>
<td>3</td>
<td>-3</td>
<td>-7</td>
<td>-</td>
<td>0</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>2010 - 2011/ Cessation</td>
<td>4</td>
<td>3</td>
<td>-4</td>
<td>-</td>
<td>3</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>

Finally, from the knowledge gained in the analyses above, the droughts of 1983 - 1984, 2005
- 2006, and 2010 - 2011 were examined closely using selected indicators in order to quantify
the above-observed lags in drought cycles (Fig. 8, Table 6). These drought years have been
selected for further analysis because they had more severe impacts in the region (see, e.g.,
From this analysis, VCI had a lag of 0 - 4 months in relation to CHIRPS in picking drought stages (onset, peak, and cessation) while the soil moisture products (CPC, ERA-Interim, GLDAS, FLDAS, and MERRA-2) had inconsistent lags amongst themselves, and in relation to CHIRPS for the considered drought episodes (e.g., Fig. 8, Table 6). Soil moisture, being an integration of rainfall anomalies over time (Dutra et al., 2008; Sheffield and Wood, 2008), is expected to have a lag in response to rainfall behavior throughout the hydrological cycle hence the soil moisture products and VCI (an indicator of moisture availability to vegetation) lag rainfall in the analysis. The inconsistency in the lags by the soil moisture products, similar to observed inconsistency in the percentage of areas under drought (Fig. 6), could be due to the different model forcing parameters used in generating various products in addition to different model thresholds as discussed above. Finally, the TWS products had different lags with GTWS having longer lag (Fig. 7). This longest lag from GTWS could be due to the fact that it is the last in the transition from rain event to moisture accumulation, and eventually groundwater change over time. Also, the under-characterization of the 2005 - 2006 drought by GLDAS already observed in Fig. 6g is clearer in Fig. 8b.

4.2. Assessing the effectiveness of drought indicators using crop production

In order to assess the effectiveness of the indicators in capturing agricultural drought, partial least square regression (PLSR) models were fitted with indices as the predictors and annual crop production data as the responses. The model with the lowest estimated mean squared prediction error was adopted in each case and the proportion of variability explained ($R^2$) used for comparison. As production is known to be related to water availability at various stages of crops growth (Steduto et al., 2012; Hane and Pumphrey, 1984), and water being a major growth determinant in the EA region (Barron et al., 2003), a good relationship is expected between drought indices that capture (characterize) drought well and crop production over the considered duration of time.

Because crop production data is reported at country level (national) while the generalization in section 4.1 (Figs. 2 and 3) had signals across countries, SIs/SAs were re-computed for each country and the resulting rotated principal components reconstructed and used in PLSR.
with country level crop production data. The SIs were computed for the long term duration (1983 – 2013) and SAs for the short term (2004 - 2013). The latter duration though shorter, was necessitated by the need to compare the performance of GRACE SA against the other products. The proportions of variabilities explained ($R^2$) from the regression using the short duration (SAs) should be interpreted with care due to the short length of the data used.

For Kenya, other than GLDAS and ERA, the rest of the products performed fairly well for the period 1983 – 2013 with CHIPS, GPCC, and VCI explaining up to 94%, 73%, and 89%, respectively of the total annual variability in crop (wheat and maize) production (Fig. 9a). Similarly for Tanzania, CHIRPS, GPCC, and VCI explained up to 96%, 85%, and 89%, respectively of the total annual variability in crop (wheat and maize) production (Fig. 9b). Finally in Uganda, other than GLDAS, all the other products performed well with CHIRPS, ERA, FLDAS, and MTWS explaining up to 88%, 92%, 84%, and 77%, respectively of the total annual variability in crop (wheat and maize) production (Fig. 9c). The poor performance of GLDAS in Kenya and Uganda compared to other soil moisture products could be linked to poor performance in drought characterization as was observed in section 4.1.3 and Figs. 6g and 8b. Most of the products explained higher proportions of annual variability in crop production ($R^2$) in 1-month standardized anomalies followed by 3 then 6-months. Also, the close performance of MERRA-2 and MTWS witnessed in drought characterization (section 4.1.2 and Table 5) is evident in the amount of variabilities explained by these products across the region.

CHIRPS performed generally better than GPCC across the region (Fig. 9a-c). This could be attributed to the fact that in addition to rain gauge input, CHIRPS has satellite-derived rainfall estimates for areas with less or no rain gauge information unlike GPCC with only rain gauge measured rainfall hence its performance is dependent on gauge density and terrain changes (see, e.g., Schneider et al., 2014; Funk et al., 2015). In relation to the rainfall products (CHIRPS and GPCC), the soil moisture products explained less variability in annual crop production over EA region except in Uganda where the performance of ERA-Interim was almost as good as rainfall-derived indicators. Since soil moisture products represent the rainfall that remains after run-off and evaporation, the effective water available to the plants (crops),
Figure 9: Proportions of variability in national annual crop (maize and wheat) production ($R^2$) explained by various drought indices for Kenya, Tanzania, and Uganda. CHIRPS, GPCC, and VCI consistently explain relatively higher variability in crop production, while the soil moisture products have inconsistent performance (a, b, and c). The figures d, e, and f should be interpreted with care as the datasets used to fit the models are only 10 years long. Both SI and SA are computed at annual scales. (The y axis indicates the crop (maize/wheat), SI (for a, b, and c), and SA (for d, e and f) while 1, 3 and 6 indicate the standardization time scales for the indicators on the x axis).

they are expected to explain higher variabilities in the annual crop production than rainfall thus their poor performance could be linked to how well they fit the region. In addition, the inconsistent performance of the soil moisture products (CPC, ERA-Interim, GLDAS, FLDAS, and MERRA-2) and MTWS across the EA region in explaining the annual variability in crop production.
production could be linked to the inconsistencies observed in the drought characterization as discussed in Section 4.1.2.

Overall, the good performance of FLDAS over GLDAS across the study region despite both being products of the same model (Noah) is due to the fact that for FLDAS, the Noah model was forced by CHIRPS, a precipitation product designed for the region. The magnitudes of the annual variabilities in crop production explained by FLDAS could be a pointer to difficulties faced by Noah in correctly partitioning precipitation into moisture, run-off, and evapotranspiration as per natural occurrence in the EA region.

Though based on a short duration data set (10 years), GRACE SA has mixed performance between wheat and maize across the countries but does better than or equals to soil moisture products across the region (Fig. 9d-f). The performance could be attributed to the fact that over a shorter duration of time such as the one considered (i.e., 1-, 3-, and 6-months anomalies), the bulk of the variation in the GRACE TWS occurs in the soil moisture compartment, which is more sensitive to climate variability than groundwater change (e.g., Yang et al., 2014b). This shows the potential of GRACE product to monitor agricultural drought although longer duration of dataset is essential.

Results from regression analysis should be interpreted with caution though, as the relationship between production and climate conditions (water availability) only hold if other factors in the production chain are held constant, e.g., areas under cultivation over the period considered and technical factors of production (e.g., fertilizers, crop cultivars, pesticides). In addition, production response to water at any stage of growth can be modified by various factors e.g., diseases, weeds, insects, crop variety (Steduto et al., 2012; Hane and Pumphrey, 1984), hence, results should not be generalized to other areas.

5. Conclusions

This study characterized agricultural drought over EA region using precipitation products (CHIRPS and GPCC), soil moisture products (CPC, ERA-Interim, MERRA-2, FLDAS, and GLDAS), and TWS products (MERRA-2 and GRACE). This was accomplished through standardized index/standardized anomaly and rotated principal component analyses. In addition,
the study carried out partial least squares regression (PLSR) analysis over Kenya, Uganda, and Tanzania to assess the utility of these products in capturing agricultural drought in these countries.

Drought characterization results showed CHIRPS and GPCC as being similar and consistent over the entire region, while all the other products were consistent for region 3 (dry lowland eastern Kenya). In terms of percentage of areas under drought, the rainfall products (CHIRPS and GPCC) covered the highest areas followed by the soil moisture products, while VCI covered the least percentage areas under drought. Results further indicated drought cycle detection in the order; rainfall, VCI/soil moisture, and TWS. VCI had 0-4 months lag in detecting drought cycle (onset, peak, and cessation) in relation to rainfall products while the soil moisture and TWS products had inconsistent lag varying from one drought to the next. Soil moisture products had different results (both lag and areas under drought), with ERA-Interim being closer to GLDAS, MERRA-2 being close to CPC while FLDAS was in between. GLDAS under-characterized the 2005 - 2006 drought to under 2 months in comparison to over 7 months of ERA and CPC. Finally, the TWS products were consistent with GTWS having few months’ lag probably due to groundwater that is missing in MTWS.

From the PLSR analysis, consistent performances by CHIRPS, GPCC, and VCI in explaining relatively high proportions of variabilities in annual crop production in Kenya, Tanzania, and Uganda over the duration of the study was noted. In addition, the lack of consistency observed from the soil moisture products in drought characterization also was evident in the amount of annual crop production variability explained by them (soil moisture products) across the region. The study identified the following indicators as suitable for agricultural drought monitoring/characterization for the region during the study period; (a) for Kenya: CHIRPS, GPCC, VCI, MERRA-2, FLDAS and MTWS; (b) for Uganda: CHIRPS, GPCC, VCI, FLDAS, ERA, MERRA-2, and MTWS; and (c) for Tanzania: CHIRPS, GPCC, VCI, FLDAS, GLDAS and ERA. Also, GTWS showed potential in explaining the annual variability in crop production, albeit a longer period of dataset is required to evaluate its potential.

Further studies need to be undertaken to determine how well the model soil moisture products (CPC, ERA-Interim, MERRA-2, FLDAS, and GLDAS) and MTWS fit the region.
Also, care should be taken in generalizing these results as production response to water at any different stages of crop growth can be modified by several factors.
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7. List of Figure Captions

1. Fig. 1: East Africa (EA) region; (a) Elevation variation from Shuttle Radar Topographical Mission (SRTM, source: http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database), (b) Temporal NDVI average (1983 - 2014) with standardised indices localization regions (see Fig. 2 and Table 3 for region details).

2. Fig. 2: Rotated principal component spatial patterns of standardized index/anomalies (SI/SA). Rows denote products while columns denote regions (also see Table 3). The spatial patterns have been scaled to ±1, thus the temporal evolutions shown in Fig. 4 indicate the actual magnitude of SI/SA for regions where the spatial patterns have values close to ±1. The spatial patterns are interpreted in conjunction with temporal evolutions in Fig. 4 and represent drought spatial patterns any time the temporal evolutions falls below −0.84, as in Table 2. The white rectangular area in all the images except CHIRPS and GTWS is Lake Victoria.

3. Fig. 3: Rotated principal component spatial patterns of standardized soil moisture indices (SSI). Rows denote products while columns denote regions (also see Table 3). The spatial patterns have been scaled to ±1, thus the temporal evolutions shown in Fig. 5 indicate the actual magnitude of SSI for regions where the spatial patterns have values close to ±1. The spatial patterns are interpreted in conjunction with temporal evolutions in Fig. 5 and represent drought spatial patterns any time the temporal evolutions falls below −0.84, as in Table 2. Patterns are consistent with those in Fig. 2 except for ERA-Interim and to some extent GLDAS in region 2. The white rectangular area in all the images except MERRA-2 is Lake Victoria.

4. Fig. 4: Temporal evolutions of SA/SI spatial patterns in Fig. 2. The temporal evolutions are interpreted in conjunction with Table 2, to classify drought and/or wet conditions. Rainfall products (CHIRPS and GPCC) exhibit similar consistent performance across the region. Also, all the products exhibit consistent performance in region 3, while VCI and GTWS show some lag in relation to rainfall.

5. Fig. 5: Temporal evolutions of SSI spatial patterns in Fig. 3. The temporal evolutions are interpreted in conjunction with Table 2, to classify drought and/or wet conditions.
All the moisture products have consistent performance in region 3 while in the rest of the
regions, CPC is similar to MERRA-2 and similarly, ERA-Interim is closer to GLDAS.

6. Fig. 6: Percentage of area affected by various drought intensities during the period 1983
– 2013. Percentage areas are computed by integrating the regional spatial and temporal
patterns (Figs. 2, 3, 4, and 5) then determining percentage of pixels under each drought
category as per Table 2. The rainfall products have the highest percentage areas under
drought followed closely by soil moisture products and finally the lowest percentage
areas are by VCI. In addition to the soil moisture products having different percentage
areas under drought, CPC is consistent with MERRA-2, GLDAS is consistent with
ERA-Interim while FLDAS is in between.

7. Fig. 7: Comparison of performance between GTWS and MTWS in terms of percentage
of areas affected by various drought categories. Percentage areas are computed as in
Fig. 6. They have consistent performance, with GTWS having a lag in drought detection
probably due to groundwater that is lacking in MTWS.

8. Fig. 8: Percentage of areas affected by various drought intensities during the 1983 –
(gradients) representing from bottom moderate, severe, and extreme droughts at the top.
Percentage areas are computed as in Fig. 6 but only for the duration of drought. VCI
has a lag of about 2 – 3 months in identifying the drought cycle in relation to CHIRPS.
The rest of the products have inconsistent lags in relation to rainfall across the three
drought episodes.

9. Fig. 9: Proportions of variability in national annual crop (maize and wheat) production
($R^2$) explained by various drought indices for Kenya, Tanzania, and Uganda. CHIRPS,
GPCC, and VCI consistently explains relatively higher variability in crop production,
while the soil moisture products have inconsistent performance (a, b, and c). The figures
d, e, and f should be interpreted with care as the datasets used to fit the models are only
10 years long. Both SI and SA are computed at annual scales. (The y axis indicates
the crop (maize/wheat), SI (for a, b, and c), and SA (for d, e and f) while 1,3 and 6
indicate the standardization time scales for the indicators on the x axis).