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Consistency of agricultural drought characterization over Upper Greater Horn of Africa (1982-2013): Topographical, gauge density, and model forcing influence.

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Abstract

The negative impact of Upper Greater Horn of Africa's (UGHA) complex topography on drought characterization exacerbated by gauge density and model forcing parameters has not been investigated. In order to fill this gap, this study employs a combination of remotely sensed, in-situ, and model products (1982-2013); precipitation (CHIRPS, GPCC, and CHIRP), soil moisture (ERA-Interim, MERRA-2, CPC, GLDAS, and FLDAS), vegetation condition index (VCI), and total water storage products (GRACE and MERRA-2) to (i) characterize drought, (ii) explore the inconsistencies in areas under drought due to topographical variations, gauge density, and model forcing parameters, and (iii), assess the effectiveness of various drought indicators over Ethiopia (a selected UGHA region with unique topographical variation). A 3-month time scale that sufficiently captures agricultural drought is employed to provide an indirect link to food security situation in this rain-dependent region. The spatio-temporal drought patterns across all the products are found to be dependent on topography of the region, at the same time, the inconsistencies in characterizing drought is found to be mainly driven by topographical variability (directly) and gauge density (inversely) for precipitation products while for soil moisture products, precipitation forcing parameters plays a major role. In addition, the inconsistencies are found to be higher under extreme and moderate droughts than severe droughts. The mean differences in the percentage of areas

under drought and different drought intensities over the region are on average 15.87% and 6.16% (from precipitation products) and 12.65% and 5.20% (from soil moisture products), respectively. On the effectiveness of various indicators, for the duration under study, the following were found to be most suitable over Ethiopia; VCI, GPCC, ERA, CPC, and FLDAS. These results are critical in putting into perspective drought analysis outcomes from various products.

Keywords: Agricultural drought, effectiveness of drought indicators, total water storage, VCI, Standardized Index, Standardized Soil Moisture Index.

1. Introduction

A majority of the population of the Upper Greater Horn of Africa (UGHA; Djibouti, Somalia, Ethiopia, Sudan, Eritrea, and South Sudan) relies heavily on subsistence agriculture, an activity that has been frequently impacted by droughts, leaving the population vulnerable to famine (*Ibrahim, 1988; Olsson, 1993; Gebrehiwot et al., 2011*). Further consequences of drought in UGHA include; population displacement, rise in food prices, malnutrition and health related complications (*Ibrahim, 1988; Edossa et al., 2010; Taffesse et al., 2012; Viste et al., 2013*). In addition, due to the fact that agriculture is largely rain-fed in Ethiopia and combination of rain-fed and irrigated in Sudan and Somalia (e.g., *Bewket, 2009; Elagib and Elhag, 2011; Longley et al., 2001*), drought occurrence frequently leads to large-scale crop failures and losses of livestock. The magnitude and severity of the drought impacts in the region emphasize the need for drought indicators that provide a clear, accurate, and consistent picture of the drought extent.

Several studies have characterized and analysed droughts in the region from meteorological, agricultural to hydrological (see, e.g., *Gedif et al., 2014; Kurnik et al., 2011; Gebrehiwot et al., 2011; Edossa et al., 2010; Viste et al., 2013; Lyon, 2014; Nicholson, 2014; Dutra et al., 2013; Awange et al., 2016; Anderson et al., 2012*). These studies have analyzed droughts based on soil moisture (model and re-analysis), rainfall (satellite-derived, in-situ, and a combination of both), Gravity Recovery and Climate Experiment (GRACE) terrestrial water storage (TWS),

and normalised difference vegetation index (NDVI). Due to the limitations associated with in-situ rainfall (see, e.g., [Naumann et al., 2014](#); [Nicholson, 2014](#); [Rojas et al., 2011](#)), most of the studies have preferred satellite or satellite - in-situ merged products which provide homogeneous, consistent, and wide coverage (e.g., [Damberg and AghaKouchak, 2014](#)). However, these satellite precipitation and the other aforementioned products do have inherent errors and uncertainties, e.g., errors arising from retrieval algorithms, data acquisition and post-processing, estimation from cloud top reflectance, model limitations, and infrequent satellite overpasses (see, e.g., [Rojas et al., 2011](#); [Damberg and AghaKouchak, 2014](#); [Hong et al., 2006](#); [Naumann et al., 2014](#); [AghaKouchak et al., 2009](#)). Even though the above uncertainties can be reduced through standardization (e.g., Standardized Precipitation Index) or percentiles over time ([McNally et al., 2016](#)), the impacts of UGHA topography on these products and subsequent propagation of these impacts on agricultural drought characterization is largely unknown.

The complex terrain-precipitation relationship in the UGHA region, especially over Ethiopia, has been reported in several research (e.g., [Romilly and Gebremichael, 2011](#); [Dinku et al., 2007, 2008](#)). Terrain has been found to be a major factor influencing rainfall distribution, and as such, has been a problem to both satellite-derived and gauge gridded (dependent on gauge density and topography) rainfall products. Satellite derived rainfall products employ either infrared or passive microwave techniques to determine the amount of rainfall ([Dinku et al., 2007, 2008](#)), both of which are impacted by topography especially for convective rainfall as is found in the UGHA. Soil moisture being an integration of rainfall anomalies over time ([Sheffield and Wood, 2008](#)) is expected to be influenced by this complex terrain-precipitation relationship.

Furthermore, the quality of model/reanalysis soil moisture is majorly influenced by the precipitation product it is forced by, and the individual model characteristics such as different operating soil wetness thresholds, i.e., differing variances and mean values; and critical hydrological thresholds, e.g., beginning of surface run-off or levels of evaporation at the potential rates ([Dirmeyer et al., 2004](#)). Despite the significant impacts of topography and gauge

density on rainfall and soil moisture products, majority of drought studies in the UGHA region (including the aforementioned) using these products have not addressed their impacts on agricultural drought analysis results.

The failure of drought studies in the region to analyze and/or incorporate the impacts of topography and/or gauge density on the analysis results could lead to confusion and/or reduced confidence on drought analysis results due to inconsistencies between various indicators. These inconsistencies could arise from propagation of varying impacts of topography and gauge density on different products during drought characterization. To this end, this study considers the impacts of *terrain*, *gauge density*, and *model forcings* on agricultural drought analysis using soil moisture, vegetation condition index, rainfall, and terrestrial water storage products over the period 1982 – 2013. Specifically, the study explores (i) spatio-temporal agricultural drought patterns, (ii) the inconsistencies in areas under agricultural drought due to topographical variations, gauge density, and model forcing parameters, and (iii), the effectiveness of various drought indicators in capturing agricultural drought over Ethiopia as evidenced from national annual crops such as maize and wheat. The first two objectives are carried out over the entire UGHA region while the third objective is carried out only over Ethiopia. This is because Sudan, South Sudan, and Somali carry out both rain-fed and irrigated agriculture (*Elagib and Elhag, 2011; Larsson, 1996*) and therefore their annual crop production does not tally with natural water changes in the environment as represented by the indicators.

The remainder of the study is organized as follows. A brief description of the study area (UGHA) and the data used are presented in Section 2, followed by methodology in Section 3. The results and discussion are presented in Section 4 and 5, respectively, and the study concluded in Section 6.

Figure 1: The Upper Greater Horn of Africa (UGHA); (a) Elevation (derived from Shuttle Radar Topographical Mission; SRTM, source:<http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database>), (b) Average annual rainfall, (c) Land cover types (modified from:<http://e4ftl01.cr.usgs.gov/MOTA/MCD12Q1.051/>), and (d), Average number of rain gauges per 0.5° by 0.5° grids between 1983 - 2013, used in deriving Global Precipitation Climatology Centre (GPCC) rainfall.

2. Study area and data

2.1. Upper Greater Horn of Africa (UGHA)

The UGHA region comprises of Djibouti, Somalia, Ethiopia, Sudan, Eritrea, and South Sudan (Fig. 1). Ethiopia has a complex topography (consisting mostly of high plateaus and chain of mountains) highlighted by the Great Rift Valley, which divides the country roughly along the centre in the northeast to southwest direction (*Romilly and Gebremichael, 2011*). Ethiopian highlands occur on both sides of the Great Rift Valley with the highest elevation on these highlands being in excess of 4500 m (Fig. 1a). The topography on the southeastern side of the highlands descend and levels off towards the border with Somalia (Fig. 1a; *Romilly and Gebremichael, 2011*). Topography plays a major role on Ethiopian climate resulting in a diverse micro-climate ranging from cold highlands to hot desert over southeastern lowlands (*Dinku et al., 2008*). Ethiopia has annual rainfall ranging from over 2000 mm over the highlands to about 300 mm over the low semi-arid lowlands (Fig. 1b), and has seen a rise in frequency of drought from one in every 10 -15 years a century ago to one in every 5 years or less in 2010 (*Edossa et al., 2010*). Sudan and South Sudan consist mostly of flat and/or undulating plains with a south-north gradient (Fig. 1a). It has annual rainfall varying from over 1200 mm in the extreme south west, reducing gradually to approximately 25 mm in the North (*Elagib, 2013*), with climate that varies from equatorial in the southern most parts, savannah in the center, and continental in the north (*Elagib and Elhag, 2011*). Somalia has a weak bimodal rainfall with the main season running from April to July and a second and/or minor season running from September to November (*Longley et al., 2001*). Agriculture is both rain-fed and irrigated with crops are grown during both the main and minor rainfall seasons. The major rain producing feature in the UGHA region is the Inter Tropical Convergence Zone (ITCZ; *Dinku et al. (2008)*). While the climate in the UGHA region is dependent on altitude, the vegetation types mirrors the rainfall zones (see, e.g., Fig. 1b and c; *Kurnik et al., 2011*). The region has relatively high concentration of rain gauges over Ethiopia highlands (Fig. 1d).

2.2. Data

Table 1 summaries the dataset used in this study.

Table 1: Overview of data-set employed in the study

	Data	Temporal resolution	Spatial resolution	Period employed	References/ Studies used in
Precipitation	CHIRPS	Monthly	$0.05^\circ \times 0.05^\circ$	1982 - 2013	<i>Funk et al. (2015)</i> ; <i>Pricope et al. (2013)</i> ; <i>Shukla et al. (2014)</i> ; <i>(McNally et al., 2016)</i> .
	CHIRP	Monthly	$0.05^\circ \times 0.05^\circ$	1982 - 2013	<i>Funk et al. (2015)</i> .
	GPCC	Monthly	$0.5^\circ \times 0.5^\circ$	1982 - 2013	<i>Schneider et al. (2014)</i> ; <i>Kurnik et al. (2011)</i> ; <i>Funk et al. (2014)</i> ; <i>Ziese et al. (2014)</i> ; <i>Dutra et al. (2014)</i> .
Soil moisture	MERRA-2	Monthly	$0.625^\circ \times 0.5^\circ$	1982 - 2013	<i>Bosilovich et al. (2016, 2015)</i> .
	GLDAS	Monthly	$1^\circ \times 1^\circ$	1982 - 2013	<i>Rodell et al. (2004)</i> ; <i>Anderson et al. (2012)</i> ; <i>Yilmaz et al. (2014)</i> ; <i>McNally et al. (2016)</i> .
	ERA-Interim	Monthly	$0.25^\circ \times 0.25^\circ$	1982 - 2013	<i>Albergel et al. (2012)</i> ; <i>Balsamo et al. (2009)</i> ; <i>Dee et al. (2011)</i> ; <i>Decker et al. (2012)</i> ; <i>Dutra et al. (2013)</i> ; <i>Viste et al. (2013)</i> .
	FLDAS VIC	Monthly	$0.25^\circ \times 0.25^\circ$	1982 - 2013	<i>Rui and McNally (2016)</i> ; <i>McNally et al. (2017)</i> ; <i>Yilmaz et al. (2014)</i> ; <i>Agutu et al. (2017)</i> .
	FLDAS Noah	Monthly	$0.1^\circ \times 0.1^\circ$	1982 - 2013	<i>Yilmaz et al. (2014)</i> ; <i>McNally et al. (2017)</i> ; <i>Rui and McNally (2016)</i> ; <i>Agutu et al. (2017)</i> .
	CPC	Monthly	$0.5^\circ \times 0.5^\circ$	1982 - 2013	<i>van den Dool et al. (2003)</i> ; <i>Dirmeyer et al. (2004)</i> ; <i>Fan and van den Dool (2004)</i> .
VCI	NDVI	15 days	5-arc-minute	1982 - 2013	<i>Verdin et al. (2005)</i> ; <i>Pinzon and Tucker (2014)</i> ; <i>Tucker et al. (2005)</i> ; <i>Rojas et al. (2011)</i> ; <i>Guan et al. (2012)</i> ; <i>Dorigo et al. (2012)</i> ; <i>Chen et al. (2014)</i> .
TWS	GRACE	Monthly	$1^\circ \times 1^\circ$	2003 - 2013	<i>Long et al. (2013)</i> ; <i>Wouters et al. (2014)</i> ; <i>Awange et al. (2016)</i> ; <i>Chen et al. (2009)</i> ; <i>Tapley et al. (2004)</i> ; <i>Chen et al. (2004)</i> .
	MERRA-2	Monthly	$0.625^\circ \times 0.5^\circ$	1982 - 2013	<i>Bosilovich et al. (2016, 2015)</i> .

2.2.1. Rainfall Products

Climate Hazard Group InfraRed Precipitation with Stations (CHIRPS) monthly 0.05° version 2 precipitation (1982–2013) obtained from <ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRPS-2.0/> is used. It is a combination of in-situ gauge and satellite-based cold cloud duration (CCD) observations (see *Funk et al. (2015)* for more details).

In addition, Climate Hazard Group InfraRed Precipitation(CHIRP), a satellite only product based on CCD observations is used. The monthly 0.05° , precipitation (1982–2013) obtained from <ftp://ftp.chg.ucsb.edu/pub/org/chg/products/CHIRP/> was used to characterize drought (see, *Funk et al.*, 2015, for more details).

Finally, Global Precipitation Climatology Centre (GPCC) (*Schneider et al.*, 2014) monthly 0.5° version 7 precipitation for the duration 1982 – 2013 from ftp://ftp.dwd.de/pub/data/gpcc/html/fulldata_v7_doi_download.html is also used.

2.2.2. Soil moisture products

Due to the complex terrain and high rainfall variability in the region, major soil moisture products (model and re-analysis) are used for agricultural drought analysis/characterization in order to decipher and compare the impacts of terrain on agricultural drought characterization consistency using these products. For MERRA-2 (second Modern-Era Retrospective analysis for Research and Applications), root zone soil moisture product was used while for ERA-Interim (European Centre for Medium-Range Weather Forecasts Interim Re-Analysis), FLDAS (Famine Early Warning System Network (FEWS NET) Land Data Assimilation System), and GLDAS (Global Land Data Assimilation System), individual soil moisture layers from 0 – 1 m (approximately equal to root zone depth) are aggregated, and CPC (Climate Prediction Center) used the way it is since it is a single depth bucket product.

ERA-Interim monthly soil moisture for the duration 1982 – 2013, at 0.25° spatial (grid) resolution obtained from <http://apps.ecmwf.int/datasets/data/interim-full-moda/levtype=sfc/> is used.

MERRA-2, an upgraded version of the MERRA reanalysis (*Rienecker et al.*, 2011; *Decker et al.*, 2012) employing Goddard Earth Observing System Model, version 5.12.4 (GEOS 5.12.4) data assimilation system (*Bosilovich et al.*, 2016), is used. The monthly root zone soil moisture at spatial resolution of 0.625° by 0.5° , for the duration 1982–2013 was downloaded from https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/.

GLDAS (*Rodell et al.*, 2004) NOAA-model variant, version 2, is used. The 1° by 1°

monthly soil moisture for the period 1982 – 2010 was obtained from <http://disc.sci.gsfc.nasa.gov/\services/grads-gds/gldas>. Like ERA-Interim’s case, GLDAS moisture layers (0 – 1 m) are aggregated before agricultural drought analysis. The Noah model variant has been used widely by the atmospheric and modeling communities thus model parameters are adequately tested (*McNally et al., 2016*). Besides (*McNally et al., 2016*), several studies (e.g., *Yilmaz et al., 2014*; *Anderson et al., 2012*) have used the model over the region.

FLDAS (*McNally et al., 2017*; *Rui and McNally, 2016*), Noah and VIC model variants at 0.1° by 0.1°, and 0.25° by 0.25° spatial resolutions, respectively, are used. The monthly soil moisture for the duration 1982 – 2013 was obtained from <https://ldas.gsfc.nasa.gov/FLDAS/FLDASdownload.php>. The Noah and VIC moisture products are from FLDAS simulation run forced by CHIRPS precipitation, and soil moisture and state fields from MERRA-2. It has been used in the region by several studies, (e.g., *McNally et al., 2016*; *Yilmaz et al., 2014*; *Agutu et al., 2017*; *Anderson et al., 2012*), among others.

Finally, Climate Prediction Center (CPC, *van den Dool et al. (2003)* and *Fan and van den Dool (2004)*) global, version 2 soil moisture is used. The monthly 0.5° by 0.5° spatial resolution mean soil moisture, from 1982 to 2013 was downloaded from NOAA’s Earth System Research Laboratory (<http://www.esrl.noaa.gov/psd/data/gridded/data.cpcsoil.html>).

2.2.3. Total water storage (TWS)

The Centre for Space Research’s (CSR) release five (RL05) monthly GRACE (see, e.g., *Wouters et al., 2014*; *Tapley et al., 2004*) spherical harmonic coefficients for the duration 2003 — 2013 obtained from <http://icgem.gfz-potsdam.de/ICGEM/shms/monthly/csr-rl05/> are used in this study. The spherical harmonic coefficients are processed following *Wahr et al. (1998)* and detailed description of the processing can be found in *Agutu et al. (2017)*.

The resulting GRACE-derived TWS over upper GHA comprises changes from biomass/canopy water content (assumed to be negligible), surface water, accumulated soil moisture, and groundwater. The surface water variations corresponding to Lake Tana (dominant water body in the region) was removed through integration of satellite altimetry lake level changes

and lake Kernel function following *Moore and Williams* (2014). Assuming the contribution of other surface water bodies in the region, e.g., from the Sudd wetland to be negligible, the removal of the dominant Lake Tana's surface contribution enabled the remaining TWS changes to be associated with groundwater and soil moisture. Further, due to shorter duration under consideration and limited exploitation of groundwater in the region, most of the variation is assumed to occur in the unsaturated zone (soil moisture) as it responds more to climate variability than the saturated zone (e.g., *Yang et al.*, 2014). The remaining components is henceforth referred to as GTWS. Its utility in drought and hydrology related analyses has been demonstrated in a number of research (see, e.g., *Awange et al.*, 2016; *Long et al.*, 2013; *Chen et al.*, 2009).

In addition, MERRA-2 Monthly 0.5° by 0.625° (spatial resolution) total land water storage (TWLAND) for the duration 1982 – 2013 obtained from https://gmao.gsfc.nasa.gov/reanalysis/\MERRA-2/data_access/ is also employed. It is hereafter referred to as MTWS. Unlike GTWS, MTWS does not contain groundwater and canopy water content (see, e.g., *Reichle*, 2012)

2.2.4. Vegetation Condition Index (VCI)

National Oceanic and Atmospheric Administration's Advanced Very High-Resolution Radiometer (AVHRR) long term series NDVI data set (see, e.g., *Pinzon and Tucker*, 2014; *Tucker et al.*, 2005) from 1982-2013, 15 days composite at $\simeq 0.0833^\circ$ (8 km) spatial resolution obtained from <http://ecocast.arc.nasa.gov/data/pub/\gimms/3g.v0/> is utilized in computing VCI (*Kogan*, 1995). VCI is preferred for agricultural drought analysis due to its ability to isolate and/or emphasize weather related vegetation stress (see, e.g., *Rojas et al.*, 2011; *Quiring and Ganesh*, 2010; *Kogan*, 1995) that correspond to water availability within the study area. It was computed following (*Kogan*, 1995) and (*Agutu et al.*, 2017). AVHRR NDVI has been used extensively globally and over Africa for drought and other related studies (see, e.g., *Chen et al.*, 2014; *Dorigo et al.*, 2012; *Rojas et al.*, 2011; *Guan et al.*, 2012; *Verdin et al.*, 2005).

2.2.5. National annual crop production

The national annual crop (maize and wheat) production data for Ethiopia obtained from Food and Agriculture Organization (FAO) data portal (<http://www.fao.org/faostat/en/#data/QC>) is employed in evaluating how well the various drought indices capture agricultural droughts.

3. Methodology

A Standardised Index (e.g., Standardised Precipitation Index, [McKee et al., 1993](#)) is employed to characterize agricultural drought using Rainfall (CHIRPS, CHIRP, and GPCC), soil moisture (MERRA, CPC, ERA-Interim, GLDAS, and FLDAS), and TWS (MERRA-derived). In addition, standardized anomalies (SA, [Wu et al., 2001](#)) is used to characterize agricultural drought using GRACE-derived TWS since its (GRACE-derived TWS) length is too short to fit SPI. Both standardizations are carried out for 3-month time scales since 3-months time scale SPI has been associated with agricultural drought in several research efforts (see, e.g., [Rouault and Richard, 2003](#); [Kurnik et al., 2011](#); [Svoboda et al., 2012](#); [Elagib, 2013](#)). The SI/SA are then decomposed through rotated principal component analysis for spatio-temporal drought patterns. All the products other than GLDAS and GRACE TWS are resampled to 1° by 1° spatial resolution before standardization.

3.1. Agricultural Drought Characterization

3.1.1. Standardized Index (SI)

Standardised precipitation index (SPI, [McKee et al. \(1993\)](#)) is a form of standardisation in which precipitation is expressed in terms of its deviation from the long-term mean. It is computed by fitting a parametric distribution to precipitation data then transforming parametric distribution function to the standard normal distribution with a mean of 0 and standard deviation of 1 (see, e.g., [Naresh Kumar et al., 2009](#); [Farahmand and AghaKouchak, 2015](#)). It is one of the most preferred drought indices due to its standardised nature, simplicity (only requires one input), and flexibility of use on different time scales e.g., 1, 3, 6, 9, 12-month (see,

e.g., [Svoboda et al., 2012](#); [AghaKouchak, 2015](#), and the references therein). A non-parametric approach of fitting SPI (see, e.g., [AghaKouchak, 2015](#)) is adopted due to the dependence of the SPI values on the choice of parametric distribution employed, especially at the tail end of the distribution (see e.g., [Quiring, 2009](#)). This approach involves the use of empirical Gringorten plotting position formula to compute empirical probability, $p(x)$, ([Gringorten, 1963](#)) as

$$p(x_i) = \frac{i - 0.44}{n + 0.12}, \quad (1)$$

where $p(x_i)$ is the empirical probability, n the sample size, and i denotes the rank of non-zero precipitation data from the smallest. The empirical probability from eqn. 1 is then transformed into a standardized index as

$$SI = \phi^{-1}(p), \quad (2)$$

where SI is SPI, SSI (standardised soil moisture index), SVCI (standardised vegetation condition index), or STWSI (standardised total water storage index) depending on the variable under consideration, ϕ is the standard normal distribution function, and p is the probability derived from Eqn. 1. This study employed Standardized Drought Analysis Toolbox (SDAT, [Farahmand and AghaKouchak \(2015\)](#)) in computing SPI values and adopted the SPI drought limit categories of [Agnew \(2000\)](#) in Table 2. 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.

3.1.2. Standardized Anomalies (SA)

SA ([Wu et al., 2001](#)), also referred to as z-scores, is a form of standardization in which a variable is expressed in terms of its deviation from its long term mean. It is computed by dividing the monthly anomalies by the multi-year standard deviation (see, e.g., [Peters et al., 2002](#); [Agutu et al., 2017](#), for formulation). It has been applied to study droughts in various studies (e.g., [Wu et al., 2001](#); [Agnew and Chappell, 1999](#); [Lough, 1997](#); [Katz and Glantz,](#)

Table 2: Drought intensities as per SPI values ([Agnew, 2000](#))

SPI	Drought Category
>1.65	extremely wet
>1.28	severely wet
>0.84	moderately wet
>- 0.84 and <0.84	normal
<-0.84	moderate drought
<-1.28	severe drought
<-1.65	extreme drought

1986). Due to the short duration of GTWS, which does not permit standardization using SPI approach, the 3-month time series of GTWS is standardised using z-scores. The 3-month time series cumulation is computed in a manner similar to SPI cumulations e.g., 3-month time series for January would involve summing from November of the previous year. Positive Z-score values represent wet conditions, zero values represent normal conditions, while negatively values represent dry conditions ([Wu et al., 2001](#)).

3.1.3. Principal Component Analysis (PCA)

PCA ([Jolliffe, 2002](#); [Preisendorfer, 1988](#); [Wilks, 2006](#); [Lorenz, 1956](#)) has been used to study the spatio-temporal drought variability in various regions across the world (see., e.g., [Santos et al., 2010](#); [Raziei et al., 2009](#); [Sigdel and Ikeda, 2010](#)) through the decomposition of spatio-temporal fields, e.g., SPI, SSI, STWSI, SVCI etc. into spatial and corresponding temporal patterns. For formulation, see e.g., [Jennrich \(1970\)](#); [Kutzbach \(1967\)](#); [Hannachi et al. \(2006\)](#); [von Storch and Zwiers \(1999\)](#).

The significant PCA decomposed SI/SA components (based on log-eigenvalue diagrams; [Jolliffe, 2002](#)) are further subjected Varimax rotation ([Jolliffe, 1995](#); [Kaiser, 1958](#); [Forina et al., 1988](#)) in order to spread the variance explained and improve interpretability. In addition, the rotation has served to localize the results from regional (GHA) to local (country) level.

The resulting spatial pattern, called the scores, properly normalized represents the correlation (relationship) between the SI/SA and the rotated principal components (RPC) while the normalized RPC represents the SI/SA (see, e.g., [Bordi et al., 2006](#)).

3.2. Percentage of Areas Under Agricultural Drought and their Consistencies

The percentage of areas under agricultural drought and different drought intensities are evaluated for Ethiopia, Sudan, South Sudan, and Somalia through determination of the percentage of pixels under various agricultural drought categories following Table 2. Differences in percentage areas under agricultural drought and different drought intensities between various products during 1983 – 1984, 1987, 1999, 2009, and 2010 – 2011 drought events are then evaluated for each country.

In order to evaluate the impact of gauge density, the differences between CHIRPS and GPCC derived percentages of areas under drought are evaluated (Eqn 3). The in-situ stations in CHIRPS (global historical networks and global teleconnection networks) are all in GPCC plus other more stations (see, [Schneider et al., 2014](#); [Funk et al., 2015](#)), though the number of stations available on monthly basis differs hence the variations in areas under drought. For the mean differences due to topography, the following differences are evaluated

$$CHIRPS_{(\% \text{ area under drought})} - GPCC_{(\% \text{ area under drought})} = \text{Influence of gauge density} \quad (3)$$

$$CHIRP_{(\% \text{ area under drought})} - CHIRPS_{(\% \text{ area under drought})} - \text{Influence of gauge density} \\ = \text{Influence of topography} \quad (4)$$

Equation 4 arises from the fact that CHIRP, a satellite only product, determines precipitation from cold cloud duration (CCD; [Funk et al. \(2015\)](#)) and the regional topography has been known to greatly hamper the satellite products ([Romilly and Gebremichael, 2011](#); [Dinku et al., 2007, 2008](#)). CHIRPS on the other hand has gauge derived rainfall estimates in addition to CCD estimates; the inclusion of gauge derived estimates serve to correct/scale the

CCD estimates to their proper values. This implies that the difference between CHIRPS and CHIRP contain the influence of both gauge and topography.

In addition, the following differences are evaluated for soil moisture products; FLDASN (FLDAS NOAH) – FLDASV (FLDAS VIC), FLDASN – MERRA2, MERRA2 – ERA, and FLDASN – GLDAS. The differences between the soil moisture products are taken to explore issues related to the role of forcing precipitation vis-a-vis model differences among other factors in contributing to the inconsistencies in areas under agricultural drought.

These differences are then analyzed using ANOVA and Bonferroni multiple comparison methods, for further details see [Kutner \(2005\)](#); [King \(2010\)](#) and [Hochberg and Tamhane \(1987\)](#); [Toothaker \(1993\)](#), respectively. The analyses are used to explore how the following factors contribute to the differences in percentages of areas under agricultural drought across the region; (i) gauge density, (ii) physical characteristics (topography of each country), (iii) products (rainfall vis-a-vis moisture; different rainfall and soil moisture products), and (iv) forcing precipitation and model types.

3.3. Evaluating the Effectiveness of Various Drought Indicators over Ethiopia

As the national annual crop production is given at country level, the SI/SA (only) over Ethiopia are decomposed through rotated principal component analyses. Then the temporal SI/SA values are extracted and regressed through partial least squares regression (PLSR; for further details, see [Geladi and Kowalski, 1986](#); [Wold et al., 2001](#)) on national annual crop production data (maize/wheat). Detailed explanation of this process can be found in [Agutu et al. \(2017\)](#). The evaluation is carried out at 1, 3, and 6 month SI/SA time scales.

4. Results

Long term dataset (rainfall, moisture, vegetation condition index, and MTWS) are standardised following SPI, while GTWS is standardised using Z-score. The resulting standardised variables are regionalised through rotated principal component analysis in order to provide spatio-temporal agricultural drought patterns. In addition, the percentage of areas affected by

agricultural droughts are analysed and the consistency of percentage of areas under drought as influenced by terrain, gauge density, and soil moisture model related parameters explored across the region. Finally, the effectiveness of various drought indicators are analyzed over Ethiopia. Only Ethiopia is considered since it is the only country in UGHA practicing rain-fed agriculture hence there is a link between crop production and drought indicators. The other countries do both rain-fed and irrigated agriculture.

4.1. Agricultural Drought Characterization

The regionalization of SI/SA through rotated principal component analysis results in largely consistent and significant spatio-temporal patterns across majority of the agricultural drought indicators (Figs. 2 - 5). The geographical coverage of these spatial, from RPCA clustering of SI/SA values, based on Fig. 2 is summarised in Table 3. When assessed in relation to Figure 1, the spatial patterns of the precipitation products (i.e., CHIRPS, CHIRP, and GPCC) are largely similar over the regions and follows the region's topography, while those of VCI and MTWS largely follow land cover classes, and GTWS patterns follow both rainfall and land cover classes (Fig. 2, compared to Fig. 1a-c). All the products show consistent patterns over Region 3, a region of relatively lowland flat topography with low-moderate rainfall (see, Fig. 1a and b). For the soil moisture products, the spatial patterns roughly resemble those of rainfall and/or land cover patterns except for CPC spatial patterns (Fig. 3, compared to Fig. 1b and c). Also, Region 4's spatial patterns are different across the soil moisture products (Fig. 4), with MERRA2's spatial pattern resembling that of MTWS in Region 4 (Fig. 3). Similar to the patterns of the rainfall group (Fig. 3), there is consistency among the soil moisture products over Region 3 (i.e., lowland region of low to moderate rainfall) though not as close as in the rainfall group.

The proportion of variances of the SI/SA explained by these components is tabulated in Table 4. The majority of the rainfall products had the lowest variability in Region 4 while the majority of the soil moisture products had the lowest variability in Region 3. Region 4, from rainfall products, comprises mostly Ethiopian highlands; a region with lots of rainfall most of

Table 3: Approximate geographical coverage of SI/SA spatial patterns, based on Fig. 2.

Region	Countries/areas
1	Sudan
2	South Sudan
3	Eastern Ethiopia and Somalia
4	Ethiopian highlands

the year hence low variability in SPI while Regions 3 comprises relatively dry regions with low soil moisture most of the year hence lowest variability in SSI. On the other hand, maximum variability as seen in Table 4 differed across products with no clear majority in any particular region. VCI had Regions 1 and 3 explaining equal magnitudes of variability probably due to similar vegetation types in the vast areas of the two locations (Fig. 2 vis-a-vis Fig. 1c). On the basis of the total variabilities explained, CHIRPS and GPCC are almost equal but lower than CHIRP while the soil moisture products fall into 3 categories i.e., FLDASV (43%); GLDAS, ERA-Interim, and FLDASN (50 – 55%); and CPC and MERRA2 (66 – 67%), see Table 4.

Table 4: Proportions (%) of variances explained in each Region by each spatial pattern. Regions are as shown in Figures 2 and 3.

Region	CHIRPS	CHIRP	GPCC	VCI	MERRA TWS	GRACE TWS	ERA- Interim	GLDAS	CPC	MERRA2	FLDASN	FLDASV
Region 1	10.03	15.78	13.68	8.08	17.50	14.28	15.84	9.95	30.47	18.01	17.53	13.85
Region 2	10.16	8.86	8.41	12.07	20.45	24.35	12.72	15.97	17.52	19.70	10.66	11.27
Region 3	11.38	11.10	11.00	8.05	12.66	23.34	10.91	10.39	8.56	13.20	12.06	10.81
Region 4	8.73	11.81	8.21	10.74	14.52	21.32	16.23	14.44	10.71	15.22	11.93	7.09
Total	40.03	47.55	41.3	38.94	65.13	83.29	55.70	50.75	67.26	66.13	52.18	43.02

FLDASN - FLDAS NOAH, and FLDASV - FLDAS VIC.

The SI/SA temporal evolutions show region-wide agricultural drought events in the years 1983/1985, 1986/1987, 1990/1991, 2000, 2005/2006, 2009/2010, and 2010/2011 (see Figs. 4 and 5).

Figure 2: Standardized Indices/Anomalies (SI/SA) spatial patterns. The patterns result from rotated principal component analyses decomposition of SI/SA. They are interpreted jointly with Figure 4, and represent agricultural drought spatial extents whenever Figure 4 falls below -0.84 , as in Table 2, continuously for at least three months. Rows and columns represent drought indicators and regions, respectively. (Y-axis are latitudes and x-axis longitudes).

Figure 3: Standardized Indices/Anomalies (SI/SA) spatial patterns. The patterns result from rotated principal component analyses decomposition of SI/SA. They are interpreted jointly with Figure 5 and represent agricultural drought spatial extents whenever Figure 5 falls below -0.84 , as in Table 2, continuously for at least three months. Rows and columns represent drought indicators and regions, respectively. (Y-axis are latitudes and x-axis longitudes).

These drought episodes and others showed in the figures are consistent with what is reported by previous studies across GHA (e.g., *Gebrehiwot et al.*, 2011; *Elagib and Elhag*, 2011; *Viste et al.*, 2013; *Nicholson*, 2014; *Williams and Funk*, 2011; *Masih et al.*, 2014).

Of the precipitation products, GPCC and CHIRPS are similar across all the regions with little differences evident in Regions 1 and 2 (Fig. 4a and b) though they are significantly different from CHIRP across the region (Fig. 4). This could be attributed to both CHIRPS and GPCC containing in-situ rainfall (rain gauge products) while CHIRP is wholly satellite derived hence differences depends on how well these products estimate rainfall across the region, which is a function of topographical changes (see, e.g., *Dinku et al.*, 2007; *Romilly and Gebremichael*, 2011; *Dinku et al.*, 2008). Also, FLDASN and FLDASV are largely close across the whole region (Fig. 5).

Over the duration considered, all the indicators are found to be consistent in Region 3 more than the rest of the UGHA regions (Figs. 4 and 5), a pattern that is also noticeable in the spatial maps (Figs. 2 and 3). This could be attributed to the facts that this region, a relatively flat region with moderate rainfall (Fig. 1a and b) does not have much topographical influence on the products as compared to high rainfall/rapid terrain changing regions like Region 4 (Fig. 2) and Region 2 (Fig. 3). The satellite and model-based products seems to work consistently well under flat topography and lower rainfall ranges while GPCC interpolation also seems to be good. The soil moisture products are mostly different in Region 2 (Fig. 3 and Fig. 5b), which could be attributed to the failure of the models to capture the complex topography-rainfall relationship in the region. Also, the large difference between the temporal evolutions across the soil moisture-based indicators compared to the rainfall indicators could be a pointer to greater inconsistency in the drought information as represented by the soil moisture based indicators. Region 4 of SSI (Fig. 5) represent the region with the largest difference in temporal evolution possibly due to different spatial patterns as observed from the spatial SSI patterns (Fig. 3).

In general, some isolated performances are also observed from MTWS and GLDAS. MTWS

Figure 4: Standardized Indices/Anomalies (SI/SA) temporal evolution. They are the corresponding temporal evolution of spatial patterns in Fig. 2, from rotated principal component analyses decomposition of SI/SA. Agricultural drought conditions occur when SI/SA falls below -0.84 , as in Table 2, continuously for at least three months. (Y-axis values are unitless).

appears to have a shift with pre-1999 being predominantly wet and dry afterward (Fig. 4a and b), while GLDAS appears to have issues in Regions 2 and 4 though consistent with other products in Region 3 (Fig. 5). Also, CPC and MERRA2 are closer over the region. Further,

there is a lag in drought events from rainfall to VCI/soil moisture followed by MTWS and eventually GTWS.

Finally, the relationships between the temporal patterns of the SI/SA (Figs. 4 and 5) ana-

Figure 5: Standardized Indices/Anomalies (SI/SA) temporal evolution. They are the corresponding temporal evolution of spatial patterns in Fig. 3, from rotated principal component analyses decomposition of SI/SA. Agricultural drought conditions occur when SSI falls below -0.84 , as in Table 2, continuously for at least three months. (Y-axis values are unitless).

Figure 6: Correlation shaded plot between drought indices by region; (a) upper triangle - Region 1, lower triangle - Region 2; and (b) upper triangle - Region 3, and lower triangle - Region 4. On average, Region 3 has higher correlations while the following products registered high correlation across the region; CHIRPS and GPCC, FLDASN and FLDASV, MTWS and MERRA2, and MTWS and CPC.

lyzed through Pearson correlation are shown in Fig. 6. From the correlation coefficients, there is high degree of consistency across the region between the following products; CHIRPS and GPCC, FLDASN and FLDASV, MTWS and MERRA2, and MTWS and CPC. In addition, the majority of the products have on average highest correlations in Region 3 signifying consistent performance. These are consistent with the results outlined above (see Figs. 2, 3, 4, and 5). For the rainfall group, while CHIRPS and GPCC have the lowest correlation in Region 2, CHIRPS and CHIRP, and GPCC and CHIRP have the lowest correlation in Region 1. However, the soil moisture group do not have any particular region in which the majority of products had lowest correlations as values varied with product pairs and region.

4.2. Percentage of Areas Under Agricultural Drought and their Consistencies

4.2.1. Consistency of Areas Under Agricultural Drought

In order to analyze the consistency of areas under drought from rainfall and soil moisture products, this section considers the mean differences in areas under drought between various products during 1983 - 1984, 1987, 1999, 2009, and 2010-2011 drought events. These drought events are considered as they had significant impacts on the region (see, e.g., [Elagib and Elhag, 2011](#); [Gebrehiwot et al., 2011](#); [Masih et al., 2014](#); [Viste et al., 2013](#)). In addition, spatial correlations of the respective Standardized Indices (SPIs and SSIs) during these drought events are used to support the analysis of the mean differences.

Overall, the rainfall products are found to have higher mean differences in the percentage of areas under drought than soil moisture products, i.e., 15.7% vis-a-vis 12.6% at $F(1,2338) = 28.5176$, with $p < 0.0001$. However, the reverse would be true if only gauge based precipitation products (CHIRPS and GPCC) are considered (overall mean percentage difference would be 9.7% as opposed to 15.9%). The larger mean difference is attributed to the inclusion of CHIRP, a satellite only product that seems to have problems capturing the regional precipitation well.

From the rainfall products, the mean differences in percentage of areas under drought due to the gauge density (spatial distribution and temporal availability) is lowest in Ethiopia, followed by South Sudan and Sudan, and highest in Somalia (Fig. 7 a). This is inversely related to the gauge density of both GPCC and CHIRPS (see, Figs. 1d and [Funk et al. \(2015\)](#)) and is further supported by relatively high correlation coefficients over Ethiopia vis-à-vis lower coefficients over Somalia (Fig. 7 b). Finally, the mean differences in percentage of areas under drought due to topographical variations are lowest over Somalia (an area of low topographical variation), and highest over South Sudan with Ethiopia and Sudan being in between Fig. 7 a. This is supported by relatively higher correlation coefficients over Somalia compared to the rest of the regions (Fig. 7, c and d)

For the soil moisture products, the mean differences in percentage of areas under drought

between various products depend on the products under consideration ($F(3, 1292) = 61.92$, $p < 0.0001$) and the specific region (country) being considered ($F(3, 1292) = 28$, $p < 0.0001$; Fig. 8). Different models with similar forcing precipitation translate into lower mean percentage difference in areas under drought across the entire region than similar models with different forcing precipitations (FLDASN-FLDASV vis-a-vis FLDASN-GLDAS; Fig. 8). This is also reflected by the higher correlation between FLDASN and FLDASV SSIs' compared to FLDASN and GLDAS SSIs' during the considered drought events (Fig. 8b and e). The mean difference in the percentage of areas under drought between reanalysis products is lower

Figure 7: Rainfall products; (a) Mean percentage differences in areas under drought due to gauge density and topography over UGHA, (b) Spatial distribution of SPI correlations for the 1983 - 1984, 1987, 1999, 2009, and 2010-2011 drought events. The correlations are a function of gauge density (b), and topography (c and d).

than that between a reanalysis and a normal model product except over Somalia (MERRA-
ERA vis-a-vis FLDASN-MERRA) as also shown by higher correlations between MERRA
and ERA SSI than between FLDASN and MERRA (Fig. 8 a, c and d) during the consid-
ered drought events. The relatively higher difference in mean areas under drought between
MERRA and ERA over Somalia, also reflected by low correlations (Figs. 8 a and d) could
be attributed to the overestimation tendencies of ERA-interim, especially over dry areas as

Figure 8: Soil moisture products; (a) Mean percentage differences in areas under drought. Lower mean percentage differences are observed from models forced by same precipitation products (e.g., FLDASN and FLDASV), (b) Spatial distribution of SSI correlations for 1983 - 1984, 1987, 1999, 2009, and 2010-2011 drought events.

was shown by [Albergel et al. \(2012\)](#). The differences involving different models with different forcing precipitation products (FLDASN-MERRA and MERRA-ERA) have the highest mean difference in the percentage of areas under drought while different models forced with similar precipitation (FLDASN-FLDASV) have the lowest mean difference in the percentage of areas under drought across the region. This is supported by higher correlation between FLDASN and FLDSV SSIs' in comparison to the relatively lower correlations between FLDASN and MERRA2, and MERRA2 and ERA SSIs' (Fig. 8 b, c, and d). Finally, concerning the regional variability of the mean percentage differences in areas under drought, Somalia has the highest mean differences while Ethiopia has the least mean differences on the majority of product differences considered (Fig. 8 a).

4.2.2. Consistency of Areas Under Different Drought Intensities

In addition to the areas under agricultural drought, it is important to assess the extent to which each area is affected hence this section analyses the differences in drought intensity between various products used in section 4.2.1 for the same drought episodes i.e., 1983 - 1984, 1987, 1999, 2009, and 2010-2011 drought events.

On average, the mean difference in areas under different drought intensities from rainfall products is higher than those from soil moisture products when the whole region is considered in entirety (6.164% vis-a-vis 5.2021% at $F(1, 7018) = 33.91, p < 0.0001$; Figs. 9). The mean differences in percentage of areas under different drought intensities (moderate, severe, and extreme) from rainfall products varies with product pairs under consideration ($F(2, 3088) = 41.13, p < 0.0001$), the country ($F(3, 3088) = 4.79, p < 0.0001$), and the drought intensity category ($F(2, 3088) = 91.6, p < 0.0001$) being considered (Fig. 9a-d).

For the rainfall products, similar to the case of mean difference in areas under drought (see, section 4.2.1), the mean difference in percentage of areas under various intensities due to gauge density is lowest in Ethiopia and highest in Somalia, with Sudan and South Sudan being in between (Fig. 9 a - d). In addition, the mean difference in percentage of areas under various drought intensities due to topography is lowest over Somalia and largely the same over

Figure 9: Mean differences in percentage of areas under different drought intensities during 1983 - 1984, 1987, 1999, 2009, and 2010-2011 drought events; (a-d) Rainfall-derived Differences (RD) due to gauge density (1) and topography (2 and 3, are CHIRPS and GPCC derived, respectively), (e-h) Soil moisture-derived differences (MD; 5 = FLDASN - FLDASV, 6 = FLDASN - MERRA2, 7 = MERRA - ERA, and 8 = FLDASN - GLDAS. FLDASN - FLDAS NOAH, and FLDASV - FLDAS VIC).

the remaining countries (Fig. 9 a - d).

Similar to the case of the precipitation products, the mean differences in percentage of areas under different drought intensities from soil moisture products are dependent on products pairs ($F(3, 3915) = 77.16, p < 0.0001$), the country ($F(3, 3915) = 49.5, p < 0.0001$), and the intensity category ($F(2, 3915) = 30.06, p < 0.0001$) under consideration (Fig. 9 e - h). The mean differences in the percentage of areas under different drought intensities are lower for FLDASN-FLDASV compared to the rest of the soil moisture pairs across the regions. The

mean differences in the percentage of areas under various drought intensities are lowest in Ethiopia and highest over Somalia (Fig. 9 e and h). Like in the case of rainfall products, the mean differences in areas under different drought intensities are lower under severe droughts compared to moderate and extreme, across the countries for all the soil moisture product differences except for FLDASN – GLDAS (5 above). As with the case of differences in the percentage of areas under drought above, similar precipitation forcing with different models contributes to lower differences in intensity information compared to similar models with different forcing precipitations (FLDASN-FLDASV vis-a-vis FLDASN-GLDAS; Fig. 9 e - h).

4.3. Effectiveness of Drought Indicators in Capturing Agricultural Drought

This section extends the work of *Agutu et al. (2017)*, who evaluated the effectiveness of drought indicators in capturing agricultural drought over East Africa (Kenya, Uganda, and Tanzania), to Ethiopia. Though the rest of the study involved the whole of UGHA, this section is only limited to Ethiopia as Sudan, South Sudan, and Somali carry out both rain-fed and irrigated agriculture (*Elagib and Elhag, 2011; Larsson, 1996*) and therefore their annual crop production does not tally with natural water changes in the environment as represented by the indicators.

Both SI (computed using approximately 30 years length of data) and SA (computed using approximately 10 years length of data) are regressed with national annual crop (maize and wheat) production, and the model with least mean prediction error has its proportion of variability explained (R^2) reported (Fig. 10). As in *Agutu et al. (2017)*, SA is necessitated by the need to compare how GTWS performs in relation to other indicators.

Based on SI regression with national annual crop production, all the indicators explain over 50% of variability in the national annual crop production (in most instances) except CHIRP and GLDAS (Fig. 10a). These results are largely consistent with those of *Bewket (2009)* and *Funk et al. (2003)* who found a good correlation between crops (teff, wheat, and maize) production and monthly rainfall anomalies over Ethiopia. VCI performs exceptionally well explaining between 67% and 93% of national annual crop production variability. GPCC

Figure 10: Ethiopian national annual crop (maize and wheat) production variability (R^2) reflected by various drought indices. VCI, GPCC, ERA, CPC, FLDASN, and FLDASV explained relatively higher crop production variabilities, while GLDAS explained lowest variability. The y axis indicates the crop (maize/wheat), SI (for a), and SA (for b) while 1, 3 and 6 indicate the standardization time scales for the indicators on the x axis.

explains higher percentage of national annual crop production variability than CHIRPS, which explains higher variability than CHIRP. In addition, ERA and CPC are seen to perform better than the rest, FLDASN and FLDASV explains largely equal variabilities while GLDAS explains the least national annual crop production variability.

SA regression generally explains higher annual crop production variabilities than SI (Fig 10b),

possibly due to the shorter duration considered. GTWS performs exceptionally well explaining between 92% – 99% of the variability in national annual crop production. In addition, FLDASN, FLDASV, CPC, VCI, and GPCC also explain high variabilities. Like in SI regression, GPCC outperformed CHIRPS, which performed better than CHIRP while FLDASN and FLDASV explain almost equal variabilities. Also, FLDASN explain more variability than GLDAS. However, the SA regression results should be interpreted with caution due to the shorter duration of the data considered.

The regression results, as pointed out in *Agutu et al. (2017)*, should not be generalized to other areas and time periods since the association of production (yield) with climatic conditions only holds if production factors e.g., areas under cultivation, and farm management practices, remain constant.

5. Discussion

The spatial patterns of rainfall, VCI, TWS, and majority of the soil moisture products derived drought indicators have been seen to mimic rainfall distribution and/or land cover patterns (Figs. 2 and 3 vis-a-vis Fig. 1b–c) both of which are majorly influenced by topographical changes (terrain variations). Topography is a major factor influencing rainfall distribution (see, e.g., *Dinku et al., 2007*; *Romilly and Gebremichael, 2011*; *Dinku et al., 2008*) and to a large extent the land cover classes over the region (*Kurnik et al., 2011*). The spatial variability of soil moisture is closely related to the scales under consideration i.e., at large scales, soil moisture spatial variability is associated with soil types, topography, and vegetation types while at small scales, precipitation and evapotranspiration play major roles (*Huang et al., 2012*; *Entin et al., 2000*). This explains the closeness of the majority of the SSI spatial patterns to the land cover classes and/or spatial rainfall distribution (Fig. 3 compared to Fig. 1a–c).

Region 3 (southeastern Ethiopia and Somalia) had high consistency in spatial and temporal patterns, largely equal percentage of variabilities explained by rainfall and moisture products, and high average correlation among different products (Figs. 2, 3, 4c, 5c and 6, and Table 4).

These could be attributed to relatively flats topography of the region coupled with low rainfall. The combination of flat topography and low rainfall does not seem to give much challenge to the different products in capturing spatio-temporal drought information from the region, hence the high consistency.

The variation in the mean differences in percentage of areas under drought due to gauge density was inversely related to the gauge density of both GPCC and CHIRPS (Figs. 7a, 1d, and *Funk et al. (2015)*). The mean percentage differences were lowest over Ethiopia and highest over Somalia (7.9% vis-a-vis 13.3%). Ethiopia has the highest gauge density from both GPCC and CHIRPS while Somalia has the lowest (Figs. 1d, and *Funk et al. (2015)*). Even though GPCC and CHIRPS have in-situ gauge measurements from global historical networks and global teleconnection networks (*Schneider et al., 2014; Funk et al., 2015*), the fluctuation in monthly number of stations available to each (see, e.g., variation in number of available stations for CHIRPS in *Funk et al. (2015)*) is the major source of this difference. In addition, this variation could also be contributed by the additional in-situ stations incorporated in GPCC but absent in CHIRPS (see, *Schneider et al., 2014; Funk et al., 2015*).

Other than gauge density, topographical factors were also found to contribute to the mean difference in percentage areas under drought (Figs. 7a and 1a). Somalia had the lowest mean difference in percentage of areas under drought (3.4%) while Ethiopia (11.3%) and South Sudan (12%) had highest mean differences. This could be due to the fact that Somalia with low topographical variation has low influence on how various products characterize rainfall while Ethiopia and South Sudan with rapid changing topography presents difficulty to various products (Fig. 1a). In general, the performance of GPCC is affected by systematic errors (errors associated with systematic gauge-measurements) and sampling errors associated with gauge densities (see, e.g., *Schneider et al., 2014*). The sampling errors are dependent on orography, season and type of rainfall, of which topography plays a large role hence differing performance across the regions. CHIRPS being a combination of satellite-based precipitation and in-situ observations, has its performance dependent on how well the infrared cold cloud

duration (CCD) observed precipitation estimates correspond to the actual rainfall and how effective the merging is done, while CHIRP purely depends on CCD (*Funk et al., 2015*). The degree of correspondence between the CCD estimated rainfall and the actual rainfall over a place is influence by topographical factors. It is the topography related difficulties in rainfall representation that translates to mean differences in percentage areas under drought on drought characterization employing these products. Similarly, the influence of gauge density and topographical variations on the mean differences in percentage of areas under different drought intensities (Fig. 9) follows the same logic as above.

The closer performance between FLDASN and FLDASV from temporal variability, higher correlations, lower mean differences in percent of areas under drought and different drought intensities, and explained amount of variabilities in crop production (Figs. 5, 8 a, 9 e - h, and 10) could be attributed to FLDASN and FLDASV being forced by CHIRPS rainfall. However, they are FLDAS versions driven by different models, Noah and VIC, respectively. Further, their lower mean differences compared to FLDASN and GLDAS, and the higher percentage of variabilities in crop production explained by FLDASN over GLDAS implies that forcing precipitation plays a bigger role in the resulting soil moisture than model difference. This is supported by the fact that both FLDASN and GLDASN are ouputs of the same model, Noah, but differing precipitation forcings; FLDASN is forced by CHIRPS while GLDASN is forced by Princeton global meteorological forcing data (see, e.g., *Sheffield et al., 2006; McNally et al., 2017*). The role of forcing precipitation in influencing the quality of resulting soil moisture has also been recognized in previous studies (see, e.g., *Dirmeyer et al., 1999, 2004; Entin et al., 1999*). In addition, different model characteristics such as different operating soil wetness thresholds, i.e., differing variances and mean values; and critical hydrological thresholds, e.g., beginning of surface run-off or levels of evaporation at the potential rate (*Dirmeyer et al., 2004*), contribute to the differences. Therefore, the largest differences occurred when different models with difference forcing precipitations were considered, e.g., FLDAS and MERRA.

Like gauge density based mean differences, the spatial distribution of the moisture mean

differences in percentage of areas under drought and different drought intensities were lower over Ethiopia and higher over Somalia (Figs. 8 a and Fig. 9 e - h). However, for the soil moisture products, this could be linked more to the amount of rainfall and/or moisture levels and the individual model thresholds over the region but not directly on topography since Ethiopia has more topography related issues than Somalia (see section 2.1). The influence of topography on the percentage of area differences from soil moisture product is indirectly through the forcing precipitation.

The larger mean differences in areas under moderate and extreme droughts than severe droughts observed in all the differences (both rainfall and soil moisture; Figs. 9) across the region could be linked to differences in extreme drought conditions, i.e., lower (moderate) and higher (extreme) as captured by these products. For the soil moisture products, it could be related to the drying thresholds implemented by different models.

Unlike in *Agutu et al. (2017)*, over East Africa where CHIRPS performed better than GPCC, here GPCC aided by a higher density of gauge distribution (and CHIRPS impeded by low and high varying number of incorporated in situ stations) explained higher variabilities in national annual crop production. Similar to *Agutu et al. (2017)*, FLDAS explained higher variabilities than GLDAS while MTWS and MERRA2 registered similar performances. The shorter duration regression results explain higher amount of variability in national annual crop production than the long duration probably due to the fact that under the short duration, the factors of production especially the areas under cultivation are constant. The influence of increase in areas under cultivation could be responsible for relatively lower percentage of variabilities explained, see e.g., *Taffesse et al. (2012)* who found a link between the increase in crop production and areas under cultivation over Ethiopia. The relationship between crop production (yields) and moisture availability (climate variables) holds subject to the area under cultivation and production factors (e.g., pesticides, fertilizers, and crop cultivars) being constant.

6. Conclusion

The study characterized agricultural drought over the upper GHA countries (Ethiopia, Sudan, South Sudan, and Somalia) using rainfall (CHIRPS, CHIRP, and GPCC), moisture (ERA-Interim, CPC, GLDAS, FLDAS Noah, FLDAS VIC, and MERRA2), and TWS (MERRA2 and GRACE) products with bias on the influence of topography and gauge density. Further, it considered the consistency of differences in the percentage of areas under drought and different drought intensities from precipitation and selected moisture products. Finally, it evaluated the effectiveness of various drought indicators in explaining agricultural drought over Ethiopia using national annual crop production. The following were the major results:

- (i) The spatial-temporal drought patterns were found to be influenced by topography over the region. All the products were highly consistent over the low land low-medium rainfall regions of Eastern Ethiopian and Somalia while lowest consistency differed across products and regions.
- (ii) The mean differences in percentages of areas under drought (15.87%) and different drought intensities (6.16%) from precipitation products were determined by gauge density (distribution and availability) and topography. The mean differences attributed to gauge density were low in areas of high gauge density (Ethiopia) and higher in areas of low gauge density (Somalia) while the mean differences attributed to topography were low in low varying topographical areas (Somalia) and higher in rapid varying topographical areas (Ethiopia and South Sudan).
- (iii) The mean differences in percentages of areas under drought (12.65%) and different drought intensities (5.20%) from soil moisture products was determined by the differences in the forcing precipitation, models pairs under consideration, and the regions.
- (iv) In evaluating the utility of various indicators in explaining agricultural drought over Ethiopia, the following were identified as suited for agricultural drought monitoring during the study period; VCI, GPCC, ERA, CPC, and FLDAS (Noah and VIC).

The information on the consistency of percentage of areas under drought and different drought intensities is critical in understanding and putting into perspective drought analysis results from different products over the region by various stakeholders. This is important for policy and decision makers as it could inform their decision on the number of people affected and the extent to which they are affected without worrying about particular product, e.g., soil moisture used in any particular analysis. These particular decisions are essential for resource mobilization, aiding mitigation of drought impacts, improving drought response plans and early warning systems, and quantifying drought impacts among others.

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