Remote Sensing of Environment 194 (2017) 287–302

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

Assessing multi-satellite remote sensing, reanalysis, and land surface models' products in characterizing agricultural drought in East Africa

N.O. Agutu[a,b,*], J.L. Awange[a,c], A. Zerihun[d], C.E. Ndehedehe[a], M. Kuhn[a], Y. Fukuda[c]

[a] Department of Spatial Sciences, Curtin University Perth, Australia
[b] Department of Geomatic Engineering and Geospatial Information Systems, JKUAT, Nairobi, Kenya
[c] Department of Geophysics, Kyoto University, Japan
[d] Centre for Crop and Disease Management, Department of Environment and Agriculture, Curtin University, Perth, Australia

ARTICLE INFO

Article history:
Received 4 July 2016
Received in revised form 15 March 2017
Accepted 30 March 2017
Available online 8 April 2017

Keywords:
Agricultural drought
East Africa
Partial least squares regression
Rotated principal component analysis
Rainfall
Standardized anomalies
Standardized index
SPI
Soil moisture
TWS
VCI

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.

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., Loewenberg, 2011; Rojas et al., 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 (IFRC, 2011; Kurnik et al., 2011; Loewenberg, 2011; Nicholson, 2014; 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 (Naumann et al., 2014; Nicholson, 2014; Rojas et al., 2011). 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

* Corresponding author.
E-mail address: nathanagutu01@gmail.com (N.O. Agutu).

http://dx.doi.org/10.1016/j.rse.2017.03.041

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 (AghaKouchak et al., 2009; Damberg and AghaKouchak, 2014; Hong et al., 2006; Naumann et al., 2014; Rojas et al., 2011).

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., Bayarjargal et al., 2006; Kogan, 1995; Rhee et al., 2010). 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., Tapley et al., 2004; Wouters et al., 2014) in EA has been limited to monitoring changes in TWS (e.g., Awange et al., 2008, 2013; Becker et al., 2010; Swenson and Wahr, 2009), and recently drought analysis (Awange et al., 2016).

Currently, drought studies carried out in the EA region range from purely precipitation based (e.g., Clark et al., 2003; Kurnik et al., 2011; Naumann et al., 2014), a combination of precipitation and climate models (e.g., Dutra et al., 2013; Yang et al., 2014a), to precipitation in combination with soil moisture and/or NDVI (e.g., AghaKouchak, 2015; Anderson et al., 2012; Nicholson, 2014). Some of the aforementioned studies and few others (see, e.g., Anderson et al., 2012; Mwangi et al., 2014; Rojas et al., 2011; Shukla et al., 2014) 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.

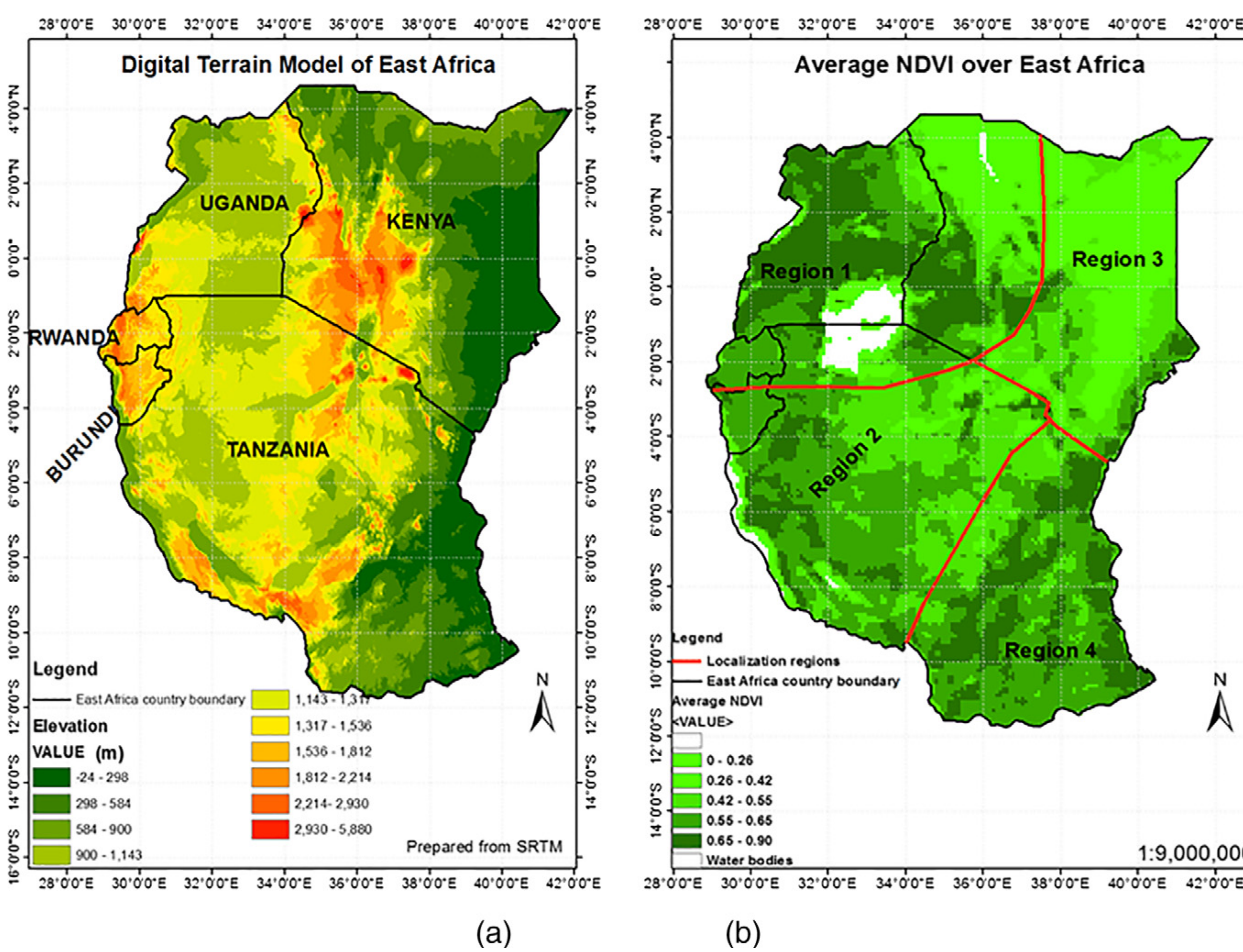

Fig. 1. East Africa (EA) region; (a) Elevation variation from Shuttle Radar Topographical Mission (SRTM, source: http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database), (b) Temporal NDVI average (1983–2014) with standardised indices localization regions (see Fig. 2 and Table 3 for region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