Response to Anonymous Referee #1

Thank you very much indeed for inviting me to review this paper. Having access to high-resolution drought dataset, especially in data-scarce region, is important for drought monitoring and management at watershed/ districts levels. I can be wetness that the paper "A pan-African high-resolution drought index dataset" could produce a valid significance for the African continent particularly in the drought vulnerable areas. This dataset is timely, and the paper is fully readable and has a good basis. When authors address the following comments and suggestions, I recommend acceptance.

Response: Many thanks indeed for your positive evaluation and constructive comments. We have revised the manuscript carefully according to your comments and suggestions. In the following, we provide an item-by-item response to your comments. Your comments are written in italic black color; our responses are shown in upright font blue color.

Comments

Line 35; I couldn't get the access to the dataset.

Response: Thanks. We have contacted CEDA team to solve the problem. The data are available now from the link.

Line 38-39; delete the key- words written in the title (i.e., high-resolution, drought index)

Response: Done.

Line 78-79; insert "and/or" between "runoff, groundwater deficiency"

Response: Done.

Line 80; references should be ordered in terms of publication year and authors alphabet. And do the same for the rest in the manuscript

Response: Thanks, changed.

Line 90; curiosity on using words/phrases "no best drought index", as multiscalar and multivariate drought indices are better than the single ones

Response: Thanks for your comment. The phrase here is reported by Van Loon (2015), which intends to note that there is no single index which is the best index and suitable for all kinds of drought events (meteorological, agricultural, hydrological, socioeconomic and environmental).

Line 93; change 'not enough' by 'inadequate'

Response: Done.

Line 113, curiosity on using words/phrases "too course".

Response: The term 'coarse' here refers to existing global products with spatial resolution of 50 km and 100 km. These datasets are not possible to provide detailed drought information at km scale that is required in district or sub-basin scale applications.

Line 121, Explain how the SPEI-HR dataset will be usefully to minimize the impact of water and food security and support to policymakers and the social sectors.

Response: Thanks for the comment. The important feature of SPEI-HR is its high spatial resolution compared to other coarse resolution datasets. The SPEI-HR dataset can be used to provide quantified drought conditions at sub-basin scales, which are essential for managing drought-related risks. One application of SPEI-HR for minimizing the drought impact on food security is our UK Space Agency's International Partnership Programme (417000001429). We have developed a framework to predict crop yield which can be used to infer the influence of droughts on agriculture and economics in general and specifically in Ethiopia.

Line 127, How can we sure that SPEI-HR can provide near-real time drought monitoring?

Response: The CHIRPS dataset is available from 1981 to near-real time, while GLEAM will be delivered in higher resolution and in near-real time. The idea here is to update SPEI-HR based on GHIRPS and GLEAM on a regular basis to make it near-real time.

Line 128; I have no problem with the name but I wonder why authors used Pan-Africa to represent the African continent. Does it actually represent the whole continent?

Response: It is a good question. The idea of using Pan-Africa is inspired by Pan-Africanism (https://en.wikipedia.org/wiki/Pan-Africanism). There is no difference for this study using either Pan-African or African.

Line 129; and any plan to provide data continuously in the future.

Response: Yes, the dataset is planned to be updated when there are new CHIRPS and GLEAM datasets released.

Line 147; I am interested to know if your or any other studies are undertaken in Africa, using CHIRPS for drought assessment. Better if you explain why you chose this dataset for Africa. This is helpful if you refer to studies done in Africa. And the same for the potential evaporation

Response: Thanks for your suggestions. The motivation of using CHIRPS for Africa is because it was recently validated over East Africa and Mozambique and demonstrated good performance compared to other precipitation datasets (Toté et al., 2015; Dinku et al., 2018). Furthermore, CHIRPS was specifically designed for drought monitoring over regions with deep convective precipitation, scarce observation networks and complex topography (Funk et al., 2014). Several studies (e.g., Toté et al., 2015; Guo et al., 2017) have used CHIRPS for drought monitoring. Similarly, GLEAM evaporation products have been widely validated/evaluated over Africa (e.g., Trambauer et al., 2014, Zhan et al., 2019). In particular, two recent studies detected global drought conditions based on GLEAM potential and actual evaporation data (Vicente-Serrano et al., 2018; Peng et al., 2019c).

Line 168, 179 and 188; explain why you have chosen these datasets in the context of Africa.

Response: All these datasets have been validated and applied by many studies. Specifically, the GLEAM root zone soil moisture is the unique long-term root zone soil moisture product that is generated based on ESA CCI surface soil moisture. And the root zone soil moisture is more relevant to drought monitoring than satellite-based surface soil moisture. The CRU-TS datasets were used because the coarse SPEIbase dataset was produced from CRU-TS datasets. And the SPEIbase dataset has been used for drought related studies in Africa. The GIMMS NDVI dataset has been selected because it has been widely applied to investigate the effects of drought on vegetation in many areas including Africa (e.g., Rojas et al., 2011; Vicente-Serrano et al., 2013; Törnros and Menzel, 2014; Vicente-Serrano et al., 2018).

Line 200-201, make sure 'The negative and positive SPEI values 201 respectively indicate dry and wet conditions' is correct.

Response: Yes. The SPEI negative values indicate dry conditions while positive values correspond to wet conditions.

Line 204-205; how did you mask out and how did you manage it in your dataset

Response: The MODIS land cover product was used to mask out the sparsely vegetated and barren areas in the SPEI datasets. All the datasets were preprocessed to have same projection (geographic lat/lon) and grid size using Python.

Line 210, insert 'full stop (.)' after 'Vicente-Serrano et al., 2013)'

Response: Done, thanks.

Line 296, why the correlations have become low, any possible reasons

Response: The lower correlations against NDVI than against RSM are likely due to complex physiological processes associated to vegetation, and the fact that ecosystem state is driven by multiple variables other than water availability. Similar results have been reported by Nemani et al., 2003.

Line 313, What value does the y-axis represent in figure 4 and 5

Response: As mentioned in section 2.3.2 'To facilitate direct comparison between SPEI and NDVI as well as RSM, both NDVI and RSM are standardized by subtracting their corresponding (1981–2016) mean and expressed the resulting anomalies as numbers of standard deviations.', the y-axis has no unit and represents both SPEI and standardized NDVI and RSM.

Finally, it will be very helpful if you include discussions on how the SPEI-HR is correlated with each of the drought types (meteorological, agricultural and hydrological). This can be useful to plan for short and long-term drought events mitigation based on the datasets provided.

Response: Thanks for the suggestions. SPEI is similar to SPI when representing drought types. In general, the short time scale (e.g., 1 and 3 month) SPI/SPEI is more suitable for identifying agriculture drought. When the time scale increases, the SPI/SPEI is more relevant for hydrological drought. There are many studies using different time scales of SPI/SPEI to represent different types of droughts. In the manuscript, the sentence below describes the ability of SPI/SPEI for representing different types of droughts.

"The advantages of SPI are its relative simplicity and its ability to characterize different types of droughts given the different times of response of different usable water sources to precipitation deficits (Kumar et al., 2016; Zhao et al., 2017)."

Response to Anonymous Referee #2

Comments on the manuscript entitled "A pan-African high-resolution drought index dataset"

Drought is recurring and posing a certain threat to water resource and food security around the globe. Accurate and timely monitoring of droughts is essential for many applications to mitigate the potential impacts. The study aimed to generate a new high-resolution drought monitoring dataset with satellite observations, which provides a timely contribution to the scientific community. I think the produced product has a great potential to benefit drought study in Africa. To the best of my knowledge, high resolution drought dataset is not existing in the community. The widely used SPI/SPEI indices are normally based on interpolated ground measurements and have spatial resolution of 0.5 degree (~50 km). The use of satellite products is a novel way, and should be highly encouraged. Although 5 km is still quite coarse for agriculture applications, it might be useful for other applications e.g., regional hydrological/meteorological drought monitoring. Based on my review, I think the presented dataset adds great values for drought related applications in Africa. The manuscript is well written. The newly generated product is clearly described. I have a few fairly minor comments/suggestions below for the authors to consider for further improving the manuscript.

Response: Many thanks indeed for your positive evaluation and constructive comments. We have revised the manuscript carefully according to your comments and suggestions. In the following, we provide an item-by-item response to your comments. Your comments are written in italic black color; our responses are shown in upright font blue color.

1. Unlike other hydrological disasters such as flood, drought is very hard to define. To this regard, there are no agreements on its definition and hundreds of drought indices have been proposed in last decades. Why do the authors choose SPEI? Why not using PDSI or others widely recognized and used index? For practical applications, how should end-user use your dataset to monitor drought? The information is missing in the manuscript, and I advise the authors to elaborate on this aspect.

Response: Thanks for your comments and questions. The motivation of choosing SPEI rather than other drought index is mainly due to its relative simplicity, which allows us to produce a high spatial resolution drought dataset that entirely replies on satellite-based products. In addition, SPEI has the ability to characterize different types of droughts given the different times of response of different usable water sources to precipitation deficits (Kumar et al., 2016; Zhao et al., 2017). Regarding practical applications, there is a wide range of studies that have used SPEI for different types of droughts. In addition, the SPEI negative values indicate dry conditions while positive values correspond to wet conditions. The table below has been added in the revised manuscript to show the categories of dry and wet conditions indicated by SPEI values.

Table 1. Categories of dry and wet conditions indicated by SPEI values.

SPEI	Category
2 and above	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

2. Drought is a global disaster and deserves research at global scale. As far as I know, the satellite products used in your dataset like CHIRPS, GLEAM cover nearly entire globe (e.g. 50 dgree N-S). Why do you only focus on Africa? Why not extending to the global scale?

Response: It is a good point. Theatrically, Yes, the dataset can be extended to global scale. The current study is supported by the UK Space Agency's International Partnership Programme (417000001429), which aims to focus on Africa. However, the whole framework has been established, we can produce the SPEI-HR at any regions once there is a request from potential users.

3. Regarding evaluation of your dataset, indirect comparison is definitely informative. Direct evaluation against ground-based measurements is essential. This part is missing in the current manuscript.

Response: Thanks for the suggestion. We fully agree validation with ground-based measurement is important. However, it is very challenging to implement due to the missing of ground-based measurements for both precipitation and potential evapotranspiration. As stated in the manuscript, the CHIRPS dataset has been validated in Africa with in situ measurements. However, the ground-based potential evapotranspiration measurement is not available in Africa, which hampers the calculation of SPEI using ground-based measurements. Therefore, we use indirect comparison to present the validity of generated SPEI dataset.

Response to Gebremedhin Haile

I am eager to use this dataset. I believe that this dataset will be very valuable and helpful in Africa where data is limited. I like how the paper is written, it is very informative.

Response: Many thanks indeed for your positive evaluation and suggested references. We have carefully revised the manuscript according to your comments. In the following, we provide an item-by-item response to your comments. Your comments are written in italic black color; our responses are shown in upright font blue color.

I have the following two minor comments that needs to be considered

Authors used high resolution datasets to develop the dataset. However, other criterias should have been considered. For example, supportive evidence should be provided as to whether CHIRPS is recommended for Africa or not. And the same for the other datasets used to develop this dataset. I also recommend to include the following recent researches on Africa and global to further enrich the quality of the paper.

https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-12-00124.1
https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-16-0287.1
https://www.nature.com/articles/s41586-019-1149-8
https://www.sciencedirect.com/science/article/abs/pii/S0012825218303519
https://www.nature.com/articles/ngeo2646
https://onlinelibrary.wiley.com/doi/abs/10.1002/wc
https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-11-00176.1
https://journals.ametsoc.org/doi/full/10.1175/BAMS-D-11-00212.1

Response: Thanks for the comments and suggestions. We fully agree. Please see our detailed responses to Referee #1 on the motivation of choosing different products. In addition, the relevant references that support the validity of CHIRPS and other datasets in Africa have been added in the revised manuscript. Most of your suggested references have also been integrated into the revised manuscript. Thanks very much.

A pan-African high-resolution drought index dataset

Jian Peng [1,2], Simon Dadson [1], Feyera Hirpa [1], Ellen Dyer [1], Thomas Lees [1], Diego G. Miralles [3], Sergio M. Vicente-Serrano [4], Chris Funk [5,6]

1. School of Geography and the Environment, University of Oxford, OX1 3QY Oxford, UK;
2. Max Planck Institute for Meteorology, Hamburg, Germany;
3. Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium;
4. Instituto Pirenaico de Ecología, Consejo Superior de Investigaciones Científicas (IPE-CSIC) Zaragoza, Spain;
5. U.S. Geological Survey, Earth Resources Observation and Science Center, Sioux Falls, South Dakota;
6. Santa Barbara Climate Hazards Center, University of California, USA;

Corresponding author: Jian Peng (jian.peng@ouce.ox.ac.uk)

Abstract

Droughts in Africa cause severe problems such as crop failure, food shortages, famine, epidemics and even mass migration. To minimize the effects of drought on water and food security over Africa, a high-resolution drought dataset is essential to establish robust drought hazard probabilities and to assess drought vulnerability considering a multi- and cross-sectorial perspective that includes crops, hydrological systems, rangeland, and environmental systems. Such assessments are essential for policy makers, their advisors, and other stakeholders to respond to the pressing humanitarian issues caused by these environmental hazards. In this study, a high spatial resolution Standardized Precipitation-Evapotranspiration Index (SPEI) drought dataset is presented to support these assessments. We compute historical SPEI data based on Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) precipitation estimates and Global Land Evaporation Amsterdam Model (GLEAM) potential evaporation estimates. The high resolution SPEI dataset (SPEI-HR) presented here spans from 1981 to 2016 (36 years) with 5 km spatial resolution over the whole Africa. To facilitate the diagnosis of droughts of different durations, accumulation periods from 1 to 48 months are provided. The quality of the resulting dataset was compared with coarse-resolution SPEI based on Climatic Research Unit (CRU) Time-Series (TS) datasets, and Normalized Difference Vegetation Index (NDVI) calculated from the Global Inventory Monitoring and Modeling System (GIMMS) project, as well as with root zone soil moisture modelled by GLEAM. Agreement found between coarse resolution SPEI from CRU TS (SPEI-CRU) and the developed SPEI-HR provides confidence in the estimation of temporal and spatial variability of droughts in Africa with SPEI-HR. In addition, agreement of SPEI-HR versus NDVI and root zone soil moisture – with average correlation coefficient (R) of 0.54 and 0.77, respectively – further implies that SPEI-HR can provide valuable information to study drought-related processes and societal impacts at sub-basin and district scales in Africa. The dataset is archived in Centre for Environmental Data Analysis (CEDA) with link: http://dx.doi.org/10.5285/bbdfd09a04304158b366777eba0d2aeb (Peng et al., 2019a)

Keywords:

Drought, Africa, Precipitation, Potential evaporation, drought management, disaster risk reduction

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1 Introduction

Drought is a complex phenomenon that affects natural environments and socioeconomic systems in the world (von Hardenberg et al., 2001; Vicente-Serrano, 2007; Van Loon, 2015; Wilhite and Pulwarty, 2017). Impacts include crop failure, food shortage, famine, epidemics and even mass migration (Wilhite et al., 2007; Ding et al., 2011; Zhou et al., 2018). In recent years, severe events have occurred across the world, such as the 2003 central Europe drought (García-Herrera et al., 2010), the 2010 Russian drought (Spinoni et al., 2015), the 2011 Horn of Africa drought (Nicholson, 2014), the southeast Australian's Millennium drought (van Dijk et al., 2013; Peng et al., 2019d), the 2013/2014 California drought (Swain et al., 2014), the 2014 North China drought (Wang and He, 2015) and the 2015–2017 Southern Africa drought (Baudoin et al., 2017; Muller, 2018). Widespread negative effects of these droughts on natural and socioeconomic systems have been reported afterwards (Wegren, 2011; Arpe et al., 2012; Griffin and Anchukaitis, 2014; Mann and Gleick, 2015; Dadson et al., 2019; Marvel et al., 2019). Thus, there is a clear need to improve our knowledge about the spatial and temporal variability of drought, which provides a basis for quantifying drought impacts and the exposure of society, the economy and the environment over different areas and time-scales (Pozzi et al., 2013; AghaKouchak et al., 2015).

Generally, drought is defined as a temporal anomaly characterized by a deficit of water compared with long-term conditions (Mishra and Singh, 2010; Van Loon, 2015). Droughts can typically be grouped into five types: meteorological (precipitation deficiency), agricultural (soil moisture deficiency), hydrological (runoff and/or groundwater deficiency), socioeconomic (social response to water supply and demand) and environmental or ecologic (Keyantash and Dracup, 2002; AghaKouchak et al., 2015; Crausbay et al., 2017). These different drought categories involve different event characteristics in terms of timing, intensity, duration, and spatial extent, making it very difficult to characterize droughts quantitatively (Panu and Sharma, 2002; Lloyd-Hughes, 2014; Vicente-Serrano, 2016). For this reason numerous drought indices have been proposed for precise applications, and reviews of the available indices have been provided by previous studies such as Heim Jr (2002), Keyantash and Dracup (2002), and Mukherjee et al. (2018). Van Loon

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(2015) noted that there is no best drought index for all types of droughts, because every index is designed for a specific drought type, thus multiple indices are required to capture the multifaceted nature of drought. Nevertheless, the Standardized Precipitation Index (SPI) is recommended by the World Meteorological Organization (WMO) for drought monitoring, which is calculated based solely on long-term precipitation data over different time spans (McKee et al., 1993). The advantages of SPI are its relative simplicity and its ability to characterize different types of droughts given the different times of response of different usable water sources to precipitation deficits (Kumar et al., 2016; Zhao et al., 2017). However, information on precipitation is inadequate to characterize drought; in most definitions, drought conditions also depend on the demand of water vapor from the atmosphere. More recently, Vicente-Serrano et al. (2010) proposed an alternative drought index for SPI, which is called Standardized Precipitation Evapotranspiration Index (SPEI). Compared to SPI, it considers not only the precipitation supply, but also the atmospheric evaporative demand (Beguería et al., 2010; Vicente-Serrano et al., 2012b). This makes the index more informative of the actual drought effects over various natural systems and socioeconomic sectors (Vicente-Serrano et al., 2012b; Bachmair et al., 2016; Kumar et al., 2016; Sun et al., 2016c; Bachmair et al., 2018; Peña-Gallardo et al., 2018a; Peña-Gallardo et al., 2018b; Sun et al., 2018).

For the calculation of SPEI, high-quality and long-term observations of precipitation and atmospheric evaporative demand are necessary. These observations may either come from ground-based station data or gridded data such as satellite and reanalysis datasets. For example, the SPEIbase (Beguería et al., 2010) and the Global Precipitation Climatology Centre Drought Index (GPCC-DI) (Ziese et al., 2014) both provide SPEI datasets at global scale. The SPEIbase provides gridded SPEI with a 50-km spatial resolution, and is calculated from Climatic Research Unit (CRU) Time-Series (TS) datasets, which are produced based on measurements from more than 4000 ground-based weather stations over the world (Harris et al., 2014). The SPEI dataset provided by GPCC-DI has spatial resolution of 1°, and was generated from GPCC precipitation (Becker et al., 2013; Schneider et al., 2016) and National Oceanic and Atmospheric Administration (NOAA)'s Climate Prediction Center (CPC) temperature dataset (Fan and Van den Dool, 2008). Both of

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these datasets have been applied for various drought related studies at global and regional scales (e.g., Chen et al., 2013; Vicente-Serrano et al., 2013; Isbell et al., 2015; Sun et al., 2016a; Vicente-Serrano et al., 2016; Deo et al., 2017). However, these global SPEI data sets' spatial resolution are too coarse to be applied at district or sub-basin scales (Vicente-Serrano et al., 2017). A sub-basin scale quantification of drought conditions is particularly crucial in regions such as Africa, in which geospatial data and drought indices can be essential to manage existing drought-related risks (Vicente-Serrano et al., 2012a) and where in-situ measurements are scarce (Trambauer et al., 2013; Masih et al., 2014; Anghileri et al., 2019). Over last century, Africa has been severely influenced by intense drought events, which has led to food shortages and famine in many countries (Anderson et al., 2012; Yuan et al., 2013; Sheffield et al., 2014; Awange et al., 2016; Funk et al., 2018; Nicholson, 2018; Gebremeskel et al., 2019). Therefore, the availability of a high-resolution drought index dataset may contribute to an improved characterization of drought risk and vulnerability, and minimize its impact on water and food security by supporting policy makers, water managers and stakeholders. Conveniently, with the advancement of satellite technology, the estimation of precipitation and evaporation from remote sensing datasets is becoming more accurate (Fisher et al., 2017). In particular, the long-term Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) (Funk et al., 2015a) precipitation and Global Land Evaporation Amsterdam Model (GLEAM) (Miralles et al., 2011) evaporation datasets provide high-quality datasets for near-real time drought monitoring. Here, we use CHIRPS and GLEAM datasets to develop a pan-African high spatial resolution (5-km) SPEI dataset, which may be useful to inform drought relief management strategies for the continent. The dataset covers the period from 1981 to 2016 and it is comprehensively inter-compared with soil moisture, vegetation index and coarse resolution SPEI datasets.

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2 Data and Methodology

2.1 Data

2.1.1 CHIRPS

CHIRPS is a recently-developed high-resolution, daily, pentadal, dekadal, and monthly precipitation dataset (Funk et al., 2015a). It was produced by blending a set of satellite-only precipitation values (CHIRP) with additional monthly and pentadal station observations. The CHIRP is based on infrared cold cloud duration (CCD) estimates calibrated with the Tropical Rainfall Measuring Mission Multi-satellite Precipitation Analysis version 7 (TMPA 3B42 v7) and the Climate Hazards group Precipitation climatology (CHPclim) The CHP$_{clim}$ (Funk et al., 2015a; Funk et al., 2015e) is based on station data from the Food and Agriculture Organization (FAO) and the Global Historical Climate Network (GHCN). Compared with other global precipitation datasets such as Multi-Source Weighted-Ensemble Precipitation (MSWEP) (Beck et al., 2017) and Global Precipitation Climatology Project (GPCP) (Adler et al., 2003), CHIRPS has several advantages: a long period of record, high spatial resolution (5-km), low spatial biases and low temporal latency. It has been widely validated and applied in various applications (e.g., Shukla et al., 2014; Maidment et al., 2015; Duan et al., 2016; Zambrano-Bigiarini et al., 2017; Rivera et al., 2018). In particular, it was recently validated over East Africa and Mozambique and demonstrated good performance compared to other precipitation datasets (Toté et al., 2015; Dinku et al., 2018). Furthermore, CHIRPS was specifically designed for drought monitoring over regions with deep convective precipitation, scarce observation networks and complex topography (Funk et al., 2014). Several studies (e.g., Toté et al., 2015; Guo et al., 2017) have used CHIRPS for drought monitoring. Its high spatial resolution makes it particularly suitable for local-scale studies, such as sub-basin drought monitoring, especially in areas with complex topography. The detailed description of the dataset was provided by Funk et al. (2015a). In this study, daily CHIRPS precipitation from 1981 to 2016 was used.

2.2.2 GLEAM

GLEAM is designed to estimate land surface evaporation and root-zone soil moisture from remote sensing observations and reanalysis data (Miralles et al., 2011; Martens et al., 2017). Specifically, the Priestley-Taylor equation is used to calculate potential evaporation within GLEAM based on near surface temperature and net radiation, while the root zone soil moisture is obtained from a multilayer water balance driven by

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precipitation observations and updated with microwave soil moisture estimates (Martens et al., 2017). The actual evaporation is estimated by constraining potential evaporation with a multiplicative evaporative stress factor based on root-zone soil moisture and Vegetation Optical Depth (VOD) estimates. The GLEAM version 3a (v3a) provides global daily potential and actual evaporation, evaporative stress conditions and root zone soil moisture from 1980 to 2018 at spatial resolution of 0.25° (Martens et al., 2017) (see www.gleam.eu). GLEAM datasets have already been comprehensively evaluated against FLUXNET observations and used for multiple hydro-meteorological applications (Greve et al., 2014; Miralles et al., 2014; Trambauer et al., 2014; Forzieri et al., 2017; Lian et al., 2018; Richard et al., 2018; Vicente-Serrano et al., 2018; Zhan et al., 2019). In particular, two recent studies detected global drought conditions based on GLEAM potential and actual evaporation data (Vicente-Serrano et al., 2018; Peng et al., 2019c). For this study, the GLEAM potential evaporation and root zone soil moisture were used.

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2.2.3 CRU-TS

The global gridded CRU-TS datasets provide most widely-used climate variables including precipitation, potential evaporation, diurnal temperature range, maximum and minimum temperature, mean temperature, frost day frequency, cloud cover and vapour pressure (Harris et al., 2014). The CRU TS datasets were produced using angular-distance weighting (ADW) interpolation based on monthly meteorological observations collected at ground-based stations across the world. The recently-released CRU TS version 4.0.1 covers the period 1901–2016 and provides monthly data at 50-km spatial resolution. The CRU TS datasets have been widely used for various applications since their release (e.g., van der Schrier et al., 2013; Chadwick et al., 2015; Delworth et al., 2015; Jägermeyr et al., 2016). The SPEIbase dataset was generated from CRU TS datasets (Beguería et al., 2010). In this study, the CRU TS precipitation and potential evaporation from 1981 to 2016 were used.

2.2.4 GIMMS NDVI

The Normalized Difference Vegetation Index (NDVI) can serve as a proxy of vegetation status and has been widely applied to investigate the effects of drought on vegetation (e.g., Rojas et al., 2011; Vicente-Serrano et al., 2013; Törnros and Menzel, 2014; Vicente-Serrano et al., 2018). The Global Inventory Monitoring and Modeling System (GIMMS) NDVI was generated based on Advanced Very High Resolution Radiometer (AVHRR) observations, and has accounted for various deleterious effects such as orbital drift, calibration loss and volcanic eruptions (Beck et al., 2011; Pinzon and Tucker, 2014). For the current study, the latest version of GIMMS NDVI (3g.v1) was used, which covers the time period from 1981 to 2015 at biweekly temporal resolution and 8-km spatial resolution (Pinzon and Tucker, 2014).

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2.3 Methods

2.3.1 SPEI calculation

The SPEI proposed by Vicente-Serrano et al. (2010) has been used for a wide variety of agricultural, ecological and hydro-meteorological applications (e.g., Schwalm et al., 2017; Naumann et al., 2018; Jiang et al., 2019). It accounts for the impacts of evaporation demand on droughts and inherits the simplicity and multi-temporal characteristics of SPI. The procedure for SPEI calculation includes the estimation of a climatic water balance (namely the difference between precipitation and potential evaporation), the aggregation of the climatic water balance over various time-scales (e.g., 1, 3, 6, 12, 24, or more months), and a fitting to a certain parameter distribution. As suggested by Beguería et al. (2014) and Vicente-Serrano and Beguería (2016), the log-logistic probability distribution is best for SPEI calculation, from which the probability distribution of the difference between precipitation and potential evaporation can be calculated as suggested by Vicente-Serrano et al. (2010) and Beguería et al. (2014). The negative and positive SPEI values respectively indicate dry and wet conditions. Table 1 summarizes the category of dry and wet conditions based on SPEI values. In this study, the CHIRPS and GLEAM datasets were used for SPEI calculation at high spatial resolution (5-km). For comparison, the SPEI at 50-km was also calculated based on CRU TS datasets for the same 1981–2016 period. It should be noted that the SPEI over sparsely vegetated and barren areas were masked out based on Moderate Resolution Imaging Spectroradiometer (MODIS) land cover

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product (MCD12Q1) (Friedl et al., 2010), because SPEI is not reliable over these areas (Beguería et al., 2010; Beguería et al., 2014; Zhao et al., 2017).

Table 1. Categories of dry and wet conditions indicated by SPEI values.

SPEI	Category
2 and above	Extremely wet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 and less	Extremely dry

2.3.2 Evaluation criteria

The SPEIbase dataset (Beguería et al., 2010) was calculated with CRU TS dataset, which has been evaluated and applied by many studies (e.g., Chen et al., 2013; Vicente-Serrano et al., 2013; Isbell et al., 2015; Sun et al., 2016a; Greenwood et al., 2017; Um et al., 2017). The newly-generated SPEI at high spatial resolution based on CHIRPS and GLEAM (SPEI-HR) is compared temporally and spatially with the SPEI calculated from CRU TS datasets. In addition, the NDVI can also serve as an indicator for drought and vegetation health, and to assess the performance of drought indices (Vicente-Serrano et al., 2013; Aadhar and Mishra, 2017). Furthermore, root zone soil moisture is an ideal hydrological variable for agricultural (soil moisture) drought monitoring. The recently-released root zone soil moisture (RSM) from GLEAM v3 provides a great opportunity to evaluate whether soil moisture drought is well represented by SPEI. To facilitate direct comparison between SPEI and NDVI as well as RSM, both NDVI and RSM are standardized by subtracting their corresponding (1981–2016) mean and expressed the resulting anomalies as numbers of standard

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deviations. This standardization has been applied by many studies to evaluate drought indices (Anderson et al., 2011; Mu et al., 2013; Zhao et al., 2017). The correlation between SPEI and the standardized NDVI and RSM is quantified using Pearson's correlation coefficient (R). In addition, the high resolution SPEI from GLEAM and CHIRPS is also resampled to the same grid size of SPEI from CRU TS in order to quantify their correlation and disentangle whether the added value of the former arises from its increased accuracy or higher resolution. In the following part, the high (5-km) resolution SPEI is referred to SPEI-HR, while the coarse 50-km resolution SPEI is referred to SPEI-CRU.

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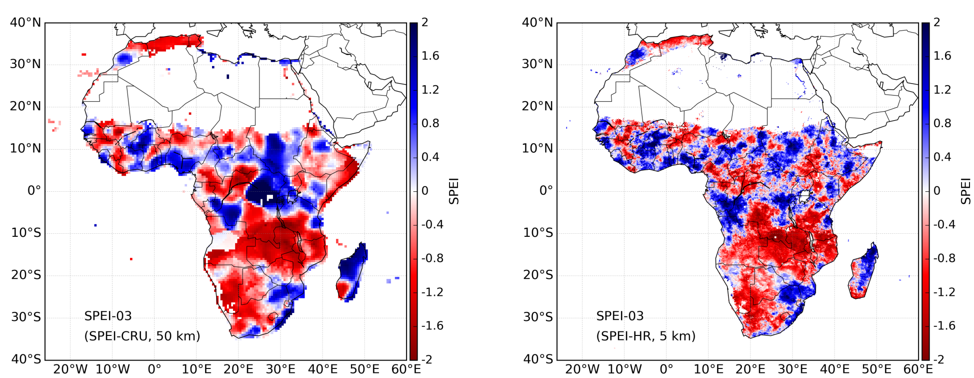
3 Results and discussion

3.1 Inter-comparison between high- and coarse-resolution SPEI

Figure 1 shows the spatial distribution of SPEI-HR and SPEI-CRU at different resolutions for an example month (June 1995). Figure 1a,b show the 3-month SPEI and 12-month SPEI, respectively. It can be seen that the high resolution and coarse resolution SPEI display quite similar dry and wet patterns over the whole of Africa for both temporal scales. However, as expected, the SPEI-HR shows much more spatial detail that reflects mesoscale geographic and climatic features, which highlights the advantages of this new dataset. The differences in patterns between 3-month and 12-month SPEI indicate the different water deficits caused by different aggregation time scales, which can further separate agricultural, hydrological, environmental, and other droughts. For example, in June 1995 southern Africa showed persistent dry conditions over a prolonged period, while western Africa only showed a short-term drought.



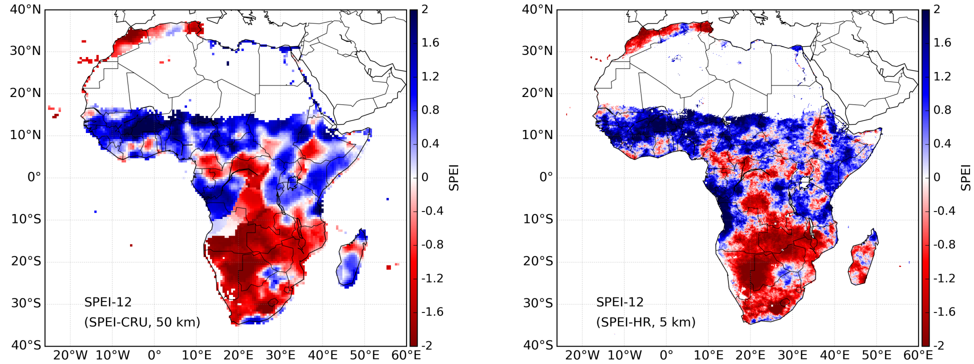
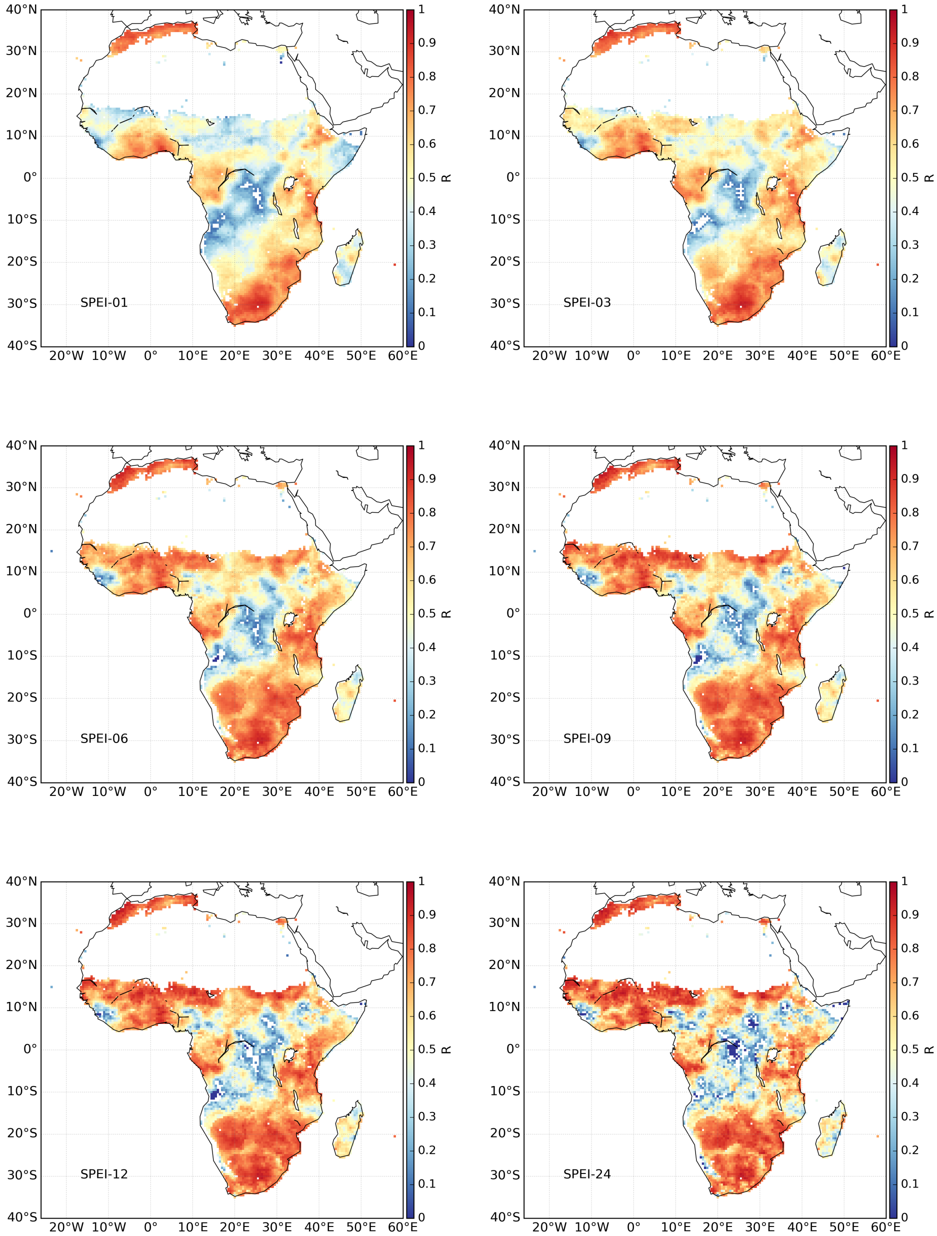


Figure 1: Spatial patterns of 3-month and 12-month SPEI at high spatial resolution (5 km) and coarse spatial resolution (50 km) in June, 1995. The high spatial resolution SPEI (SPEI-HR) is based on CHIRPS precipitation and GLEAM potential evaporation, while the coarse spatial resolution SPEI (SPEI-CRU) is calculated from CRU TS datasets.

In order to quantify how different is SPEI-HR from SPEI-CRU, the correlation between them is calculated for each grid cell over the whole study period. Figure 2 shows the correlations for time-scales 1, 3, 6, 9, 12, 24, 36, and 48 months. In general, the SPEI-HR and SPEI-CRU agree well in terms of temporal variability with high positive correlations over most of Africa for every time scale. However, relatively low correlations appear in central Africa, and they become lower as the SPEI time-scale increases. This region has very few station observations. It should be noted that the correlations shown here are statistically significant with p value less than 0.05. In addition, the average correlation between 6-month SPEI-CRU and SPEI-HR for each month of the year is summarized in Figure 3 using box plot. In general, positive correlations, with a median larger than 0.6 ($p<0.05$), are found for every month. There are no substantial differences in correlations between different months. Figure A1 in Appendix shows additional box plots for SPEI at other time scales.


SPEI-01
SPEI-03
SPEI-06
SPEI-09
SPEI-12
SPEI-24
40°N 30°N 20°N 10°N 0° 10°S 20°S 30°S 40°S
20°W 10°W 0° 10°E 20°E 30°E 40°E 50°E 60°E
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1
R

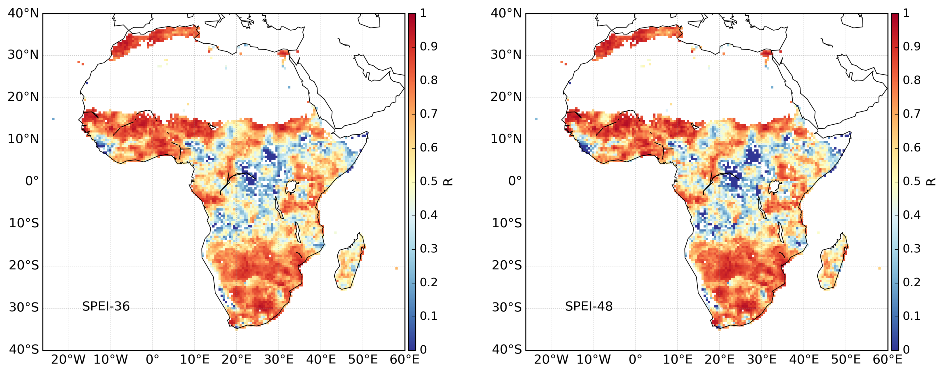


Figure 2: Correlation ($p<0.05$) between SPEI-HR and SPEI-CRU, with the number indicating different months.

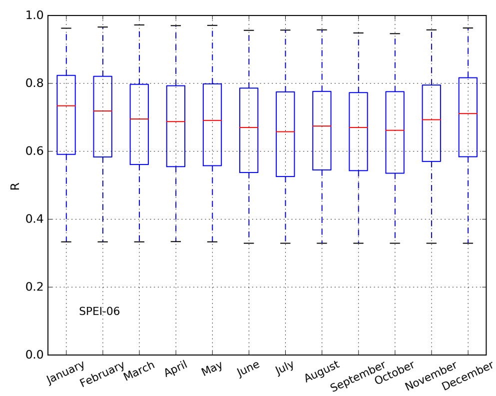
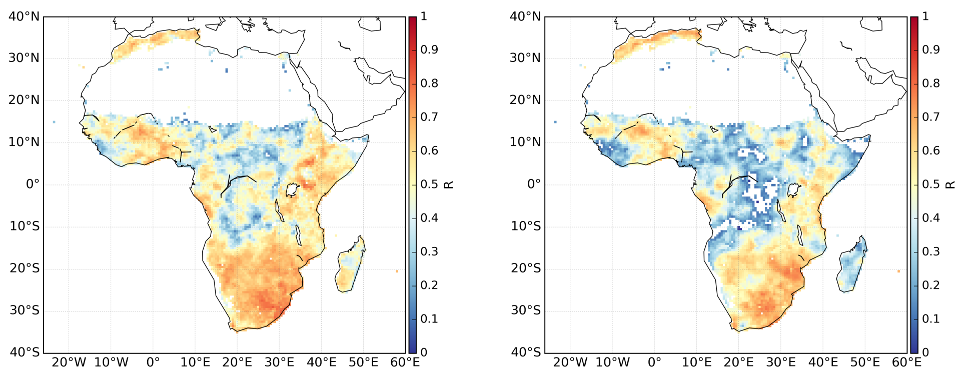


Figure 3: Box plot of the correlation ($p<0.05$) between SPEI-HR and SPEI-CRU for each month of the entire record. The results here are based on 6-month SPEI and the red line in each box represents the median.

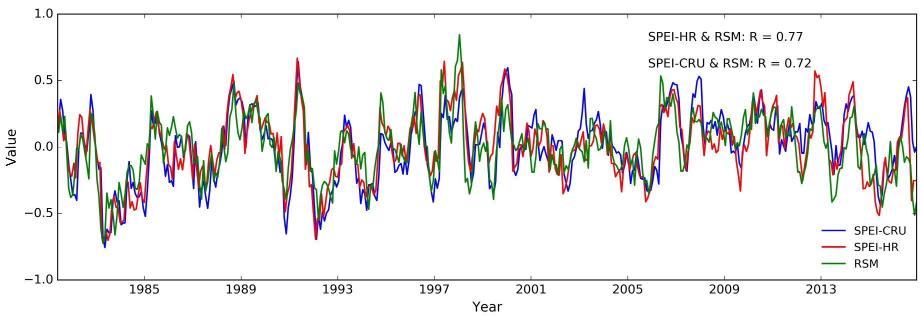
3.2 Comparison against root zone soil moisture and NDVI

To gain more insights into their significance and applicability, the SPEI datasets are compared with NDVI and RSM. Figure 4 shows the results of the spatial and temporal comparison between 6-month SPEI and RSM as indicated by Törnros and Menzel (2014). Figure 4a,b display the correlation ($p<0.05$) of SPEI-HR and SPEI-CRU against RSM during the whole time period respectively. In general, both SPEI-HR and SPEI-CRU show strong correlations with RSM over the whole African continent. Compared to SPEI-CRU, the SPEI-HR shows higher correlations, particularly over central Africa. Since Section 3.1 shows that relatively large discrepancy between SPEI-CRU and SPEI-HR exists over central Africa, the results presented here suggest a potentially better performance of SPEI-HR compared with SPEI-CRU in this region.

The time series of SPEI and RSM, averaged over the entire study area, are shown in Figure 4c, together with the corresponding correlations. It can be seen that both SPEI-HR and SPEI-CRU agree well with each other and with the RSM dynamics. Consistent with the results from the spatial correlation analysis, the SPEI-HR and SPEI-CRU show similar results when compared with RSM (R = 0.77 for SPEI-HR, R = 0.72 for SPEI-CRU). Furthermore, the scatterplots between 6-month SPEI and RSM for the entire data record are shown in Appendix Figure A2, where positive and significant correlations with RSM are found for both SPEI-HR (R = 0.51) and SPEI-CRU (R = 0.42). To explore the correlation between RSM and different time scales of SPEI, Table 2 summarizes the correlation value calculated in the same way as Figure 4c. It can be seen that the highest correlations against RSM are found at 3- and 6-month time scales. It should be noted that satellite data-driven estimates of root zone soil moisture is more suitable for evaluating SPEI compared to satellite-based top-layer soil moisture or reanalysis soil moisture data (Mo et al., 2011; Xu et al., 2018).



(a) (b)



(c)

Figure 4: Spatial maps of correlation between SPEI and root zone soil moisture (RSM) for 6-month SPEI: (a) SPEI-HR and (b) SPEI-CRU. The time series of Africa area-mean RSM and SPEI are shown in (c), where R refers to the correlation coefficient. The correlations shown here are all significant at the 95% confidence level.

Table 2: The correlation (p<0.05) between area-mean RSM and SPEI at different time scales.

	SPEI-01	SPEI-03	SPEI-06	SPEI-09	SPEI-12	SPEI-24	SPEI-36	SPEI-48
R (SPEI-CRU)	0.52	0.74	0.72	0.64	0.56	0.41	0.26	0.16
R (SPEI-HR)	0.49	0.76	0.77	0.69	0.62	0.44	0.29	0.18

Similar to the above analysis between SPEI and RSM, the comparison of results between SPEI and NDVI are shown in Figure 5. First, Figures 5a,b present the spatial distribution of the correlations (p<0.05) between SPEI-HR and NDVI and between SPEI-CRU and NDVI, respectively. While correlations are overall lower than for RSM, it can be seen that both SPEI datasets are positively correlated with NDVI over most of the continent. It is also clear that SPEI-HR shows higher correlations. The time series comparison between the area-mean SPEI and NDVI is shown in Figure 5c. Both SPEI-HR and SPEI-CRU show agreement with NDVI, with R=0.54 and R=0.47, respectively. In addition, the comparison between 6-month SPEI and NDVI for the entire data record was also calculated, with R=0.24 for SPEI-HR and R=0.21 for SPEI-CRU significant at 95% confidence level (Figure A3). While these correlations are admittedly low, overall results suggest that the SPEI has a positive relation with NDVI, which is also reported by previous studies (e.g., Törnros and Menzel, 2014; Vicente-Serrano et al., 2018). The lower correlations against NDVI than against RSM are likely due to complex physiological processes associated to vegetation, and the fact that ecosystem state is driven by multiple variables other than water availability (Nemani et al., 2003). Furthermore, there

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are also clearly documented lags between precipitation and NDVI, with NDVI time series typically peaking one or even two months after the period of maximum rainfall (Funk and Brown, 2006). Finally, Table 3 summarizes the correlation between SPEI and NDVI at different time scales. Compared with the results presented in Table 2 for RSM, the correlation with NDVI shown in Table 3 is also generally lower, and the highest correlations appear between 9- and 24-month SPEI (R>0.5).

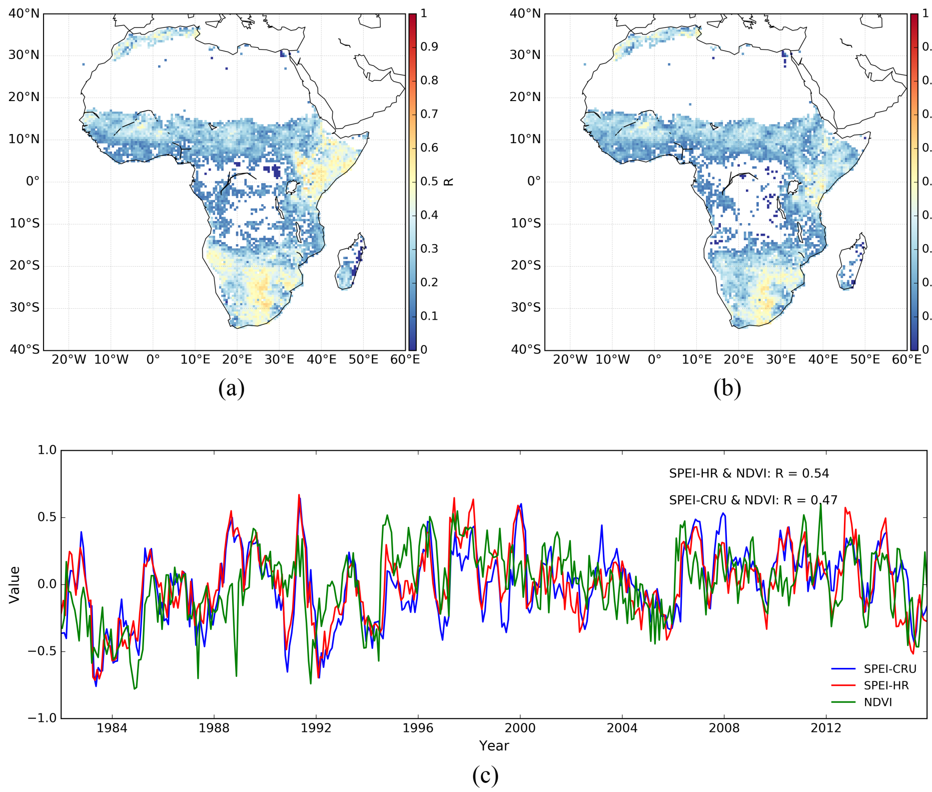


Figure 5: Spatial maps of the correlation between SPEI and NDVI for 6-month SPEI: (a) SPEI-HR and (b) SPEI-CRU. The time series of area-mean NDVI and SPEI are shown in (c), where R refers to the correlation coefficient. The correlations shown here are all significant at the 95% confidence level.

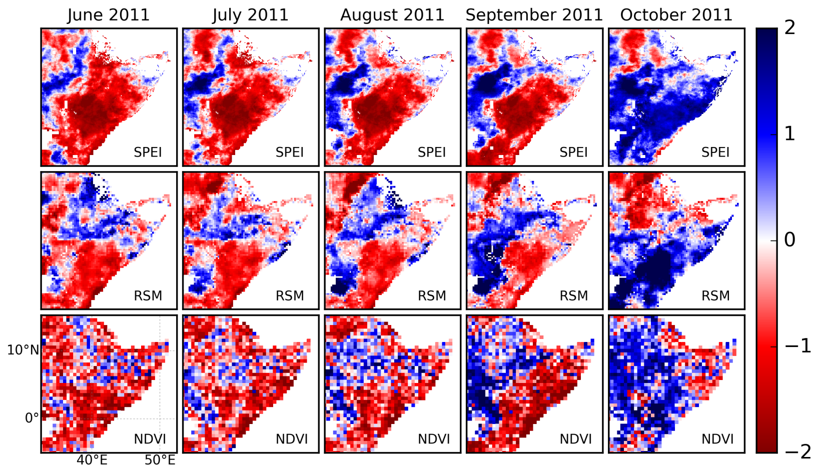
Table 3: The correlation (p<0.05) between area-mean NDVI and SPEI at different time scales.

	SPEI-01	SPEI-03	SPEI-06	SPEI-09	SPEI-12	SPEI-24	SPEI-36	SPEI-48
R (SPEI-CRU)	0.23	0.42	0.47	0.48	0.47	0.50	0.34	0.20
R (SPEI-HR)	0.31	0.51	0.54	0.56	0.57	0.57	0.44	0.29

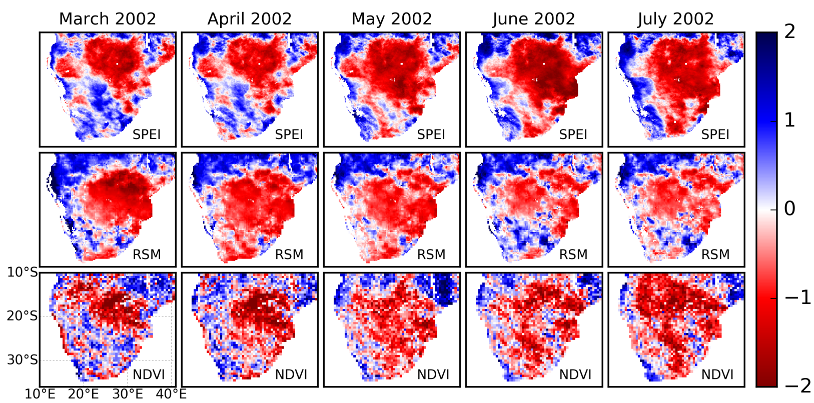
Altogether, the comparisons between SPEI and RSM and between SPEI and NDVI indirectly indicate the validity of the generated SPEI datasets. Therefore, the generated high-resolution SPEI-HR from satellite products has potential to improve upon the state of the art in drought assessment over Africa.

3.3 Patterns of SPEI, RSM and NDVI during specific drought events

Most of Africa has suffered severe droughts in past decades (Naumann et al., 2014; Blamey et al., 2018). Among them, the 2011 East Africa drought (Anderson et al., 2012; AghaKouchak, 2015) and 2002 southern Africa drought (Masih et al., 2014) were extremely severe and had devastating effects on the natural and socioeconomic environment. Taking these two events as case studies, the spatial patterns of the newly-developed high-resolution 6-month SPEI-HR are analyzed, together with the variability in NDVI and RSM. Figure 6a,b show the evolution of 6-month SPEI, NDVI and RSM during the 2011 East Africa and the 2002 southern Africa drought, respectively. The 6-month periods end in the named month, with the 6-month June 2011 SPEI values based on data for January to June. In general, these three variables reflect the progressive dry-out during the events. For example, strong, severe drought is revealed by the SPEI with values less than -1.5, coinciding with a decline in NDVI and RSM, from June to September 2011 over East Africa; the drought was offset in October. Similarly, dry and wet conditions variations during the 2002 southern Africa drought were also captured by the three variables. Despite differences over space and time, results here demonstrate that the generated SPEI-HR captures the main drought conditions that are reflected by negative anomalies in NDVI and RSM, and can thus be used to study local drought related processes and societal impacts in Africa.



(a)



(b)

Figure 6: Evolution of the spatial patterns of 6-month SPEI-HR, NDVI and root zone soil moisture (RSM) during the 2011 East Africa drought (a) and 2002 southern Africa drought (b), respectively.

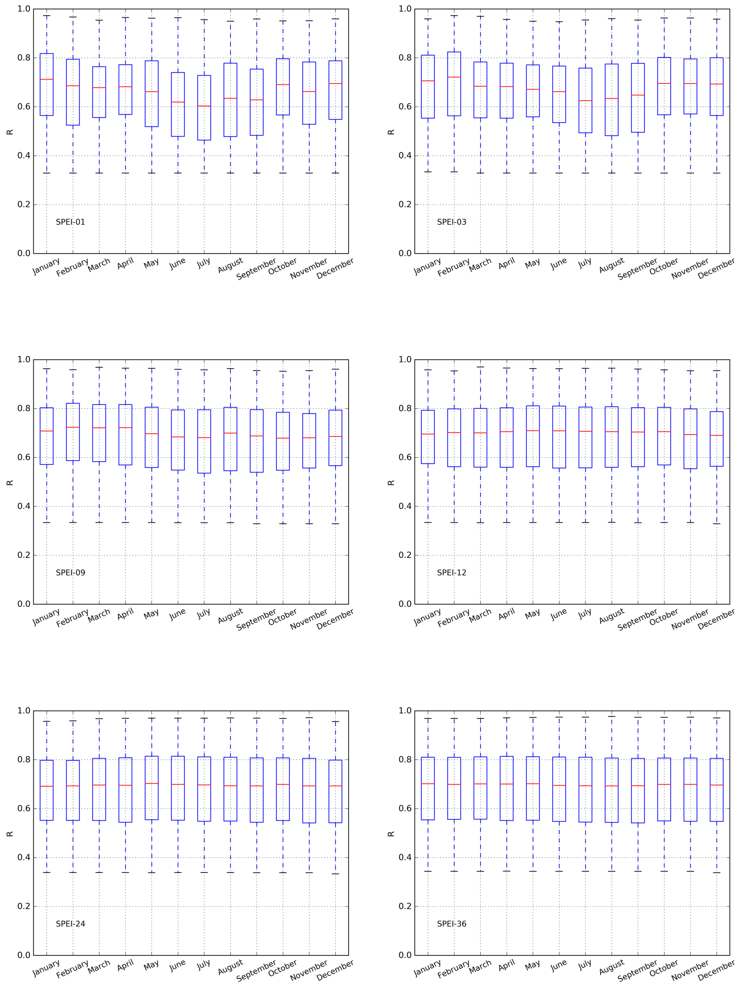
4. Data availability

The high resolution SPEI dataset is publically available from the Centre for Environmental Data Analysis (CEDA) with link: http://dx.doi.org/10.5285/bbdfd09a04304158b366777eba0d2aeb (Peng et al., 2019a). It covers the whole Africa at monthly temporal resolution and 5 km spatial resolution from 1981 to 2016, and is provided with Geographic Lat/Lon projection and NetCDF format.

5. Conclusion

The study presents a newly-generated high-resolution SPEI dataset (SPEI-HR) over Africa. The dataset is produced from satellite-based CHIRPS precipitation and GLEAM potential evaporation, and covers the entire African continent over the time period from 1981 to 2016 with spatial resolution of 5-km. The accumulated SPEI ranging from 1 to 48 months is provided to facilitate applications from meteorological to hydrological droughts. The SPEI-HR was compared with widely used coarse-resolution SPEI data (SPEI-CRU) and GIMMS NDVI as well as GLEAM root zone soil moisture to investigate its capability for drought detection. In general, the SPEI-HR has good correlation with SPEI-CRU temporally and spatially. They both agree well with NDVI and root zone soil moisture, although SPEI-HR displays higher correlations overall. These results indicate the validity and advantage of the newly developed high resolution SPEI-HR dataset, and its unprecedentedly high spatial resolution offers important advantages for drought monitoring and assessment at district and river basin level in Africa.

Appendix


SPEI-01
SPEI-03
SPEI-09
SPEI-12
SPEI-24
SPEI-36
R
0.0
0.2
0.4
0.6
0.8
1.0
January
February
March
April
May
June
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August
September
October
November
December

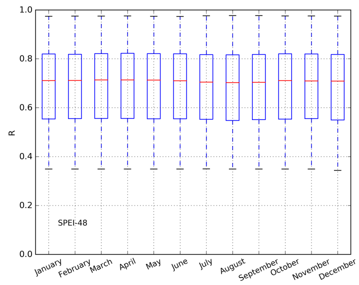

Figure A1: Box plots of the correlation (p<0.05) between SPEI-HR and SPEI-CRU for each month and entire monthly record.

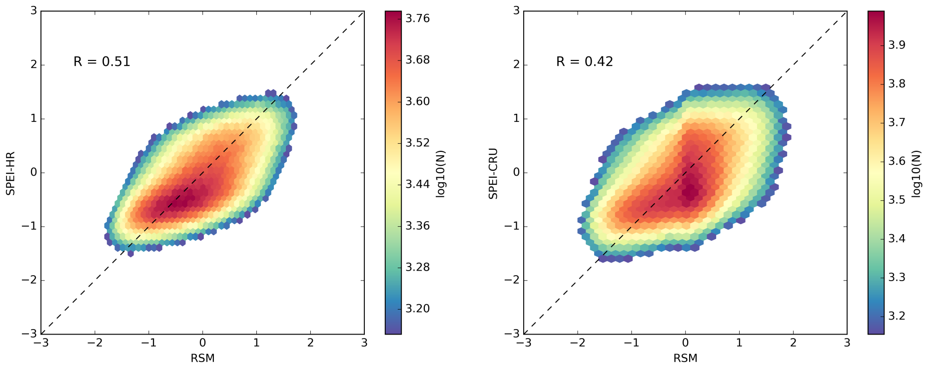

Figure A2: Scatterplots between 6-month SPEI and RSM for the entire data record. R is correlation coefficient with p<0.05, and the colors denote the occurrence frequency of values.

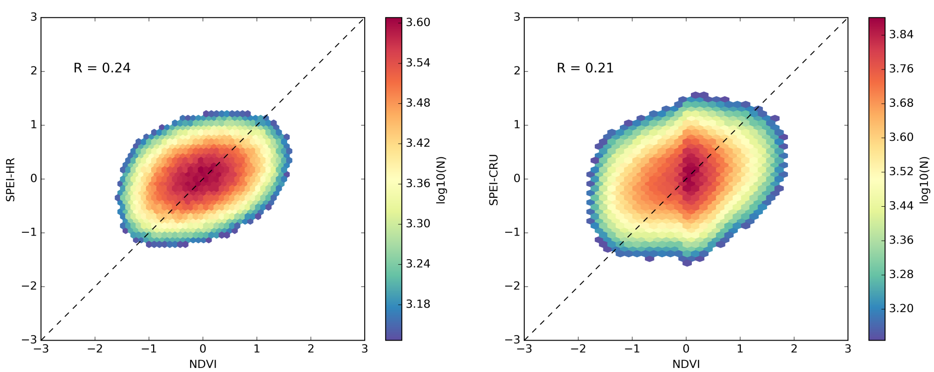

Figure A3: Scatterplots between 6-month SPEI and NDVI for the entire data record. R is correlation coefficient with $p<0.05$, and the colors denote the occurrence frequency of values.

Author contributions

JP developed the processing algorithm, generated the dataset and drafted of the manuscript. DGM and CF produced the GLEAM and CHIRPS data as input. SD, FH, ED and TL supported the generation of the dataset and the analysis of the results. All authors contributed to the discussion, review and revision of this manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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