Spatiotemporal Drought Assessment over Sahelian Countries from 1985 to 2015

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ABSTRACT

Due to infrequent rainfall, high temperatures, and degraded land, the Sahel region often suffers from droughts. The Sahel region is considered as one of the world’s driest and extreme environmental conditions. In order to assess spatiotemporal vulnerability of potential drought impacts, we used remote sensing and ground station data to evaluate drought conditions in the Sahel region from 1985 to 2015. The standard precipitation index (SPI), standard precipitation evapotranspiration index (SPEI), vegetation condition index (VCI) anomaly, along with socioeconomic indicators were performed. In addition, Pearson correlation coefficient (PCC) was computed between drought indices and three main crops (sorghum, millet, and maize) in the region to estimate the effects. The analysis showed that temperature increased by 0.78°C from 1985 to 2015, which had a significant impact on crop yield for sorghum, maize, and millet with a statistical significance value of $P > 0.05$. In the decade spanning 1994 to 2005 alone, the temperature increased by 0.57°C, which resulted in extreme drought in Algeria, Sudan, Chad, Nigeria, and Mauritania. For the effect of drought on crop production, high significance was noted on the SPI and SPEI-3 timescale: sorghum with SPI-3 ($r = 0.71$) and SPEI-3 ($r = 0.65$), millet with SPI-3 ($r = 0.61$) and SPEI-3 ($r = 0.72$), and maize with SPI-3 ($r = 0.81$) and SPEI-3 ($r = 0.65$) during the study period. In the growing season, VCI anomaly had strong correlations with sorghum and millet ($r = 0.67$ and $r = 0.75$, respectively). A significant agreement was also noticed between the combined drought index (CDI) and vulnerability index (VI) in Burkina Faso ($r = -0.676; P < 0.00$), Mali ($r = -0.768; P < 0.00$), Mauritania ($r = 0.843; P < 0.001$), Niger ($r = -0.625; P < 0.001$), and Nigeria ($r = -0.75; P < 0.005$). The results show that the above indices are effective in assessing agricultural drought and its impact on crop production in the Sahel, and in identifying areas most affected by drought.

Key words: vegetation condition index (VCI), drought, vulnerability index (VI), Sahel region

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1. Introduction

The world has experienced significant climate changes in the past century (Chen T. T. et al., 2016). These changes led to more frequent and severe drought events across the globe (IPCC, 2014). Drought is an extreme climate event that is caused by below-average rainfall, which has a negative impact on the environment (Elhag and Zhang, 2018). It is a serious phenomenon and ranks first among all natural hazards in terms of the number of people affected globally (McKee et al., 1993). Nowadays, most of the countries in the world have suffered from drought (Masud et al., 2015). Among the four classifications of drought (i.e., meteorological, hydrological, agricultural, and socioeconomic drought) (Quiring and Ganesh, 2010; Vicente-Serrano et al., 2012; Senay et al., 2015; Huang et al., 2016; Mohmmed et al., 2018b), meteorological drought is considered the most pivotal, since

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it usually triggers all the other types of droughts (Li et al., 2015; Shah et al., 2015). Meteorological drought results from the precipitation deficit, increased temperature, and increased evapotranspiration in a region for a significant period of time (Livada and Assimakopoulos, 2007; Rao et al., 2015), and agricultural drought happens at a critical time during the growing season due to soil moisture deficit.

The drought in agriculture is mainly caused by lack of water, which leads to a decrease in plant productivity. The drought is mainly due to the instability of the rain. The lack of rainfall on agricultural productivity is more serious compared to other hazards (Yang et al., 2016). In Africa, the Sahelian region, which encompasses 10 countries in western, north-central, and eastern Africa, i.e., from Senegal in the west to Eritrea in the east, has been classified as one of the most prone, sensitive, and susceptible regions to the impact of drought events (Park et al., 2016). In particular, more severe and longer drought periods have been observed in the area since the 1960s (Masih et al., 2014). The region’s vulnerability to drought has had a significant negative impact on agriculture. Crop yields have declined significantly in recent decades due to the extreme drought in the region. Recently, IPCC reports have projected a significant reduction in crop productivity in sub-Saharan countries, which could worsen the existing conditions for regional food insecurity and the livelihoods of the rural poor. It is also expected that the climate change will further intensify these conditions, by increasing the return frequency of droughts, mainly due to fluctuations in annual precipitation (IPCC, 2007).

Several indices have been developed for the estimation of meteorological droughts. These include the Palmer modified drought index (Palmer, 1965), the re-connaisance drought index (Jamshidi et al., 2011), standard precipitation index (SPI; McKee et al., 1993), and the standardized precipitation evapotranspiration index (SPEI; Li et al., 2015). The use of the SPI in climate and hydrology research has increased (Beguería et al., 2014). In addition to the SPI, the SPEI is one of the most frequently used drought indices (Spinoni et al., 2015). The SPEI is based on the difference between the accumulated precipitation ($Q$) and the potential evapotranspiration ($PET$) over a certain period (Zhang et al., 2015). The $Q$ and $PET$ factors are two main components of agricultural drought monitoring, which reflect irrigation needs in both arid and semi-arid regions, where there is not enough rainfall during the growing season (Moorhead et al., 2015). For instance, most of the agriculture in Sahelian regions is rainfed agriculture, which has a strong correlation with meteorological and agricultural drought (Bezdan et al., 2019).

SPI is the most widely used and highly recommended for characterization of droughts (Cheval et al., 2014). SPI is used for defining and monitoring drought and determining the shortage of rainfall for different timescales such as 3, 6, 9, 12, 24, and 48 months (McKee et al., 1993). In addition, SPEI is reported as an updated drought index based on precipitation and PET (Vicente-Serrano et al., 2010). The SPEI calculation steps involve computation of potential monthly or weekly water deficit/surplus (i.e., monthly or weekly difference between precipitation and PET). Droogers and Allen (2002) considered not only temperature but also the effects of wind speed and relative humidity when calculating PET, compared to the Thornthwaite equation (Thornthwaite, 1948), which only takes into account the effect of temperature. The SPEI index is based on the fact that the SPI does not consider evapotranspiration, and the PET is compared with the actual precipitation to obtain the regional water deficit.

Remote sensing is a valuable resource for drought monitoring. Nowadays, satellite platforms allow acquisition of frequent, high-resolution, and near real-time spatial data (Dike et al., 2019). There are many drought indices constructed based on near-infrared and red band data of vegetation, such as the normalized difference vegetation index (NDVI), vegetation condition index (VCI), and temperature vegetation drought index (TVDI; Baniya et al., 2019). The sensitivity of VCI for drought monitoring is significantly higher than NDVI and TVDI (Jiao et al., 2019). The efficiency of remote sensing derived VCI in assessing agricultural drought was ascertained as the correlation analysis between VCI and major rainfed crops showed correlation coefficient of 0.75 (Dutta et al., 2015). Therefore, VCI can be used in non-homogenous areas to monitor and analyze drought more accurately than other remote sensing-based indices.

In semi-arid areas, remote sensing datasets are vital for drought evaluation. For instance, studies in Sudan (Elnagag and Zhang, 2018) and Eritrea (Measho et al., 2019) used remote sensing datasets to evaluate drought conditions. In addition, evaluated drought conditions in North Darfur in Sudan provided a comprehensive description of the drought situation by combing four drought indices (Mohmmed et al., 2018a). A study by Kamali et al. (2018) in southern African countries and some regions of the Sahelian strip showed drought vulnerability due to water stress conditions. It is therefore evident that these remote sensing datasets have the benefit of simplicity in semi-arid areas.

Sahelian countries have a large coverage area in the
Sahara zone and complex climatic conditions. Therefore, long-term spatiotemporal assessment of drought in Sahelian countries is important for societies and their environment. However, large spatiotemporal scale studies of seasonal drought using remote sensing methods remain a challenge. With the exception of the above-mentioned countries, there are no specific studies at regional scale that have investigated the effect of drought on the main crops grown in Sahel countries using remote sensing data. We used the Global Inventory Modeling and Mapping Studies (GIMMS) NDVI, ERA5 reanalysis temperature, and Climate Hazards Group Infrared Precipitation with Stations (CHIRPS) precipitation dataset from 1985 to 2015 to study the influence of spatiotemporal drought event on crop production using SPEI, SPI, and VCI anomaly with yield anomalies during growing season. To get a full image of drought effects in the Sahel region, we evaluate the vulnerability index (VI) by using the biophysical, social, and economic indicators. Quantification of drought vulnerabilities supports better characterization of droughts and identification of regions where investment in drought preparedness and mitigation is essential.

2. Materials and methods

2.1 Study area

The Sahel region of Africa is an arc-like landmass covering about 3 million km$^2$, stretching east to west across the breadth of the African continent. It stretches out from 19.06°N, 13.54°E (shown in Fig. 1) and is located to the immediate south of the Sahara Desert where it cuts across 10 countries, namely, Senegal, Mauritania, Mali, Burkina Faso, Algeria, Niger, Nigeria, Chad, Sudan, and Eritrea. The climate of these countries is characterized by a long dry period and a short humid season. The Sahelian countries are substantially dependent on rainfall, which varies greatly in the region where the average annual rainfall in the Sahel region is between 100 and 600 mm (Visser and Sterk, 2007). Traditional rainfed agriculture is the major economic activity of households in these countries (Abdi et al., 2013). Drought is a dominant natural disaster among these countries and has significant impacts on their agricultural productivity (Giannini et al., 2008). During the past years, the agricultural households in these areas have been at high risk of income shocks due to recurrent and prolonged periods of drought (Kinsey et al., 1998).

2.2 Remote sensing datasets

A 30-yr NDVI time series data from NOAA Advanced Very High Resolution Radiometer (AVHRR) sensors under the framework of GIMMS is used. There are two spectral channels [red and near-infrared (NIR)] on the NOAA AVHRR sensor that are used to calculate the daily NDVI value. The data is the latest version of the dataset, namely, NDVI3g.v1 downloaded from https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/, which has been used in this study to calculate the VCI of 30 yr from 1985 to 2015. The GIMMS NDVI product has 8 km × 8 km spatial resolution and a 15-day temporal resolution. The monthly temperature datasets of this study are obtained from ERA5 reanalysis dataset. ERA5 is a new generation of ECMWF reanalysis data for the global atmosphere (climate and weather) of the past seven decades (https://cds.climate.copernicus.eu). The native resolution of the ERA5 atmosphere and land reanalysis is 31 km in a reduced Gaussian lattice (TL639) and 63 km

Fig. 1. (a) Study area of Sahelian countries and (b) Africa land use and land cover [LULC; Moderate Resolution Imaging Spectroradiometer (MODIS) 2017] to present the Sahelian climatic zones and Sahelian location over Africa continent.
VCI = ND
VIm NDVImin
ND
VImax NDVImin
100; (1)

VCIA = VCIi VCIa
ve
VCIa
ve
; (2)

Supplementary data

2.4 Supplementary data

Population and gross domestic product (GDP) data were obtained from the World Resources Institute (available online at http://cait.wri.org), as auxiliary data to estimate drought vulnerability in Sahel countries. The selection of drought susceptibility indicators was relevant to the risk of drought in the local context of the study area. We calculate population and GDP weights to reconcile the data with other data in this study to understand drought susceptibility.

2.5 Agricultural drought index

In this study, NDVI data for the Sahelian countries for the period 1985–2015 were obtained during the growing season (July to October) to calculate the VCI anomaly. The maximum value composite method was used to reduce the cloud and aerosol contamination after which annual NDVI data were generated by summing up monthly NDVI values of the growing season. First, from the monthly NDVI datasets, the spatiotemporal change of agricultural drought was calculated by using VCI. VCI enhances interannual changes of NDVI in response to weather variations while reducing the impact of ecosystem-specific responses that are driven by climate, vegetation type, and geography (Liu and Kogan, 1996). For the Sahelian countries, a monthly VCI was computed at pixel level from the filtered NDVI data:

$$VCI = \frac{NDVI_{m} - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \times 100,$$

where $NDVI_{m}$ is a value of the pixel during a specific month $m$, and $NDVI_{max}$ and $NDVI_{min}$ are respectively maximum NDVI and minimum NDVI, calculated by the corresponding pixels in the same month from the entire NDVI records (1985–2015). The VCI variations range from 0 to 100, consistent with the changes in vegetation condition (VC) from extremely unfavourable to optimal (Kogan et al., 2003).

The VCI anomaly was used in this study to analyze agricultural drought changes based on VCI index and was calculated by using the following formula (Kogan, 1995; Liang et al., 2017):

$$VCIA = \frac{VCI - VCI_{ave}}{VCI_{ave}},$$

where $VCI$ is the VCI value during a specific period, and $VCI_{ave}$ is the average VCI value from 1985 to 2015. A positive VCI anomaly (VCIA; optimal condition) indicates that soil moisture is relatively abundant and a better than average VC, while a negative VCI anomaly (drought condition) indicates that soil is deficient in moisture and a worse than average VC.

2.6 Meteorological drought indicators

SPI developed by McKee et al. (1993) was applied in this study. In general, the first step in calculating the SPI transformation precipitation was applied to obtain the estimated gamma parameters, and then perform gamma fitting on the precipitation distribution (Patel et al., 2007) for each country in the Sahel region during the study period (1985–2015) for each month. The gamma probab-
ility density function is defined by the following algorithm (Dutta et al., 2015):

\[ g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}}, \]  
(3)

where \( x (> 0) \) is the precipitation, \( \alpha (> 0) \) is the shape parameter, and \( \beta (> 0) \) is the scale parameter.

\[ \alpha = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}}\right), \]  
(4)

\[ \beta = \frac{x}{\alpha}, \]  
(5)

\[ A = \ln(\bar{x}) - \frac{1}{n} \sum_{i=1}^{n} \ln(x_i), \]  
(6)

where \( n \) represents the number of observations of precipitation. After that, the cumulative precipitation probability of the country is integrated by \( g(x) \).

\[ G(x) = \int_0^x g(x) \, dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^x x^{\alpha-1} e^{-\frac{x}{\beta}} \, dx. \]  
(7)

In the actual precipitation data of the country, there will be data with zero precipitation, and the gamma function is undefined when \( x = 0 \), so the probability distribution when the precipitation is zero needs to be considered, as shown below:

\[ H(x) = q + (1 - q)G(x), \]  
(8)

where \( H(x) \) is the cumulative precipitation probability of the country, and \( q \) is the probability that the precipitation is zero. The skewed precipitation distribution is then converted to the normal distribution so as to obtain the SPI, as follows:

\[ \text{SPI} = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), \quad 0 < H(x) \leq 0.5, \]  
(9)

\[ \text{SPI} = t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}, \quad 0.5 < H(x) \leq 1.0, \]  
(10)

where \( t = x/\beta, \) and

\[ t = \sqrt{\frac{1}{[H(x)]^2}}, \quad 0 < H(x) \leq 0.5, \]  
(11)

\[ t = \sqrt{\frac{1}{[1.0 - H(x)]^2}}, \quad 0.5 < H(x) \leq 1.0, \]  
(12)

where \( c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, \) and \( d_3 = 0.001308. \)

SPI was then calculated following the main steps proposed by Vicente-Serrano et al. (2013). First, the PET of the area was obtained by model calculation. Following Thornthwaite (1948), the determined PET of a certain area in a given period of time \( t \), was then used to calculate the precipitation deficit value \( D_t \) in the time period as follows:

\[ D_t = \text{PET} - Q, \]  
(13)

where \( Q \) is the measured cumulative precipitation value during the regional time period. The log-logistic density function used by SPEI was calculated as follows:

\[ f(x) = \frac{\beta}{\alpha} \left(\frac{x - \gamma}{\alpha}\right)^{\beta-1} \left[1 + \left(\frac{x - \gamma}{\alpha}\right)^{\beta}\right]^{-2}, \]  
(14)

where \( \alpha, \beta, \) and \( \gamma \) are the scale, shape, and position parameters, which are respectively calculated by the following formulas:

\[ \beta = \frac{2w_1 - w_0}{6w_1 - w_0 - 6w_2}, \]  
(15)

\[ \alpha = \frac{(w_0 - 2w_1)\beta}{\Gamma(1 + \frac{1}{\beta}) \Gamma(1 - \frac{1}{\beta})}, \]  
(16)

\[ \gamma = w_0 - \alpha \Gamma\left(1 + \frac{1}{\beta}\right) \Gamma\left(1 - \frac{1}{\beta}\right), \]  
(17)

\[ w_s = \frac{1}{n} \sum_{i=1}^{n} \left(1 - \frac{l - 0.35}{n}\right^s \right), \]  
(18)

where \( w_s \) is the probability weight moment \( (s = 0, 1, \) and \( 2) \), \( l \) is the ascending order of the cumulative water deficit \( X \) at different timescales, and \( \Gamma \) is the gamma function, and then the three-parameter log-logistic probability distribution function can be written as follows:

\[ F(x) = \left[1 + \left(\frac{\alpha}{x - \gamma}\right)^{\beta}\right]^{-1}. \]  
(19)

Finally, the probability distribution function \( F(x) \) of \( D_t \) is calculated and normalized. When \( Q \leq 0.5, W = -2\ln Q, \) and this SPEI is calculated by:

\[ \text{SPI} = W - \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}. \]  
(20)

When \( Q > 0.5, W = -2\ln(1 - Q), \) and this SPEI is calculated by:

\[ \text{SPI} = -W + \frac{c_0 + c_1 W + c_2 W^2}{1 + d_1 W + d_2 W^2 + d_3 W^3}. \]  
(21)

In the two equations, \( c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328, d_1 = 1.432788, d_2 = 0.189269, \) and \( d_3 = 0.001308. \) In essence, there is no big difference between SPI and SPEI calculations: one is the normalization of precipitation and the other is the normalization of water deficit. In this study, the FAO56 Penman–Monteith...
method was applied for monthly evapotranspiration ($E_{T_a}$) estimation (Chen C.-P. et al., 2016).

The SPI and SPEI can be calculated at varying time scales (1, 3, 6, and 12 months; Li et al., 2015). Drought at these monthly timescales is related to many fields such as agriculture, water resources, and socioeconomics (Potop et al., 2014). In addition, the 1-timescale of SPI signifies short season, the SPI 3-timescale explains the monthly evaluation of precipitation, and the SPI 12-timescale also reflects medium-season variation in precipitation patterns. Due to the similarity in the calculation principles of SPEI and SPI, the negative and positive values were classified to the same categories: the negative values indicate the dry time while the positive values indicate the wet time (Table 1; Wang et al., 2015; Drumond et al., 2016; Yuan et al., 2016). This study used the SPI and SPEI at different timescales (1, 3, and 6 months) to evaluate the drought events and its impact on crop production.

### 2.7 Yield anomalies

The variability of crop yield in the Sahelian countries demonstrated its response to drought conditions in the region. This measure indicates the variation of the interannual yield of sorghum, millet, and maize among these countries. We calculated the standard deviation (SD) of the relative yield anomaly over 30 yr for all countries in the Sahel region. The Sahelian countries have different climate conditions ranging from desert zone to savanna zone, and different soil types (Mohmmed et al., 2018b). Therefore, there are some problems in calculating crop yield from different countries, and the crop anomalies were used for each country to address most of the problems as follows:

$$\text{SD} = \frac{\sum_{t=1}^{N} \text{SD}(Y_{A,1}, Y_{A,2}, \ldots, Y_{A,f})_t}{N},$$

$$Y_{A,i} = \frac{100 \times \left( y_i - \frac{\sum_{t=1}^{N} y_i}{N} \right)}{\sum_{t=1}^{N} y_i / N},$$

where SD is the standard deviation of relative yield anomalies ($Y_{A,i}$) of country $i$ ($i = 1, 2, \ldots, f$) per year $t$ ($t = 1, 2, 3, \ldots, N$). Yield anomaly per country and year was calculated from the actual yield ($y_i$) relative to the average of the study period.

### 2.8 Assessment of drought vulnerability

#### 2.8.1 Combined drought index (CDI)

Drought has a mix of several driving forces such as lack of rainfall, temperature rise, and soil moisture deficit. The indices of drought developed in the last decade tried to combine and exploit the maximum of information that is readily available and proved to be suitable for determining the appropriate drought indices (Balint et al., 2013; Mohmmed et al., 2018b). These indices used in this paper (SPI, SPEI, and VCI) use different information and take into account different aspects of the drought, all of which can quantify the drought and its severity. In fact, each index has its own strengths and weaknesses, and its benefits are often tailored to a particular application or decision-making activity. As a result, in this study, attempts were made to integrate meteorological and agricultural drought indices into a single index, and combined drought index (CDI) was used to obtain a comprehensive description of the drought situation. The concept behind the CDI is informed by an idealized causality for agricultural drought. This cause–effect relationship assumes that a shortage of precipitation (the cause) leads to a reduction of vegetation production (the effect). The combination of meteorological data and remote sensing derived land surface information would be the most desirable way to paint a full picture of a drought situation. Therefore, we merged CDI including the SPI, SPEI, and VCI, to produce a CDI as below:

$$\text{CDI} = \frac{\text{SPI} + \text{SPEI} + \text{VCI}}{3}.$$ (24)

#### 2.8.2 Selection of drought vulnerability indicators and standardization of data

Drought vulnerability is different for different nations and individuals. In the Sahelian countries, drought vulnerability constitutes a threat to food security and socio-economies. In developed economies, drought presents significant economic risks and costs for individuals, public enterprises, commercial organizations, and governments (Panda, 2017; Kamali et al., 2018; Mohmmed et al., 2018b; Buotte et al., 2019). The following indicators, namely, population, GDP, yield anomaly index, food production index, and harvesting areas were chosen for the drought vulnerability. A linear standardization approach was used to make the indicators dimensionless in order to eliminate the influence of different indicators in computation of weight. This operation is named data

| Value       | Class             |
|-------------|-------------------|
| ≤ −2.00     | Extreme drought   |
| −1.99 to −1.50 | Severe drought     |
| −1.50 to −0.99 | Moderate drought   |
| −0.99 to 0 | Near normal drought |
| >0          | No drought         |
standardization (Sadeghravesh et al., 2016), which means that the criteria with different units are transferred to the same level unit to have a standard unit so that they can be compared to each other. Therefore, Eq. (25) is used for data standardization considering a range between 0 and 1 (Naumann et al., 2014):

\[ U = \frac{x_i - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}, \]  

where \( U \) is weight, \( x_i \) is the mean value of indicator \( i \), and \( x_{\text{max}} \) and \( x_{\text{min}} \) are the maximum and minimum values of the indicator \( i \), respectively.

Standard vulnerability (SV) factors were then applied in the multicriteria evaluation for the effective use, linking, and analysis of all indices and factors, as follows:

\[ SV = \frac{\text{POP} + \text{GDP} + \text{FPI} + \text{YAI} + \text{HA}}{5}, \]  

where POP is the population, GDP is the gross domestic product, FPI is the food production index, YAI is the yield anomaly index, and HA is the harvesting area.

### 2.9 Pearson correlation coefficient (PCC)

The PCC was generated from the mean values of the meteorological indices (SPI/SPEI-6 monthly timescale) and VCI with yield anomalies of three main crops. Here, we analyzed the value of PCC in Sahel region to understand the role of climatic factors on crop production and relationships during growing season using the commonly used Eq. (27):

\[ p_{xy} = \frac{\sum^n_{i=1}[(x_i - x)(y_i - y)]}{\sqrt{\sum^n_{i=1}(x_i - x)^2 \sum^n_{i=1}(y_i - y)^2}}, \]  

where \( p_{xy} \) is the PCC of \( x \) and \( y \) variables, \( y_i \) represents yield anomalies of each crop of the \( i \)th year, and \( x_i \) represents either mean of drought indices (SPI, SPEI, and VCI) during growing seasons of the \( i \)th year; \( x \) is the average of drought indices for the study period (30 yr), and \( y \) is the total mean yield anomalies of three main crops.

### 3. Results and discussion

#### 3.1 Meteorological drought assessment

The SPI and SPEI were calculated at varying timescales (1, 3, and 6 months) in Sahelian countries between 1985 and 2015 (Fig. 2). According to the SPI, the main drought episodes occurred in the decade of 1985–1994. These drought events are also clearly identified by the SPEI especially in the SPEI-6 timescale. Few differences were apparent between the SPI and the SPEI series, for the respective varying timescale of analysis.

The results demonstrate that under climate conditions involving low interannual temperature variability, both drought indices respond mainly to the changes in precipitation, in which the annual precipitation decreased by 2.59 mm (Fig. 2). According to the results in Fig. 2, there were drought events observed in Algeria, Sudan, Chad, Nigeria, and Mauritania (both SPI-6 and SPEI-6), in the two decades following 1985–1994 and 1995–2004. In contrast, these episodes were not clearly evident as extreme drought for the SPI and SPEI timescales of one and three months. Meroni et al. (2017) examined the performance and timeliness of the SPI in anticipation of deviations from mean seasonal vegetation productivity in the Sahel, and they revealed that the SPI-6 timescale was more appropriate for identification of extreme drought conditions in the region.

The mean temperature in the region was observed to increase remarkably by 0.78°C between 1985 and 2015, of which a 0.59°C increase was recorded in the decade spanning from 1995 to 2004 alone (Fig. 2; red color). This increase would have produced a higher water demand due to increased PET in the region (Siebert, 2016; Kamali et al., 2018). In turn, drought severity would have increased, as was clearly recorded by SPEI in the decade of 1994–2005. The role of temperature increase in drought conditions is represented in the SPEI, and SPEI can therefore duly document the severe drought conditions as was the case for 1995–2004.

Several drought episodes were detected from the temporal evolution of the SPEI (Fig. 2), and the most severe droughts occurred in Algeria, Nigeria, and Eritrea. According to Thomas et al. (2016), the classification of severe and extreme droughts corresponds to the categories of SPI \( \leq -1.5 \) and SPI \( \leq -2.0 \), respectively. It was also observed that the climate regime of the Sahel shifted from dry to mildly wet from 2005, especially in Mauritania, Senegal, Mali, Burkina Faso, Niger, Nigeria, Chad, Sudan, and Eritrea (Fig. 2). Haarsma et al. (2005) found increased precipitation over the past decade, based on the observed data from the wider Sahel region. Odekunle et al. (2008) confirmed that the climate of Nigeria indicated a tendency towards wetter conditions rather than the increasing aridity. According to Park et al. (2016), the historical main driver of Sahel drought was the anthropogenic warming of the Mediterranean Sea and therefore, droughts have been persistent in the Sahel region, particularly in the northern areas. SPI-3 results further confirmed the phenomenon, whereby the northern zones of the Sahel had SPI \( < -1.5 \) between 2004 and 2013. These results also agree with a previous study by Misra (2014), which reported that precipitation over sub-
Saharan Africa could drop 10% by 2050 based on climate change projections.

3.2 Remote sensing drought assessment and drought characteristics

VCI is only useful for monitoring drought conditions during the growing season as it measures vegetation health. In this section, the annual VCI anomaly was calculated based on VCI to estimate the drought events in Sahel countries from 1985 to 2015. As shown in Fig. 3, the drought events from 1985 to 1994 were considered as a severe drought period, which affected the entire region, particularly in 1986 and 1988 in Sudan and Algeria. Additionally, a non-drought year was identified during the growing season of 2011/2012. In the 1990s, the drought condition is very clear in 1996, and the average VCI anomaly is less than 1.5. The drought condition maps showed that the most severe droughts occurred in 1988, 2012, and 2015 during the study period. We can identify the drought conditions throughout the northern part of the Sahel (Fig. 3). For example, in Algeria, the patterns highlighted drought along the coastal zone in the north-
east. However, the southern areas of the Sahel, i.e., Nigeria, were not as severely affected by the drought according to the VCI anomaly results (Fig. 3). Patches in the northern and southwest regions, which are in general drier compared to the rest of the Sahel with regard to climatic conditions, show drought conditions even in normal years. With regard to the full season, severe drought conditions cannot be identified over larger areas and over a longer duration of several time steps based on VCI (Qian et al., 2016). Figure 3 shows the development of VCI and its drought severity classification during the growing season of a drought year, e.g., 2003, 2011, 2014, and 2015.

3.3 The relation of SPI, SPEI, and VCI anomaly with yield anomaly

The Sahel is exposed to extreme temperatures, fluctuating rainfall, and drought. The unpredictability of rainfall combined with the drought in these countries is extremely vulnerable to the slightest decrease in rainfall or a rise in temperature. However, all climate models predict a global increase in temperature. The decrease in precipitation is strongly linked with increases in temperature. Certainly, under its current climate, sub-Saharan Africa is already facing recurrent food crises and water scarcity triggered or exacerbated by climate variability and extreme events such as droughts and floods, which affect agricultural productivity and hence rural household food security (Twongyirwe et al., 2019). To investigate the impact of drought on three crops in 10 countries of the Sahel region, we used the average of SPI and SPEI-1, -3, and -6 timescales and VCI anomaly as drought indices (Fig. 4). The average of SPI and SPEI as drought indices was calculated based on the results in Section 3.1. The drought was persistent in the Sahel countries, but the severity varied among the 10 countries. In addition, the average of SPI and SPEI is appropriate and is usually used for long-term drought over regions. For instance, Ghebrezgabher et al. (2016) and Haile et al.
used the long-term average of SPEI to assess the drought over the Horn of Africa (HOA) and Greater Horn of Africa, respectively.

The SPI and SPEI at 1-, 3-, and 6-month timescales compare the precipitation and temperature for that period with the same month period over the historical record. SPI and SPEI-3 can be very effective for showing the precipitation and temperature over distinct seasons. Results show that there was a significant relationship of SPI and SPEI (3-month timescale) with crop anomaly (Fig. 4). The correlation analysis of SPI-3 timescale shows high significance with sorghum \( r = 0.71 \), millet \( r = 0.61 \), and maize \( r = 0.81 \) anomalies, where SPEI-3 also shows a high correlation with sorghum \( r = 0.65 \), millet \( r = 0.72 \), and maize \( r = 0.65 \) anomalies. The VCI anomaly showed a decrease and increase similarity to the yield anomaly of three crops. There was a strong correlation of VCI anomaly with sorghum and millet \( r = 0.67 \) and 0.75, respectively. The correlations of the SPI-6, SPEI-6, and VCI anomaly with the yield anomaly of sorghum, millet, and maize are shown in Fig. 4. The highest correlations were obtained between annual VCI anomaly and crop production, as well as between the 3-month timescale SPI/SPEI and crop production. In addition, the averaged correlations for each accumulation period were generally low, indicating that the vegetation growth was insensitive to meteorological moisture deficit.

As drylands suffer from drought, which is the main determining factor in crop yield and biomass production, and given the low soil moisture available and the high losses of PET in the region, it is not surprising that crops have had moderately low productivity as a result of the drought condition. Short-term droughts, when rainfall decreases during the growing season, have proved even more damaging to crop productivity (Elhag and Zhang, 2018), and therefore, we compared SPI and SPEI at 3-month timescale with the yield anomaly time series of sorghum, millet, and maize (Fig. 4; Measho et al., 2019). Based on the correlation analysis and drought patterns, the study confirmed that low precipitation highly contributed to the slowly declining vegetation trends and increased drought conditions in semi-arid regions.

From the results, it was observed that Sahelian countries, especially Mauritania, Mali, Niger, Chad, and Sudan, were more affected by severe drought conditions from 1985 to 2015. In the southwestern region of the Sahel, the annual precipitation is generally above 300 mm, and thus in such moist conditions, the sensitivity of vegetation growth to precipitation is naturally low. The results were generally consistent with Dutta et al. (2015) and Mohmmed et al. (2018b) who reported that the highest correlation between VCI and SPI was obtained in regions with the lowest precipitation, and vice versa. The increased drought frequency mainly affected the rainfed crops (maize, sorghum, and millet; Chen T. T. et al., 2016). Nevertheless, by examining either the averaged correlations or maximum correlations between the VCI anomaly and SPI/SPEI, it was found that the SPEI was somewhat superior to the SPI, which was similar to the results of monitoring soil moisture but with a slight difference. Therefore, the superior performance of SPEI in the Sahel region has been well demonstrated.

### 3.4 Drought vulnerability characteristics

The findings from the vulnerability assessment (Fig. 5) highlighted that Mauritania, Nigeria, and Mali are more vulnerable to droughts. The correlation analysis between CDI and VI indicated a high correlation between the two indices in Burkina Faso \( r = -0.676; P < 0.00 \), Mali \( r = -0.768; P < 0.00 \), Mauritania \( r = 0.843; P < 0.001 \), Niger \( r = -0.625; P < 0.001 \), and Nigeria \( r = -0.75; P < 0.005 \), which highlights that the important role drought plays in controlling vulnerability of agricultural communities across the region. In other words, these regions are highly sensitive and susceptible to droughts and climate change. The Sahel region is highly vulnerable to the impacts of drought due to its high exposure and sensitivity. The vulnerability is caused by not only natural meteorological conditions, but also the low level of socioeconomic development. Ahmadalipour et al. (2019) showed that drought risk is expected to increase in future across Africa with varied rates for different models and scenarios. Although northern African countries indicated aggravating drought hazard, drought risk ratio is found to be the highest in central African countries as a consequence of vulnerability and population rise in that area. If climate change adaptation is not implemented in a timely fashion, unprecedented drought hazard and risk will occur decades earlier. In addition, controlling population growth is found to be imperative for mitigating drought risk in Africa (even more effective than climate change mitigation), as it improves socioeconomic vulnerability and reduces potential exposure to drought (Mohmmed et al., 2018a; Nasrollahi et al., 2018).

Since the water and temperature play a main role in the vegetation development (NourEldeen et al., 2020), climate variability implies serious production risks that would affect small landholders who have lower capacity to get the required resources to overcome these circumstances. We determined that recurring drought events
Fig. 4. The correlation coefficients of SPI, SPEI (1, 3, and 6-fold scale), and VCI anomaly with crop yield anomaly.
have had massive impacts on Sahelian countries. The unpredictability of precipitation combined with aridity in these countries causes them to be exceptionally vulnerable to the slightest decrease in precipitation or increase in temperature. However, considering that climate prediction models indicate a global increase in temperature and that the prevailing decrease in precipitation is strongly linked to corresponding increases in temperature, drought vulnerability may be further exacerbated.

4. Conclusions

This study demonstrated the application of SPI and SPEI as meteorological indices for the assessment of drought consequences on major field crops in Sahelian countries for the period of 1985–2015 based on meteorological data. The result of SPI (1-, 3-, and 6-month timescales) in the drying climate corresponds to what was determined by using the SPEI (1-, 3-, and 6-month timescales). The trend of drought occurrence was low in the first decade (1985–1994). However, it then increased in the second decade (1995–2004). The annual precipitation decreased slightly by 2.59 mm, while the annual mean temperature increased significantly by 0.78°C during the study period. A significant correlation of SPI and SPEI (3-month timescale) with the mean annual crop yield (sorghum, millet, and maize) based on the yield anomalies was revealed more than SPI and SPEI at 1- and 6-month timescales. The correlation was much higher between the growing season VCI anomaly and
sorghum/millet yield anomaly. Spatial variability and fluctuations in rainfall contributed to an overall limited vegetative cover, and the region experienced moderate to extreme drought conditions.

In general, the VCI anomaly has shown a decreasing trend. In the north and west of the region, the trend of VCI correlates with increasing patterns of aridity and regular drought, mainly due to lack of precipitation and increased temperature. Agricultural drought and climate change in crop production have a strong impact on food security in the Sahel region. The correlation analysis between CDI and VI indicated strong correlation between the two indices in Burkina Faso, Mali, Mauritania, Niger, and Nigeria, which were most vulnerable countries to drought and climate change in Sahel region. Overall, this information can be used to identify areas that are most vulnerable to drought and can also be used as a relative assessment among Sahelian countries. Additional (i.e., current or future) socioeconomic indicators can be further included to generate drought risk maps for scenario analysis and to develop strategies to minimize the socioeconomic impact of the drought.

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