

SPECIAL ISSUE ARTICLE

Analysis of drought and vulnerability in the North Darfur region of Sudan

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Abstract

North Darfur of Sudan is located on the edge of the Sahara Desert and endures frequent droughts due to water shortages and high summer temperatures. Monitoring and understanding drought characteristics are essential for integrated drought risk mitigation and prevention of land degradation. This study evaluates drought conditions in North Darfur by analyzing the spatiotemporal distribution of drought using three drought indices (Standardized Precipitation Index, Vegetation Condition Index, and Soil Moisture Content Index) and their combined drought index (CDI) from 2004 to 2013. Biophysical and socioeconomic indicators are further used to measure vulnerability to drought risk and its three components (exposure, sensitivity, and adaptive capacity) through a comprehensive risk assessment framework. The results show that most of North Darfur has experienced prolonged droughts during the study period, especially from 2007 to 2011. There is also a significant correlation between the monsoon season CDI and annual crop yield anomaly. The results confirm the validity of the CDI index, which provides a comprehensive description of the drought situation by combining four drought indices quantifying different drought aspects. The vulnerability results show that the majority of this region is highly exposed and sensitive to drought risks. In particular, the northern zone of the region is highly vulnerable, which is categorized by less-crop diversity, higher land degradation, frequent droughts, and high-poverty levels. This study provides valuable information for coping with climate change-induced drought risk in this region and demonstrates that there is still a large room for enhancing the adaptation capacity in this region.

KEYWORDS

drought, meteorology, North Darfur region, remote sensing, vulnerability index

1 | INTRODUCTION

Drought results from a substantial hydrological deficit due to insufficient or total lack of rainfall for an extended period of time and can cause a significant reduction in crop yield (Fahad et al., 2017; Franco-Andreu, Gomez, Parrado, Knicker, & Tejada, 2017), rangeland livestock fatalities (McClaran & Wei, 2014), vegetation degradation (Hua, Wang, Zhang, Lang, & Li, 2017; Zhang et al., 2015), and changes in soil properties (de Santiago, Lucas-Borja, Wic-Baena, Andres-Abellan, & de las Heras, 2016). Severe and prolonged drought can also trigger political conflicts and social instability (Kelley, Mohtadi, Cane, Seager, & Kushnir, 2015; Selby & Hoffmann, 2014). Several studies have demonstrated that many drought-prone areas are also susceptible to social and political conflicts. One study revealed that episodes of seasonal droughts resulted in a series of conflict events in Ethiopia, from 2000 to 2013 (Delbiso, Rodriguez-Llanes, Donneau, Speybroeck, & Guha-Sapir, 2017), whereas another study showed a causal relationship between droughts and local violent conflicts in Somalia (Maystadt & Ecker, 2014). Similar findings were also reported in other drought- and conflict-prone countries such as Sudan (Selby & Hoffmann, 2014) and Syria (Gleick, 2014).

Sub-Saharan Africa is one of the regions that is most adversely affected by recurrent droughts (Gizaw & Gan, 2017). This region has scarce freshwater supplies and relies heavily on agriculture to support its economy. Living stress in this region has been further amplified by recent political conflicts, which can be partially attributed to climate change-induced droughts and socioeconomic problems (Shahum, 2017). Studies have shown that ocean temperature alterations resulting from global climate change have caused prolonged drought conditions during the late 20th century in Sahel (Giannini, Biasutti, & Verstraete, 2008; Giannini, Saravanan, & Chang, 2003). Consequently, precipitation reduction-induced droughts and associated land degradation in Darfur stimulated disputes over arable land and water and triggered violent conflicts over resources, which resulted in a 2003 civil war in this region (Selby & Hoffmann, 2014).

As part of drought-prone sub-Saharan Africa, North Darfur of Sudan has endured a series of conflicts over the past two decades, which was partially attributed to climate change-induced droughts (Flint & De Waal, 2008; Selby & Hoffmann, 2014). Previous studies on drought and its social implications in sub-Saharan Africa were mainly focused on the linkage between country-specific climatic metrics such as rainfall and temperature and their roles in the wars (Buhaug, 2010; Couttenier & Soubeyran, 2014; Hendrix & Glaser, 2007; Hendrix & Salehyan, 2012; Maystadt & Ecker, 2014). However, very few studies have been conducted to analyze the drought risk and its linkage to vulnerability in North Darfur. In general, drought risk is considered to be the product of hazard and vulnerability to drought condition (Wilhite, 2016). Drought risk analysis involves determining the existence and extent of drought risk and requisite management actions (Dahal et al., 2016; Hao, Zhang, & Liu, 2012). It is the basis for designing drought management strategies to reduce adverse drought impacts on agriculture (Geng et al., 2016). Several studies have developed methodological frameworks to assess the risk and impact of drought by incorporating an analysis of vulnerability and adaptation strategies (Krishnamurthy, Lewis, & Choularton, 2014; Richardson et al., 2018).

In this study, we conducted a comprehensive assessment of drought risk and socioeconomical vulnerability in North Darfur by analyzing the spatiotemporal characteristics of drought based on meteorological and satellite-based records. Vulnerability to drought and climate change risks was assessed through a risk assessment framework. Therefore, the objectives of this study are as follows: (a) To provide a detailed assessment of seasonal drought dynamics to characterize the spatiotemporal distribution of drought conditions in North Darfur and (b) to assess the overall vulnerability in rural communities by studying the biophysical, social, and economic indicators representing the three components of drought vulnerability in this region, including exposure, sensitivity, and adaptive capacity. To the best of our knowledge, this research is the first of its kind for the North Darfur region, in which drought risk and root causes of drought vulnerability are assessed.

2 | MATERIAL AND METHODS

2.1 | Study area

North Darfur is one of the five states forming the Darfur region, which is located in western Sudan (Figure 1). North Darfur occupies more than half of the territory of the Darfur Territory and has an area of approximately 296,420 km². The population of North Darfur is approximately 1.6-million people. North Darfur borders Libya on the northwest and Sudan's Northern State to the north, whereas the Republic of Chad and Sudan's West Darfur lie adjacent on its west and southwest, respectively (Figure 1). North Darfur also borders Sudan's Northern State and North Kordofan to the east and adjoins Sudan's South Kordofan and South Darfur to the southeast and south, respectively (Figure 1). North Darfur is composed of five districts, including Mellit, Kabkabiya, Kutum, Alfasher, and Umkadada (Figure 1). This state is a hot and dry area with regional average annual maximum and minimum temperatures of 42°C and 11°C, respectively, whereas regional average annual rainfall is 262 mm. The majority of northern North Darfur is desert. The volcanic Marrah Mountains (Jebel Marra) occupy most of North Darfur's southwestern part. According to Sudan's National Livelihood Zone Map developed by the Famine Early Warning Systems Network (FEWS NET; FEWS NET, 2011), there are seven livelihood zones across this region, including pastoral, agropastoral millet and groundnuts, tobacco, mixed highland cultivation, wadi cultivation, agropastoral millet, and gum arabic zones (Figure 1). Sorghum, millet, maize, and peanuts are the major crops cultivated in this state.

2.2 | Data

The historical observed monthly precipitation data from 20 meteorological stations within North Darfur for the period of 1989–2013 were acquired from the Sudan National Meteorological Centre. The production data for sorghum, which is the main crop in this region, were provided by Sudan's Ministry of Agriculture for the same period. The SPOT vegetation 10-day composites of Normalized Difference Vegetation Index (NDVI) were obtained from the EUMETCAST

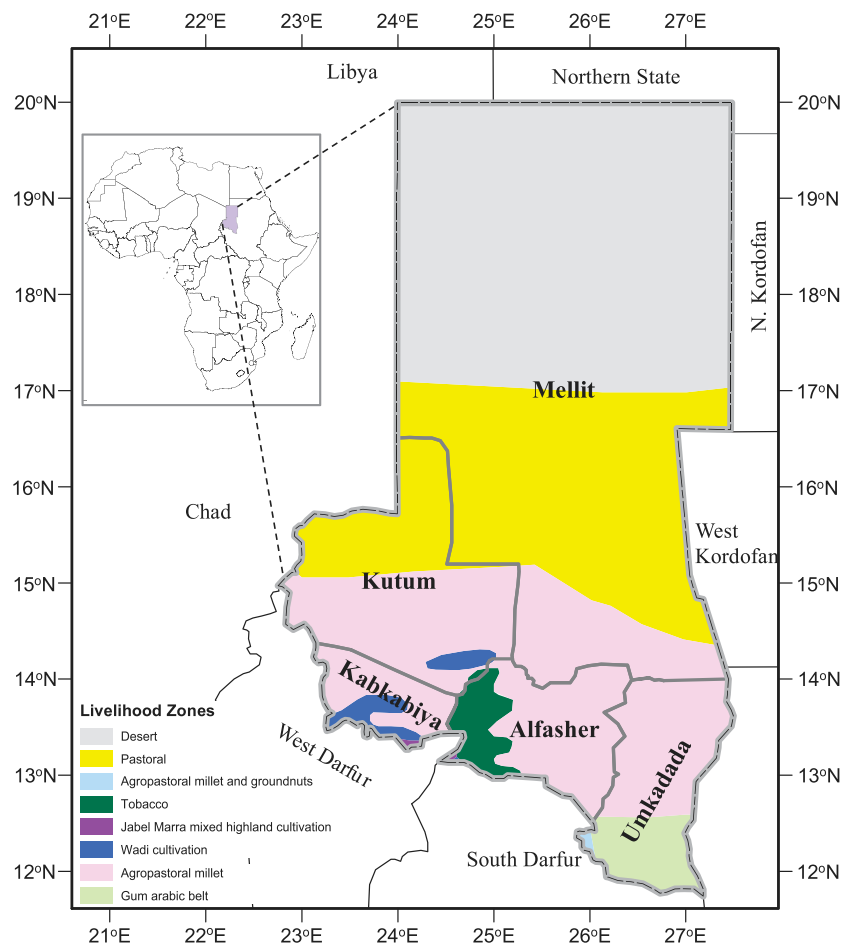


FIGURE 1 Locations of North Darfur and its five districts and distribution of livelihood zones derived from the Famine Early Warning Systems Network (FEWS NET, 2011) [Colour figure can be viewed at wileyonlinelibrary.com]

(vgt4africa) database (<http://www.vgt4africa.org>) for the April 2004–December 2013 period. The multitemporal NDVI data set was selected because it provides critical information to identify vegetation changes over a long period of time. The SPOT NDVI data with a spatial resolution of 1 km are valuable observation-based data for monitoring crop growth, identifying failing-growing seasons, and detecting drought conditions (Gebrehiwot, van der Veen, & Maathuis, 2011).

2.3 | Precipitation-based drought analysis

The Standard Precipitation Index (SPI) has been widely used for real-time drought monitoring and drought assessment across the world (McKee, Doesken, & Kleist, 1993; Spinoni, Naumann, Vogt, & Barbosa, 2015; Zhang & Jia, 2013). SPI can be used to detect drought and measure its severity during various time periods, for example, 1–48 months. However, it is better to use SPI on shorter time scales such as 3–6 months to determine the drought conditions affecting agricultural practices (Raziei, Saghafian, Paulo, Pereira, & Bordi, 2009). Therefore, the three-month SPI series were computed in this study to identify the drought characteristics on short and medium time scales.

The calculation of SPI first requires the frequency distribution of precipitation totals (x) be fit on a defined time scale at a given location

using a gamma probability density function with two parameters (McKee et al., 1993):

$$g(x) = \frac{1}{\beta^a \Gamma(a)} x^{a-1} e^{-x/\beta}, \quad (1)$$

where a is a shape parameter, β is a scale parameter, and $\Gamma(a)$ defines the gamma function. Then, the maximum likelihood solutions are used to optimally estimate the a and β parameters:

$$\hat{a} = \frac{1}{4A} \left(1 + \sqrt{1 + \frac{4A}{3}} \right) \text{ and} \quad (2)$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{a}}, \quad (3)$$

where A is equal to $\ln(\bar{x}) - \frac{\sum \ln(\bar{x})}{n}$ and n is the number of precipitation observations. The derived gamma density function can be easily converted to a mathematical cumulative probability function. Finally, the cumulative probability is transformed to the standardized normal distribution to produce SPI. More details on the calculation of SPI can be found in other studies (McKee et al., 1993; Vicente-Serrano, Cuadrat-Prats, & Romo, 2006).

The regional SPI for North Darfur was calculated using the mean areal precipitation and maximum and minimum temperatures. The

SPI series were also computed at each of the meteorological stations, and then, the series were spatially interpolated using the inverse distance-moving average interpolation method to create drought severity maps for the region at multiple time scales. In this study, the three-month SPI series were calculated from 1989 to 2013, to characterize seasonal droughts that occur due to rainfall deficits for short-time scales. To map the spatial extent of a meteorological drought based on the intensities measured by the SPI values, we followed the previous studies by McKee et al. (1993) and Edwards (1997) to classify the droughts into five categories: No drought ($SPI > 0$), near normal or mild drought ($-0.99 \leq SPI \leq 0$), moderate drought ($-1.49 \leq SPI \leq -1.00$), severe drought ($-1.99 \leq SPI \leq -1.50$), and extreme drought ($SPI \leq -2.00$).

2.4 | Vegetation-based drought analysis

Meteorological drought indices such as the SPI integrate information on precipitation to quantify the drought severity, but these indices cannot directly reflect drought impacts on vegetation and agriculture. Instead, satellite remote sensing provides spatially distributed information on vegetation status at regular time intervals. Many studies have proven that vegetation indices derived from multiband satellite imagery can be used to observe drought over a large area (Keshavarz, Vazifedoust, & Alizadeh, 2014; Xue & Su, 2017). The NDVI index is one of the most well-known vegetation indices and can be converted to the Vegetation Condition Index (VCI) to quantify the vegetation status (Tucker, 1979):

$$VCI = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right) \times 100\%, \quad (4)$$

where NDVI is the NDVI time series on a given time scale, and $NDVI_{min}$ and $NDVI_{max}$ are the multiyear minimum and maximum values of the NDVI series, respectively. VCI is calculated on a grid cell-by-cell basis and can be used to detect the impacts of abnormal weather conditions on vegetation. VCI is valuable for distinguishing the short-term weather signal from the long-term ecological signal and is a better indicator of water stress conditions relative to NDVI (Kogan, 1997; Maselli, Conese, Petkov, & Gilbert, 1993). According to Kogan (1995), VCI values of $\leq 35\%$ reflect drought conditions, whereas VCI values between 35 and 50% are regarded as normal or near normal conditions. VCI values of 50% or above are considered as favourable conditions.

In this study, we first derived the 10-day composite NDVI data for each month of the monsoon season (July, August, and September) at each grid cell. Then, the multiyear minimum and maximum NDVI values for each 10-day period were derived from their corresponding records of the study period (2004–2013). Following Equation (4), we produced the VCI series. The resulting 90-decadal images were used to produce the drought maps on multiple time scales (10 days–3 months) and to determine the relationship between monthly precipitation and vegetation status.

2.5 | Soil moisture-based drought analysis

Soil moisture is important for assessing agricultural droughts because it balances the fluxes of precipitation, runoff, and evapotranspiration

(Bai, He, Xing, & Li, 2015; Sheffield & Wood, 2008). We derived the monthly soil moisture data from 2004 to 2013 from NASA's Global Land Data Assimilation System Version 2.0 (GLDAS-2) three-hourly products (<http://ldas.gsfc.nasa.gov/gldas/>). Then, the Soil Moisture Condition Index (SMCI) was calculated by scaling the soil–water content between 0 and 100% using the minimum and maximum soil–water content on a given temporal scale at each grid cell:

$$SMCI = \left(\frac{SM - SM_{min}}{SM_{max} - SM_{min}} \right) \times 100\%. \quad (5)$$

2.6 | Combined drought index

The above drought indices are all capable of quantifying the drought and its severity, although these indices use different information and account for different aspects of drought. Drought is a natural phenomenon caused by a mixture of several factors, such as precipitation deficiency, persistence of lower-than-normal rainfall, temperature excess, and soil moisture deficit (Balint, Mutua, Muchiri, & Omuto, 2013). In fact, the above drought indices are usually correlated with each other (Balint et al., 2013; Esfahanian et al., 2017). Therefore, we combined drought indices including the VCI, SMCI, SPI, and rainfall anomaly index (RAI) to produce a Combined Drought Index (CDI) in this study. By doing so, critical meteorological and remote-sensing information are aggregated for a comprehensive evaluation of drought. Thus, the four indices (VCI, SMCI, SPI, and RAI) are first normalized individually using their respective means and standard deviations. The normalized indices are marked with the subscript 'st.' The final CDI is defined as follows:

$$CDI = \frac{(VCI_{st} + SMCI_{st} + SPI_{st} + RAI_{st})}{4}. \quad (6)$$

2.7 | Crop yield analysis

To evaluate drought impacts on agriculture, the most direct way is to investigate agriculture productivity (Foster, Brozović, & Butler, 2015). An increase or decrease in productivity depends mainly on precipitation amount in the study region because rainwater is the primary water source for crop production in this region. Therefore, we adopted the yield anomaly index (YAI) to assess the impacts of droughts on crop production. Years with low-yield values indicate negative deviations from the normal productivity, which are considered to confirm the existence of drought (Dutta, Kundu, Patel, Saha, & Siddiqui, 2015). The YAI index is calculated as follows:

$$YAI = \left[\frac{Y - \mu}{\sigma} \right] \times 100\%, \quad (7)$$

where Y is annual crop yield, μ is the long-term mean crop yield, and σ is the standard deviation of Y .

2.8 | Drought vulnerability analysis

Next, we adopted the indicator-based risk assessment framework developed in a recent study (Panda, 2017) to assess regional vulnerability to drought and climate change risks in North Darfur. Similar to the other risk assessment frameworks (Krishnamurthy et al., 2014; Richardson et al., 2018), the indicator-based risk assessment framework computes a vulnerability index (VI) based on the three components of vulnerability, which include exposure, sensitivity, and adaptive capacity. To quantify the three components, we first developed a structured questionnaire that contains a series of classified indicators (Table 1). For the exposure component, we selected two climate indicators and three hazard indicators, whereas two environmental indicators and three agricultural indicators were chosen for the sensitivity component (Table 1). For the adaptive capacity component, we identified two education indicators, two economic structure indicators, two infrastructure indicators, and three coping technique indicators (Table 1). We, then, collected data for the relevant indicators at the household level through questionnaire surveys and at the regional level through reports by the Ministry of Agriculture in North Darfur. The survey was conducted in 500 households from July to October in 2015, across 10 farming subregions of North Darfur: Alfasher, Umkadada, El Le Aeit En Nabi, Kornoy, Kottom, Serif, Serif Omer, Kabkabia, Koma, and Mellit.

To quantify each of the three vulnerability components, we first standardized each of these indicators, which are measured on different scales or have different units, by following Panda (2017):

$$\text{indicator}_{sd} = \frac{\text{indicator}_{org} - \text{indicator}_{min}}{\text{indicator}_{max} - \text{indicator}_{min}}, \quad (8)$$

where indicator_{org} , indicator_{sd} , indicator_{min} , and indicator_{max} are the original, standardized, minimum, and maximum values of a given indicator, respectively. Once all indicators of a given component are

standardized, the vulnerability component value is calculated as the arithmetic mean of the indicators' standardized values (Panda, 2017):

$$C_x = \frac{\sum_{i=1}^n \text{indicator}_{sdi}}{n}, \quad (9)$$

where C_x represents one of the three vulnerability components, indicator_{sdi} is the value of the i th indicator of C_x , and n is the number of indicators of C_x . The final VI is computed as a function of the three component values according to Hahn, Riederer, and Foster (2009) and Panda (2017):

$$VI = (C_{Exposure} - C_{Adaptive}) \times C_{Sensitivity}, \quad (10)$$

where $C_{Exposure}$, $C_{Adaptive}$, and $C_{Sensitivity}$ are the scores of the exposure, adaptive capacity, and sensitivity components, respectively.

By following Krishnamurthy et al. (2014), we categorized the exposure, adaptive capacity, and sensitivity into five classes: Very low ($C_x < 0.2$), low ($0.2 \leq C_x < 0.4$), medium ($0.4 \leq C_x < 0.6$), high ($0.6 \leq C_x < 0.8$), and very high ($C_x \geq 0.8$). On the basis of the study by Panda (2017), we also classified vulnerability into five classes: Very low ($VI < 0.15$), low ($0.15 \leq VI < 0.30$), medium ($0.30 \leq VI < 0.45$), high ($0.45 \leq VI < 0.60$), and very high ($VI \geq 0.60$).

3 | RESULTS

3.1 | Spatiotemporal characteristics of droughts in North Darfur

Annual SPI series of the five North Darfur districts generally show similar temporal trends from 1989 to 2013 (Figure 2). From 1989 to 1995, all five districts show increases in annual SPI, indicating a wetting trend during this period. Then, the SPI values of all five districts

TABLE 1 Summary of components and indicators used for the vulnerability assessment

Component	Input		Description	Unit
	Profile	Indicator		
Exposure	Climate	Warming	Percentage of families that perceive rising temperature	%
		Drying	Percentage of families that perceive decreasing rainfall	%
	Hazard	Drought occurrence	Number of droughts that occurred between 2004 and 2013	Unitless
		Drought impact	Percentage of households that underwent drought disasters	%
		Severe droughts	Percentage of households that were severely impacted by droughts	%
Sensitivity	Environmental sensitivity	Drought-prone population	Percentage of population living in drought-prone areas	%
		Landless household	Percentage of households without land	%
	Agriculture	Dependency on agriculture	Percentage of families that depend on agriculture as the main income source	%
		Livestock ownership	Percentage of households that own livestock	%
		Crop homogeneity	Inverse values of crop diversity index	%
Adaptive capacity	Education	Adult education	Percentage of adults who were educated	%
		Female adult education	Percentage of female adults who were educated	%
	Economic structure	Farming importance	Ratio of farming income to total income	%
		Microfinance	Percentage of households that use microfinance	%
	Infrastructure	Market accessibility	Percentage of population within 1–10 km to crop markets	%
		Fertilizer supply	Percentage of population within 1–10 km to supply sources	%
	Technology	Insecticide usage	Percentage of households that use insecticide	%
		Crop variety	Percentage of families that alter crop variety	%
		Planting date alteration	Percentage of families that change the planting dates of crops	%

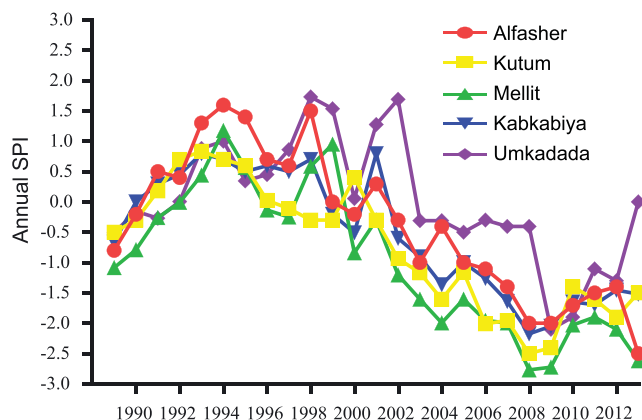


FIGURE 2 Annual standard precipitation index series of the five North Darfur districts from 1989 to 2013 [Colour figure can be viewed at wileyonlinelibrary.com]

turn downward from 1996 to 2013 (Figure 2). Although there are similar trends in the SPI series of all five districts, the five districts show different temporal variations and interannual variabilities in the drought conditions measured by SPI. Generally, Umkadada has the lowest level of drought conditions during this period among the five districts and is characterized by a mild to moderate drought severity (Figure 2). In contrast, Mellit has the driest conditions according to the SPI index, as most of this region is desert. The other three districts have SPI values in between relative to Umkadada and Mellit, whereas Kutum is generally drier than Kabkabiya and Alfasher (Figure 2). By considering the minimum SPI values, 2008 and 2009 are the driest years across North Darfur with annual SPI values for the five districts ranging between -1.0 and -2.5 (Figure 2). The other years with medium to severe droughts include 2004–2007 and 2010–2013 (Figure 2). It is clear that 2004–2013 is a dry phase for the entire region. These results indicate that this region has experienced repeated and prolonged droughts during 2004–2013.

We further applied the monsoon season (July–September) SPI to measure the monsoon droughts because monsoon rains are the dominant water source for this region. Figure 3a shows the spatial patterns of the monsoon season SPI from 2004 to 2013, which is the driest period in the past 25 years. Clearly, Mellit is constantly under extreme drought conditions because it is a desert region (Figure 3a). For the other regions, moderate droughts occur frequently and cover many areas during the 10-year period, whereas severe to extreme droughts occur only in the northern regions of Kutum, Alfasher, and Umkadada (Figure 3a). Monsoons in 2007–2009 are the three driest monsoons during the 10-year period. Only the southernmost parts of North Darfur are droughtfree during the monsoon seasons (Figure 3a). These results indicate that droughts are common phenomena in most of North Darfur, even during the monsoon seasons (Figure 3a).

The spatial gradients of VCI in this region are similar to those of SPI (Figures 3a,b), indicating that meteorological conditions play a critical role in regulating vegetation growth in the region. Most of the northern regions show low-monsoon season VCI values from 2004 to 2013 (Figure 3b), indicating a constant dry condition and low-vegetation productivity in these areas. Relatively, Mellit has the lowest VCI values, followed by Kutum and Alfasher, whereas Kabkabiya and Umkadada have the highest VCI values (Figure 3b). Although there

are apparent differences between the spatial patterns of VCI and SMCI, their interannual variations are similar (Figure 3b,c). The years with lower VCI values also have lower SMCI values.

On the regional scale, the standardized SPI, RAI, VCI, and SMCI indices, that is, SPI_{st} , RAI_{st} , VCI_{st} , and $SMCI_{st}$ are highly correlated with each other ($P < 0.01$) and show similar interannual variabilities in all five districts (Figure 4a). These close correlations confirm the effects of varying rainfall on vegetation status and soil-water content. According to the four standardized indices, different districts show somewhat different interannual variabilities in drought conditions. For example, 2009 and 2013 are the driest years in Alfasher, whereas 2008 and 2009 are the driest years in Kutum (Figure 4a). For Kabkabiya, Mellit, and Umkadada, the driest years occur over the periods of 2008–2009, 2007–2009, and 2008–2009, respectively (Figure 4a). In addition, the five standardized drought indices are also significantly correlated with CDI ($P < 0.01$) in the five districts. This correlation further confirms the necessity to combine these drought indices to avoid redundant analysis.

3.2 | Relationship between droughts and crop yield

To evaluate the drought impact on agriculture, we further analyzed the relationship between CDI and crop yield. The time series of annual CDI and YAI indices are quite similar to each other (Figure 4b) and have correlation coefficients larger than 0.82 in all of the five districts ($P < 0.001$; Figure 4c). These results indicate that drought conditions clearly control crop production in this region.

For most of North Darfur, the 2007–2009 period was the driest period, during which these areas experienced severe to extreme droughts, resulting in the lowest crop productivity (Figure 4b). The lowest CDI and RAI values in Darfur are -2.5 in Mellit, which occurred in 2008 and 2009. The RAI series have the lowest values in the monsoon seasons of 2008 and 2009 in nearly all five districts (Figure 4b), which are consistent with the results of satellite-based VCI (Figure 4b) and confirm the occurrence of droughts during the monsoon months of these two years. Notably, Umkadada has been impacted by civil war since 2007, which has also impacted the crop productivity in this region (Pretty, Toulmin, & Williams, 2011). The war-induced crop productivity reduction can partly explain the general lower-than-normal productivity from 2007 to 2013 despite normal meteorological conditions occurring during some of these years (Figure 4b).

3.3 | Drought exposure and sensitivity

The above results clearly demonstrate that climate change is apparent in the study area (Figure 2), and that droughts occurred across North Darfur during 2004–2013 (Figures 2–4). The droughts largely impacted vegetation and crop productivities in this region. To further stratify drought impacts on the communities across North Darfur and identify vulnerability and its causes, we further investigated vulnerability due to drought and climate change risk in this area. These analyses were conducted in 10-farming subregions of North Darfur, which include Alfasher, Umkadada, El Le Aeit En Nabi, Kornoy, Kottom, Serif, Serif Omer, Kabkabia, Koma, and Mellit (Figure 5a).

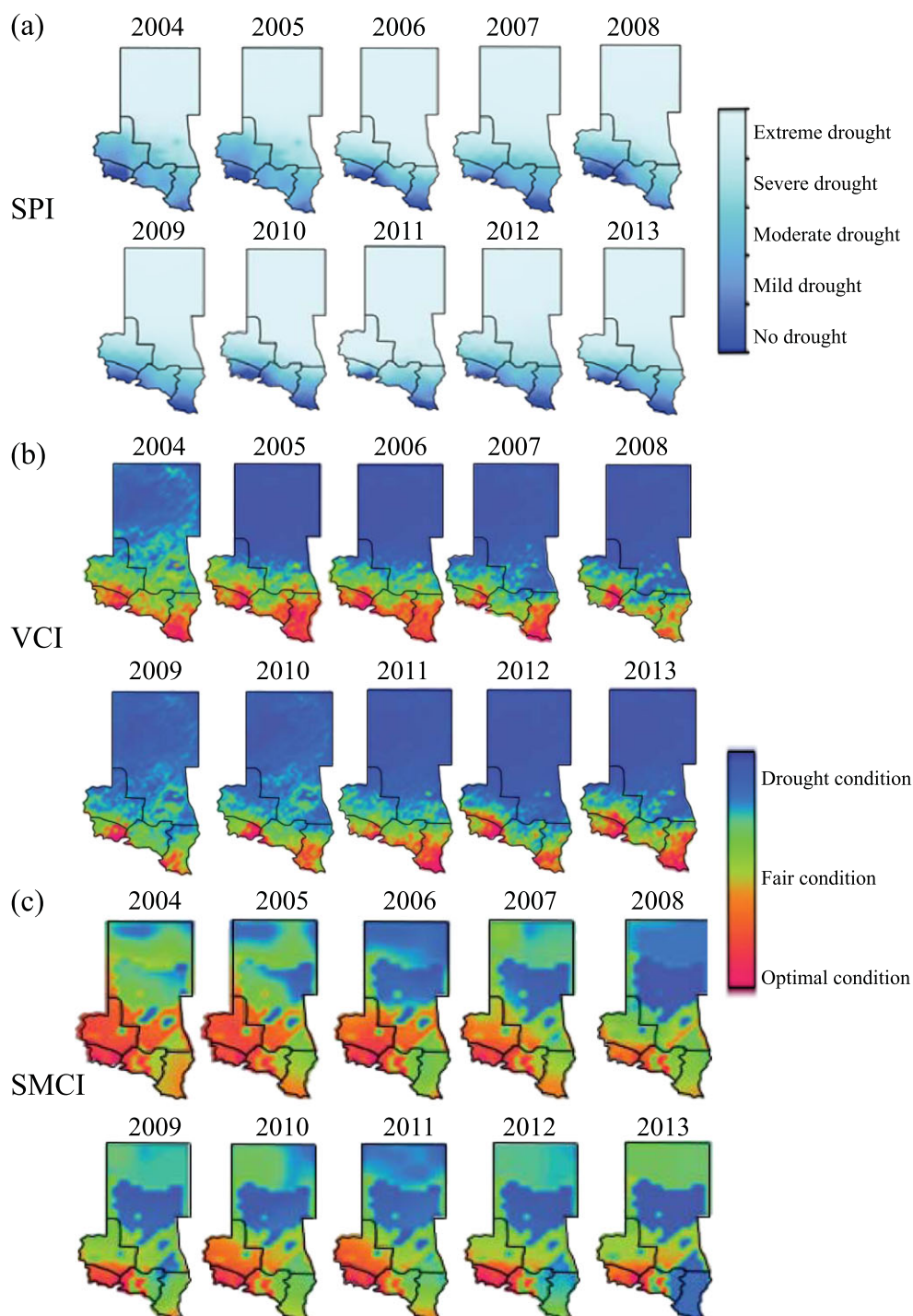


FIGURE 3 Spatial maps of monsoon season (July–September; a) Standard precipitation index, (b) Vegetation condition index, and (c) Soil moisture content index from 2004 to 2013 [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 5a shows the results of the exposure scores across the 10 subregions of North Darfur. Three (Alfasher, Umkadada, and El Le Aeit En Nabi), six (Kornoy, Kottom, Serif, Serif Omer, Kabkabia, and Koma) and one (Mellit) of the 10 subregions have medium, high, and very high exposures to drought and climate changes, respectively (Figure 5a). Among the 10 subregions, the highest exposure appears in Mellit (0.82), and the lowest is in El Le Aeit En Nabi (0.47; Table 2). The spatial distribution of the exposure index is generally consistent with the distribution of the drought indices (Figure 3), indicating that

the natural climatic conditions and spatial distribution of droughts are the main contributing factors to the exposure distribution.

As shown in Figures 6a–c, the two climate (warming and drying) indicators are the top contributors to the exposure scores in the 10 subregions. These results indicate that people across all of these subregions have recognized climate change and its risks and that climate change is a ubiquitous phenomenon in these regions. In terms of the magnitude of these climate indicators, the subregions in the north have higher values than those in the south. In addition, drought



FIGURE 4 Time series of (a) monsoon season vegetation condition index, soil moisture content index, standard precipitation index, and rainfall anomaly index and (b) monsoon season combine drought index and yield anomaly index from 2004 to 2013 and (c) correlation between monsoon season combine drought index and yield anomaly index in the five districts [Colour figure can be viewed at wileyonlinelibrary.com]

occurrence frequency is another dominant component of the exposure index in the driest regions, including Mellit, Kornoy, and Kottom and in the intermediate dry regions such as Kabkabiya and Korma (Figures 5 and 6a–c). For the other five subregions, the drought

occurrence frequency has lower values than the two climate indicators and higher values than the other exposure indicators. Drought impact measured by the percentage of households that underwent drought disasters and severe drought occurrence quantified by the percentage

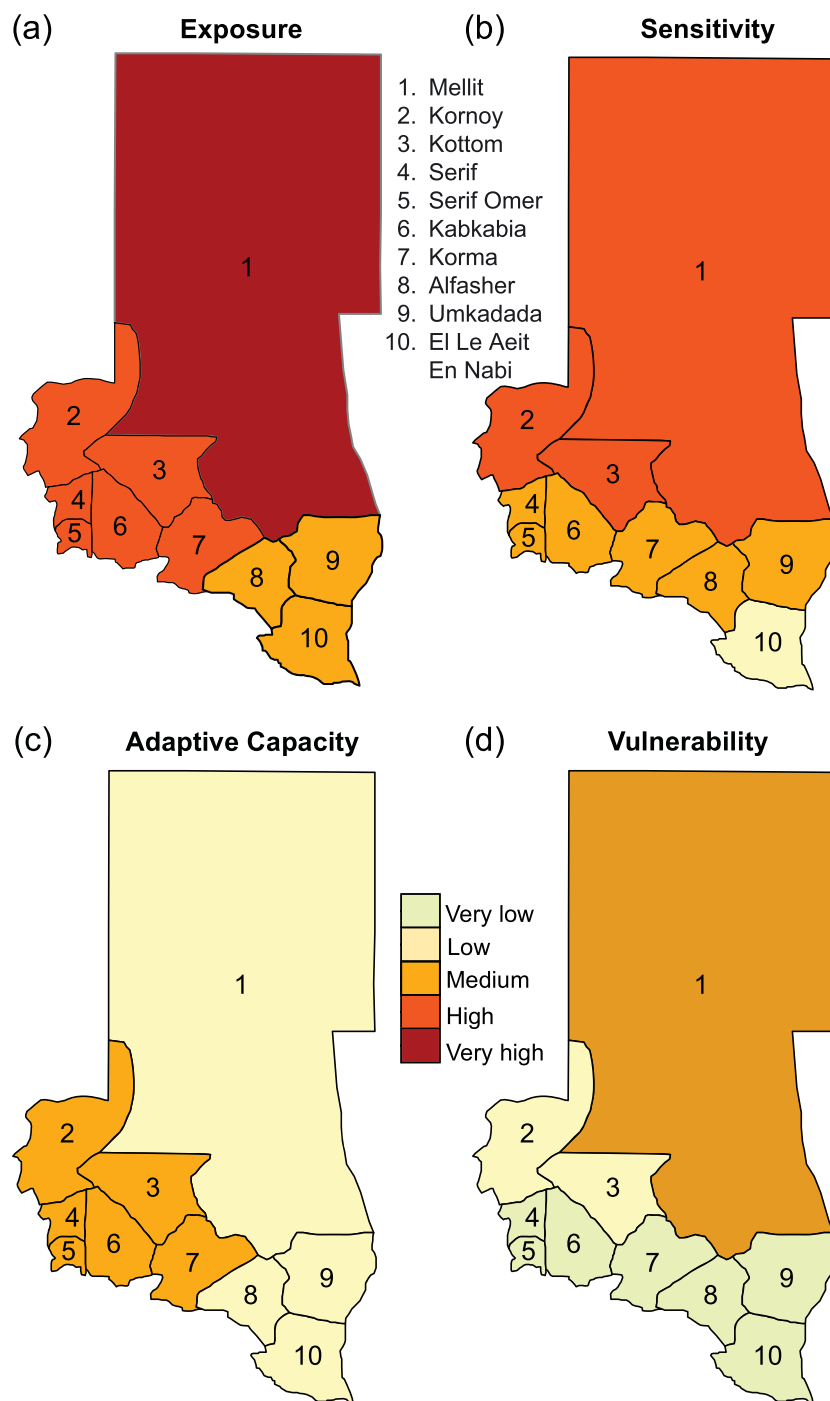


FIGURE 5 Maps showing the distributions of vulnerability components: (a) Exposure, (b) adaptive capacity and (c) sensitivity, and (d) the vulnerability indices across 10 subregions in North Darfur [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

of households severely impacted by droughts are relatively less important but nontrivial contributing factors to exposure to drought and climate risks in these subregions (Figures 6a–c).

The spatial distribution of the sensitivity index is similar but different to that of the exposure index. The driest subregions, including Mellit, Kornoy, and Kottom have the highest sensitivity scores of 0.65, 0.65, and 0.61, respectively, which are classified as high-level sensitivity (Figure 5b and Table 2). In contrast, only El Le Aeit En Nabi with a sensitivity score of 0.33 is classified as having a low-level sensitivity, whereas the other six subregions have medium sensitivities (Figure 5b and Table 2). The above results indicate that the subregions

with higher exposure values are also more sensitive to drought and climate change risks than the regions with lower exposure scores.

For the subregions located in harsher environments, such as Mellit, Kornoy, Kottom, and Serif, the environmental sensitivity indicators including drought-prone population and landless households are the dominant contributors to the sensitivity scores, whereas the agricultural indicators are relatively minor contributing factors (Figure 6d,e). One exception is that Mellit also has a high value for the agriculture dependency score (0.78; Figure 6d). For the other six subregions (Serif Omer, Kabkabia, Korma, Alfasher, Umkadada, and El Le Aeit En Nabi), differences between these different sensitivity indicators are generally small

TABLE 2 Average values of the vulnerability index and its three components in the selected areas for vulnerability assessment

Area	Exposure	Sensitivity	Adaptive capacity	VI
Mellit	0.82	0.65	0.29	0.34
Kornoy	0.79	0.65	0.53	0.17
Kottom	0.75	0.61	0.48	0.17
Serif	0.65	0.51	0.47	0.09
Serif Omer	0.65	0.50	0.42	0.11
Kabkabia	0.64	0.50	0.40	0.12
Korma	0.60	0.50	0.41	0.10
Alfasher	0.53	0.45	0.29	0.11
Umkadada	0.53	0.44	0.38	0.07
El Le Aeit En Nabi	0.47	0.33	0.31	0.05

Note. VI: vulnerability index.

(Figure 6d,e). In terms of agricultural dependency, the field surveys show that most of the households in the southern regions (Alfasher, Umkadada, and El Le Aeit En Nabi) are also conducting other income-generating activities such as hunting animals, collecting forest products, and taking small business and government jobs. Thus, these subregions have lower agriculture dependency scores (<0.45) than the other seven subregions (>0.50, Figure 6d–f). The crop homogeneity indicator is the highest in Kornoy (0.69) and lowest in El Le Aeit En Nabi (0.30). The northern subregions (Mellit, Kornoy, and Kottom) are observed to have the highest crop homogeneities, that is, the least diversified crop cultivation, which is followed by Alfarser, Umkadada, and Kabkabia. In contrast, El Le Aeit En Nabi has the lowest (highest) crop homogeneity (diversity). In other words, the subregions in North Darfur with more favourable climates and less exposure to drought risks have higher crop diversities than subregions with harsher environments.

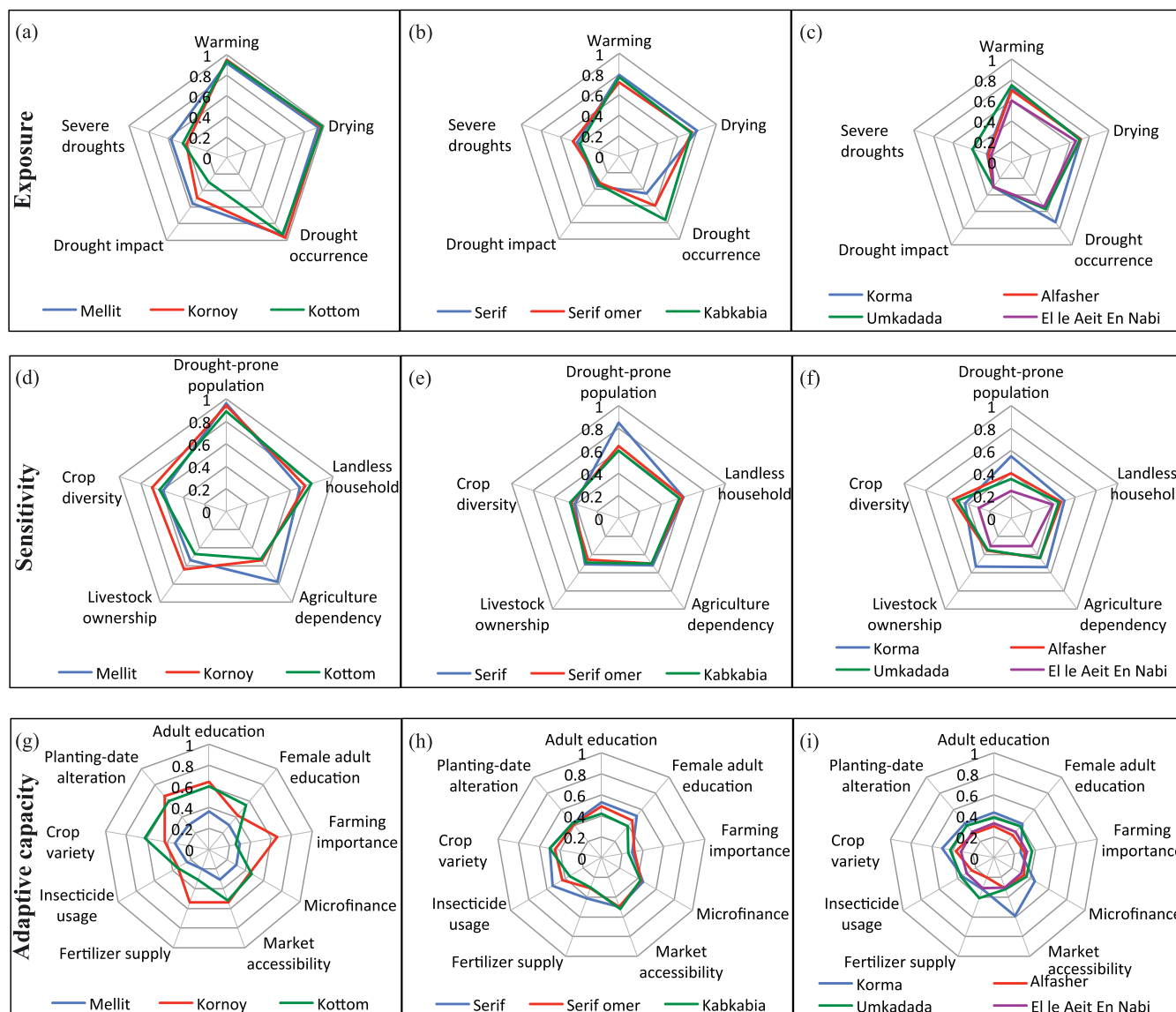


FIGURE 6 RADAR diagrams showing the contribution of indicators to (a–c) vulnerability, (d–f) sensitivity, and (g–i) adaptive capacity in the 10 subregions of North Darfur; (a), (d), and (g) show the results for Mellit, Kornoy, and Kottom; (b), (e), and (h) show the results for Serif, Serif Omer, and Kabkabia; and (c), (f), and (i) show the results for Korma, Alfasher, Umkadada, and El Le Aeit En Nabi [Colour figure can be viewed at [wileyonlinelibrary.com](https://onlinelibrary.wiley.com)]

3.4 | Adaptive capacity

Unlike the spatial distributions of the exposure and sensitivity indices, all 10 subregions show low to medium adaptive capacities (Figure 5c). Specifically, four subregions (Mellit, Alfasher, El Le Ait En Nabi, and Umkadada) have low-adaptive capacities, whereas the other six have medium adaptive capacities (Figure 5c). Mellit, Alfasher, and El Le Ait En Nabi have relatively low scores than the other subregions for nearly all nine adaptive capacity indicators (Figure 6g–i). For education capacity, Kornoy, Kottom, and Serif have the highest scores, which are followed by Serif Omer, Kabkabia, and Korma (Figure 6g–i). Conversely, Umkadada, Mellit, Alfasher, and El Le Ait En Nabi have the lowest education capacity scores.

In terms of the economic structure, Kornoy has an obviously higher score for farming dependency than the other nine subregions (Figure 6g–i). For the microfinance indicator, Mellit, Alfasher, Umkadada, and El Le Ait En Nabi have lower scores relative to the other six subregions. Overall, households in all 10 subregions have limited access to crop markets and fertilizer supply. Umkadada, Mellit, Alfasher, and El Le Ait En Nabi have relatively low accessibility to crop markets than the other six subregions (Figures 6g–i). In terms of fertilizer supply, Kornoy, Serif, and Umkadada have higher scores, whereas the other seven subregions have similar scores.

In terms of coping technology utilization, farmers in all 10 subregions have reportedly undertaken different types of adaptation actions to address drought. The farmers reported using insecticide, increasing crop variety, and changing planting dates as their primary adaptation means. For example, Kottom has a value of 0.62 for the crop variety indicator, which is the highest value in the 10 subregions (Figure 6g). However, only ~32% of the households have changed their crop varieties in El Le Ait En Nabi, which has the lowest values of crop variety (Figure 6i). Approximately 66% of households in Kornoy reported changing their planting times. However, 30% of households confirmed altering planting times in Mellit and Alfasher, which are the two subregions with the lowest scores for planting date alteration. Using insecticide is another important adaptation action among farmers in North Darfur. Approximately 54% of households in Serif reported usage of insecticide, which is followed by Serif Omer (43%). In contrast, only 24% of households reported using insecticide in Mellit and Alfasher.

The above results show that the nine adaptive capacity indicators have high variability across all 10 subregions. The spatial distributions of these adaptive capacity indicators also differ from each other.

3.5 | Overall vulnerability

The overall vulnerability map shows that Mellit is the most vulnerable area among the 10 subregions (Figure 5d and Table 2). Mellit has a very high exposure, high sensitivity, and low-adaptive capacity to drought and climate risks. Mellit is food insecure and prone to repeated droughts (Table 2). Kornoy and Kottom are the second most vulnerable subregions in terms of their VI values (Figure 5d and Table 2). In contrast, the remaining subregions have low vulnerability (Figure 5d). These findings, which are based on the vulnerability assessment, confirm that the northern and central zones of North Darfur are more vulnerable to droughts than the southern zones. In particular, Mellit, which has the highest exposure and sensitivity values, is the most vulnerable to drought impacts. Both natural climate conditions and low-level socioeconomic development contribute to vulnerability in this region.

Finally, we compared the CDI and VI values across the 10 subregions and analyzed the spatial correlation between the two indices. The correlation between CDI and VI is very high ($r = 0.944$; $P < 0.001$; Figure 7), highlighting the important role of droughts in controlling agricultural community vulnerability across this region. In other words, these regions are highly sensitive to droughts and climate changes. Climate change-induced droughts may increase the vulnerability of this region.

4 | DISCUSSION

Droughts have been persistent in North Darfur, particularly in its northern areas. The spatial extent of the 3-month SPI shows that the northern zones have severe to extreme drought conditions during most of the 2004–2013 period (Figure 3a). SPI has been proven to be a simple but effective index to measure droughts for agricultural applications on a standard, consistent scale (Shah & Mishra, 2015). In addition, another advantage is that SPI can be calculated and evaluated on variable time scales, making it useful for diagnosing the temporal

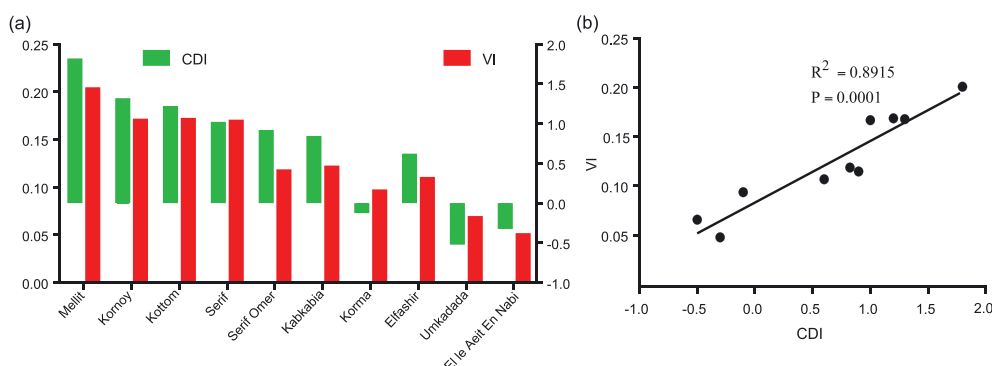


FIGURE 7 (a) Regional average combine drought index and vulnerability index values and (b) the relationship between regional average combine drought index and vulnerability index across the 10 subregions of North Darfur [Colour figure can be viewed at wileyonlinelibrary.com]

evolution of particular events (Santos, Pulido-Calvo, & Portela, 2010). The SPI maps indicate that meteorological droughts appear regularly in the study region during monsoon seasons (Figure 3). The results of the drought analysis on the three-month scale suggest that North Darfur is vulnerable to droughts. These results agree with a previous study by Gizaw and Gan (2017), who studied drought activities and severities over sub-Saharan Africa from 1971 to present.

Our results show that VCI is very sensitive to SMCI. The correlation coefficient between VCI and SMCI is more than 0.89, revealing a strong positive correlation between the two indices. This result conforms to the fact that soil–water content during the rainy season plays a significant role in controlling vegetation status in arid areas, where vegetation growth is heavily dependent on water availability (Klema & Pieterse, 2015). Generally, VCI shows low values in the entire region as a consequence of dry climate and traditional agricultural practices. These findings are in line with previous studies (Brown, Hammill, & Mcleman, 2007; Dutta et al., 2015; Hua et al., 2017; Vicente-Serrano, 2006), which showed that variations in vegetation type and land use practices are the key factors controlling VCI response to drought conditions. Some other studies have reported a lagged VCI response to soil moisture conditions due to the buffer effect of soil–water storage for vegetation growth response to drought (Anderson et al., 2012). For wet regions with more soil–water storage and higher buffer effects, drought impacts on deep-rooted vegetation usually require a prolonged period of lower-than-normal precipitation (Klema & Pieterse, 2015). However, most of this study region has a dry climate and experiences a prolonged dry period nearly every year, which results in a lower buffer effect. In addition, the effects of summer droughts on crop production have been acknowledged in sub-Saharan African environments in previous studies (Mulangu, Chauvin, & Porto, 2012). Our study also clearly identified regional droughts and their impacts on vegetation productivity, soil moisture condition, and crop yield during 2004–2013 (Figure 3b,c). The monsoon season (July–September) CDI and YAI indices have a high correlation ($r = 0.87$; $P < 0.001$). From a botanical viewpoint, this high correlation is reasonable. July–September is both a wet season and growing season in most parts of the study region, which is accompanied by hot weather. In other words, water deficiency can easily result in a large amount of physical stress to crops. The results also suggest that SMCI is a good metric to quantify soil–water availability in this region and can reflect the impacts of droughts on vegetation and crops.

The results of this study also show various remarkable findings regarding drought vulnerability at the community level across the region. The areas with the highest exposure to drought and climate change risk are also the regions that are the most sensitive and vulnerable to drought (Figure 5a,b). Our study shows that vulnerability in this region gradually decreases from north to south (Figure 5d), whereas the livelihood zones identified by FEWS NET (2011) shows similar north-to-south gradients. Nearly the entire northern half of Mellit is a desert zone, which is not suitable for habitation (Figure 1). A pastoral livelihood zone, which is chronically food insecure due to having less livestock and less mobility than its neighboring zones, covers most of the southern half of Mellit, all of Kornoy, and part of Kottom (Figure 1). The agropastoral millet livelihood zone, which also experiences chronic food insecurity resulting from poor cropping conditions,

limited market access, and few labor opportunities, spans a large area south of North Darfur, including Serif, Alfasher, Umkadada, a large part of Kornoy, most of Kottom and Kabkabia, and half of Korma (Figure 1). About half of Korma is a tobacco livelihood zone in which people are relatively wealthy and can plant the valuable tobacco crops (Figure 1). However, tobacco production is often and acutely reduced by drought. Small parts of Kottom, Serif Omer, and Kabkabia are wadi cultivation zones, which allow households to add valuable market garden crops to their production of staple millet and sorghum (Figure 1). Households in most of El Le Ait En Nabi are usually self-sufficient and able to plant perennial cash crops such as gum arabic. Obviously, the spatial distribution of the livelihood zones and levels of food insecurity in these zones are generally consistent with our independent survey and quantitative drought vulnerability analyses.

In the past, droughts have resulted in several extreme famines. A severe famine known as the “white bone” occurred between 1873 and 1874. Later, the 1888–1892 drought also resulted a massive famine and triggered the ensuing civil war between Mahdist forces under the governor of Darfur and the rebel army (Takana, 2008). Another drought between 1913 and 1914 also resulted in a famine, resulting in massive migrations and ultimately, the failure of the local government (Takana, 2008). The severe drought-induced regional famine between 1983 and 1984, led to massive north–south population movements, loss of livestock, and destruction of property (Young et al., 2005). According to the local record in North Darfur, there were 16 drought years between 1972 and 2001 (Young et al., 2005). Among the famines that occurred between 1972 and 2001, the 1984–1986 famine led to the largest number of deaths (a total of 176,900 actual deaths), which were 3-times higher than normal (Young et al., 2005). Clearly, the North Darfur region is vulnerable to drought and has frequently undergone droughts. Climate change is expected to increase drought risk in this region (Gizaw & Gan, 2017; IPCC, 2013), which makes the drought-prone areas more vulnerable (Cheeseman, 2016; IPCC, 2012). In the context of climate change, the livelihoods in most of the study region are expected to become more vulnerable to drought if there are no substantial adaptations.

In addition to recurrent droughts, several interrelated factors such as the civil war and its attendant displacement, lack of food security policies, and poor rural infrastructure have collectively resulted in the food insecurity and malnutrition situation in this region according to the reports from the World Food Programme (WFP) and the Food and Agriculture Organization of the United Nations (FAO; FAO, 2017; Nkunuzimana et al., 2016). Although recovery strategies have been implemented in recent decades by various aid agencies and returnee farmers, North Darfur still endures food security and livelihood challenges, such as limited water resources for crops and livestock, decreasing soil fertility, drought, and physical insecurity. According to recent surveys by WFP (WFP, 2016) and the outlook of Sudan food security in 2016, by FEWS NET, nearly a third of sampled households in North Darfur continue to be food insecure as of May 2016, because there were abnormal rainfall conditions in part of this region, and the cultivation season was by displaced people.

Our study further reveals that all 10 subregions in North Darfur have medium to low adaptive capacities for drought risks (Figure 5). Adoption of techniques to cope with droughts and climate change is

generally low, especially in the most drought-prone region of Mellit. This result is similar to the findings of a study in Ethiopia by Bryan, Deressa, Gbetibouo, and Ringler (2009), which reported that a large portion of farmers in Ethiopia did not make any adjustments to their farming practices even though there were perceived changes in temperature and rainfall. Based on the survey of the farmers, the main barriers to adaptation were lack of access to land, information, and credit in Ethiopia (Bryan et al., 2009; Gebrehiwot & van der Veen, 2013). Similar barriers also exist in North Darfur, Sudan. The relatively low education level in North Darfur may also contribute to the low-adaptive capacity in this region. Regions showing high vulnerability are enormously affected by food insecurity and susceptibility to frequent drought cycles. Accordingly, the current limited human and infrastructural capacity will undermine the region's capability of responding to both direct and indirect influences of drought and climate variability (Campbell et al., 2016; Wright et al., 2014). In practice, farmers in the study area have implemented different adaptation strategies to cope with droughts such as increasing crop variety and changing planting dates. However, there remains ample room for enhancing the adaptation capacity in this region.

Because the study region has a large variety of farms in terms of size, intensity, land use type, objective, and farmer perception, it is difficult to develop and implement universal adaptation techniques. The most vulnerable regions are those with a high percentage of farmers who depend on rainfed agriculture for their livelihoods. These regions have been repetitively affected by drought conditions and are known to have prevailing food shortages. Furthermore, these regions are characterized by inadequate resources, limited sources of income, low-human capital, and high degrees of desertification. Mohammed and Inoue (2013) and Mohammed et al. (2018) also reported that the dependency of rural farmers on agriculture and other natural resources makes them very vulnerable. In general, the prevalent drought occurrence in these regions is expected to lead to increased food shortages, vulnerability, and loss of livelihoods in the context of climate change.

5 | CONCLUSIONS

In this study, we provide an overall assessment of drought occurrence in North Darfur using different drought indices for the period from 1989 to 2013. The meteorological, remote sensing, and crop yield indices reveal that North Darfur has experienced region-wide droughts from 2004 to 2013, which has massively affected crop productivity in this region.

The results also reveal that vulnerability to drought and climatic variability is characteristically connected to the social and financial structure and advancement in this region. Vulnerability across North Darfur is also highly correlated with drought conditions. In addition, the root causes of vulnerability are traced for the subregions of the study area. This vulnerability evaluation provides a scientific basis for policy making targeted disaster mitigation and adaptation. The vulnerability analysis and associated indices provide a useful way to quantitatively prioritize adaptation efforts in Darfur. Our study also highlights the most vulnerable communities, which include farmers

dependent on rainfed agriculture and those living in the northern parts of Darfur. This study also provides a framework for decision makers and aid agencies to prioritize specific interventions to aid farmers in adapting and responding to drought impacts using available resources.

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