Assessing drought vulnerability and adaptation among farmers in Gadaref region, Eastern Sudan

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ABSTRACT

Agricultural productivity in rural areas is severely affected by climate variability, and this elevates the vulnerability of rural households to food insecurity. This study examines the socio-economic vulnerability of farmers who are susceptible to droughts in the five agricultural-based regions of Gadaref, Eastern Sudan. A survey was carried out in 500 households to collect data on socio-economic and livelihood indicators. The data analyzed from these indicators were used to generate the three components of drought vulnerability: exposure, sensitivity and adaptive capacity. The analysis revealed that the regions deemed to be most vulnerable to both drought and climate variability were also projected to have the most vulnerable communities. The most exposed farming communities of Alfaw, Algadaref and Alfushqa regions showed a relatively low capacity for adaptation. Moreover, the study determined that vulnerability to drought and variability is associated with social and economic development in the Gadaref region. The results show that highly vulnerable regions are characterized by features such as low levels of productivity, elevated levels of financing, low crop diversity, agriculture as the primary income source and a low level of agricultural insurance. This research shows the importance of diversified livelihoods in building resilience against hazards linked to climate change.

1. Introduction

Most countries in the world depend primarily on rainfed agriculture for their food (Raju and Wani, 2016) and soils play a key role. This is because soils are a key component of the Earth System as they supply the nutrients, water and substrate for the crops (Mol and Keesstra, 2012). Therefore, soils are the strategic component of agricultural sustainability as the United Nations highlighted (Keesstra et al., 2014). As a result, agriculture is remarkably sensitive to changes in climate with a degree of seasonal variations, and this is attributed to the fact that climate change affects the two most significant direct inputs to agricultural production: precipitation and temperature (Gornall et al., 2010). According to Yang et al. (2017) and Delphine et al. (2014), climate change also has an indirect effect on agriculture by controlling the development and distribution of crops, extending the regularity and distribution of unfavorable weather conditions and reducing water availability.

As reported by Solomon (2007) some developing countries are expected to experience considerable adverse influences of climate change and variability in the future. Also, Serdeczny et al. (2016) predicted that the increase of temperature on the African continent would be above the global annual mean warming. Consequently, the adverse impact of climate change is predicted to be higher in the different African countries because of the continent's weak adaptive capability, the economic value of climate-sensitive sectors to these countries and their insufficient human, institutional and business ability to predict and respond to climate change and variability (Heltberg et al., 2009; Hertel and Rosch, 2010). The idea of vulnerability is analyzed as the net

effect of potential impacts and the potential to ultimately cope with the consequences; where possible results combine the systems of exposure and sensitivity. This relationship is used to develop an implicit model, which can help as a basis for indicator development and measurement of the overall vulnerability (Adger, 2006; Hinkel, 2011; Smit and Wandel, 2006).

Vulnerability framework assessment for potential effects of climate change and variability has increased over the last two decades with increasing emphasis on climate change studies (Adger, 2006; Hinkel, 2011; Malone and Engle, 2011; Smit and Wandel, 2006). The different definitions and methods for assessing vulnerability have led to several attempts to simplify the concepts (Eakin and Luers, 2006; Hinkel, 2011; Turner et al., 2003; Wiréhn et al., 2015), classify the data on vulnerability into various approaches (Füssel, 2007; O'Brien et al.,2004) and analyse of the study to vulnerability indicators (Eakin and Luers, 2006). The idea of vulnerability is hard to define but usually, it is defined using components that cover exposure and sensitivity to external strains and the capacity to adapt it (Adger, 2006; Malone and Engle, 2011; Moss et al., 2001). The most common definition for climate change vulnerability was developed by the Intergovernmental Panel on Climate Change (IPCC), and it defines vulnerability as a purpose of the character, magnitude, and rate of climate change and adaptation to which a system is exposed, its sensitivity and its adaptive capacity. This definition showed vulnerability could cover several dimensions or aspects with more attention to the scarcity of resources and inequality. However, the recent assessment report of the IPCC defines vulnerability simply "as the propensity or predisposition to be adversely affected" by identifying vulnerabilities through societal risks (IPCC, 2014).

Several procedures have been adopted for assessing vulnerability to climate change like statistical methods, comparative analysis, geographical information system and mapping techniques, historical narratives, agent-based modelling and indicator-based approach. Recently an indicator-based approach for understanding vulnerability to climate change has been broadly used (Dovie, 2017; Pandey and Jha, 2012; Reed et al., 2013; Salik et al., 2015; Shah et al., 2013). Realizing that vulnerability is a complicated phenomenon that is difficult to estimate directly, an indicator-based approach is useful for taking the complex phenomenon with some chosen representatives or variables describing different aspects of vulnerability to climate change. Regardless of criticisms that vulnerability studies have emphasized the analysis of aggregate states rather than guidance on social processes that can be directed to decrease vulnerability (Eriksen and Kelly, 2007), it considers a valuable method in ranking vulnerable communities, areas and sectors to climate change for the policy-making process. It provides the combination of biophysical and socioeconomic components in the assessment of vulnerability and allows a public and policy-makers response in prioritizing adaptation methods (Gbetibouo et al., 2010; Yiran et al., 2017; Žurovec et al., 2017).

In Sudan, drought is one of the most prevalent climate change-related natural hazards affecting the country (Elagib, 2015). Repeated droughts form the main threats to the rural resources and food security of the country. Nearly each year, the country undergoes localized drought disasters leading to crop failure and endangering development activities (Elagib, 2015; Elagib and Elhag, 2011). As a consequence, the livelihoods and agricultural practices in the rural areas in the country are subject to continuous and comprehensive changes (Zhang et al., 2012).

This is a worldwide problem that is part of a multifaceted process of land degradation that intensively affect Sudan and the neighboring countries, which need a proper strategy to fight against Desertification (Mekonnen et al., 2016; Villacís et al., 2016; Mekonnen et al., 2017).

Gadaref region in eastern Sudan has semi-arid climate, characterized by high temperature, medium to low rainfall. The mean annual rainfall of the region is estimated to be 560 mm, while the mean annual monsoon rainfall is 473 mm, 84% of the annual rainfall (Sulieman and Buchroithner, 2009).

Even though the rainfall in southern part of the Gadaref region is quite high, in Alrahd and Algalabat regions, its distribution during the monsoon season is highly irregular and erratic.

Drought and floods occur often with varying frequency in the region. The regions of Alfaw and Alfushqa are among the least developed in Gadaref (Gbenga, 2008). The regions face high level of poverty, with around 50% of the population living below the poverty line and they are among the more agriculture drought-prone regions of the country (Mahgoub, 2014; World Bank, 2011).

This paper aims to study drought vulnerability of the farming community and to identify hot spot areas across five regions of Gadaref, Eastern Sudan. It examines the vulnerability among five regions exposed to drought. The study evaluates different components of Vulnerability Index (VI) among the communities in the study region. It further compares the level of vulnerability with the specific livelihood indicators at the region level. The study includes biophysical, social and economic indicators depicting the three components of drought vulnerability: exposure, sensitivity and adaptive capacity. A geographic information system (GIS) was then applied to produce vulnerability maps by taking the region as a spatial unit of analysis.

2. Materials and methods

2.1. The study area

Gadaref is one of the regional states located in the eastern part of Sudan. The region lies between longitudes 33–36° E and latitudes 13–16°N with an area estimate of 65,000 km². It borders Ethiopia and four other Sudanese states; Khartoum and Kassala States in the North, Gezira state in west and Sennar state in the south. Gadaref region is divided into five administrative zones (Alfaw, Alfushqa, Algadaref, Alrahad and Algalabat) (Fig. 1), and ten rural districts which include Gadaref, Central Gadaref, Alrahad, Alfaw, Eastern Algalabat, Alfashqa, Albutana, Western Algalabat, Galaa alnahal and Alquresha. The number of villages and towns in the state is 657 distributed in the localities of the district mentioned above (OCHA, 2012).

The region has a total population that exceeds 4.3 million people, about 80.5% of whom live in rural areas. The region belongs to the semiarid area where monsoon weather dominates throughout the year. In general, three distinct seasons can be recognized in Gadaref. The first is the main monsoon season that lasts from June to September, the second is the dry winter period from October to February and the third is pre-monsoon summer season from March to May. The local climate is marked by high spatial and temporal variations and periodic drought. Seasonal rainfall ranges from about 1000–1300 mm in some areas in the southwest to less than 260 mm in the northern part. The mean annual rainfall of the region is estimated to be 560 mm, while the mean annual monsoon rainfall is 473 mm, 84% of the annual rainfall (Sulieman and Buchroithner, 2009).

Agriculture is the main economic activity in the Gadaref region and constitutes most of the total regional gross domestic product. The importance of agriculture to the local economy can be estimated by the fact that it directly helps about 80% of the population with regards to employment and livelihood (Mahgoub, 2014; World Bank, 2011). Agricultural systems in the region are mostly rain-fed and dominated by small and large scale farmers; our study focuses on farmers with an ownership of less than 5 ha per family, who have been adopting low input and output rain-fed techniques combined with traditional farming technologies.

Gadaref region is dry for most of the year except during the rainy season. Repeated droughts form the main threat to rural livelihoods and food security. Almost every year, the study area experiences localized drought disasters causing crop failure and jeopardizing development activities (Elagib, 2015). As a result, rural livelihoods and agricultural systems in the region are subject to continuous and widespread changes in climate variability and seasonal shifts which have a direct impact on
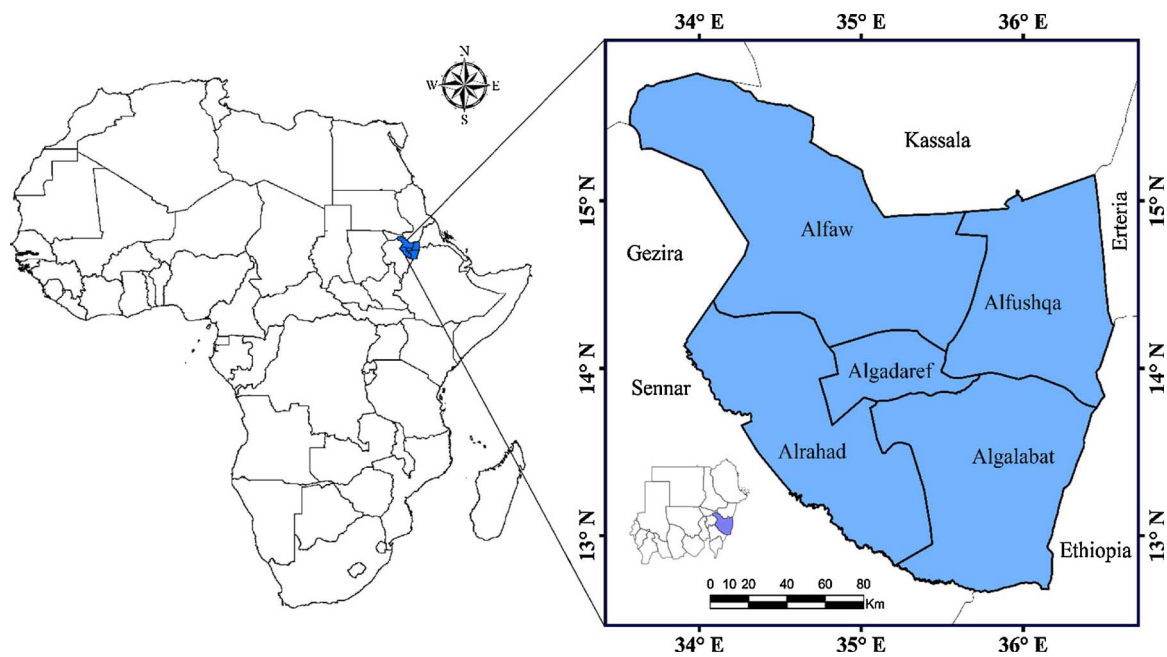
Fig. 1. Study area.

food security.

2.2. Data collection

For this study we used structured questionnaires as well as reports from the ministry of agriculture and forests in Gadaref region to collect the relevant indicators for VI at both the household and regional level. The questionnaire considered socio-economic, demographic and farmer's information. The questions covered drought, climate variability perceptions and coping techniques used by farmers. The survey was conducted in households in the five regions of Gadaref from June to October in 2016. We surveyed 500 households in five regions to apply the vulnerability index.

The surveys of the household questionnaire were conducted in order to collect the data on different indicators of all the five regions. Based on the information from respondents, the study also determined the minimum and maximum values for each of the indicators used. Climate exposure at the region level was captured by the perception of household respondents on decreasing rainfall, increasing temperature, increasing frequency of droughts, the average number of natural disaster episodes that they have experienced and percentage of land without irrigation facilities. Perception-based questions were asked about the personal experience of the farmers regarding different weather variables. In the IPCC definition of vulnerability, exposure has been represented as an external dimension or "exposure" of a system to climate variations (Füssel, 2007). However, due to lack of climate adaptive capacity, Füssel and Klein (2006) argues that it is not the mere availability of adaptation options but the ability of people to implement these options that determine their vulnerability to climate change.

For mapping farming communities' vulnerability to climate change and variability at the region level, the IPCC's definition was applied, whereby the region's vulnerability was obtained as a function of three components: exposure, sensitivity and adaptive capacity (IPCC, 2014). Each element and the selected indicators representing these vulnerability components are presented in Table 1. The rainfall and yield data were obtained from ministry of Agriculture and Forests, Gadaref state, Sudan.

2.3. Methods

The selection of indicators certainly matters for vulnerability studies. Studies have shown that different indicators can lead to many vulnerability rankings at the sub-national level (Alcamo, 2008; Smit and Wandel, 2006). This study is based on the IPCC vulnerability framework with three factors: vulnerability, exposure, sensitivity and adaptive capacity forming the vulnerability index (VI), which has been reviewed over the drought-prone areas in the region (Panda, 2016). The chosen indicators were designated to reflect the exposure, sensitivity and adaptive capacity among farmers in a drought-prone region and are based on available literature. Each component in the framework is composed of several sub-components and is based on a review of the literature and some indicators that are specific to the study area, as mentioned in Table 1. The VI was created by implementing basic data from the family surveys which ranked the regions based on their corresponding vulnerability. Adaptive capacity describes the ability of a system to adjust to climate stresses, to moderate potential damages or to cope with the consequences (Esperón-Rodríguez et al., 2016). It includes both particular adaptation actions by farming households to deal with climate risks such as changing crops, changing planting dates and are combined with indicators representing generic adaptive capacity indicators such as use of climate information, access to crop insurance and years of farming experience which also play an important part in discovering the extent of vulnerability (Araya et al., 2012). The most vulnerable districts and communities are those that are highly exposed to expected changes in climate and have limited adaptive capacity (Muluneh et al., 2015, 2017).

The selection of villages was based on the statistics available at an administrative unit below the district on the worst drought-affected areas. The purpose was to identify the farmers within the regions facing a severe drought problem. Our selection of farmers was based on the statistics available at the block level of villages, we found that many villages in the selected blocks were affected by droughts. The Lottery method of the sampling was used in order to select affected villages from each selected block for the in-depth household survey.

The literacy rate is another factor contributing to adaptation to drought. With lack of education being associated with poverty and marginalization, the least educated and lower skilled members of society are likely to be the most vulnerable to climate hazards regarding

Table 1
Selected variables used in vulnerability assessments.

Major components	Subcomponents	Unit Measurement	Max value	Min value
Exposure	Temperature change	C^0	100	0
	Change in precipitation	Mm	100	0
	Rural population density	Population per Km^2	100	0
	Frequency of drought	%	100	0
	Long-term average VCI for 25	%	100	0
Sensitivity	irrigated land	%	100	0
		%	100	0
	Landless population	the population who own Ownership of radio %	100	0
	Dependent population	population who own Non-agricultural %	100	0
Adoptive capacity	Livestock ownership	the population who own Farm holding size %	100	0
	Crop diversity index	%	100	0
		%	100	0
	Income	the population within km to supply sources %	100	0
	Adult literacy rate	the population within km to supply sources %	100	0
	Adult female literacy rate	the population within km to supply sources %	100	0
	Insecticide and pesticide	the population within km to supply sources %	100	0
	Hectares supply sources	Population within 1–4 km to supply sources %	100	0
	Fertilizer supply	the population within 1–4 km to supply sources %	100	0
	Change crop variety	the population within 1–4 km to supply sources %	100	0
	Changing planting date	the population within 1–4 km to supply sources %	100	0
	Crop insurance	the population within 1–4 km of %	100	0
	Crop market	the population within 1–4 km to supply sources %	100	0
	Micro finance	the population within 1–4 km of %	100	0

livelihoods and geographical location. Cohen et al. (2016) indicated that countries with higher levels of human knowledge are considered to have greater adaptive capacity than emerging nations and those in transition. Populations with low overall levels of literacy are more likely to depend on climate-sensitive economic activities such as agriculture. Increasing the overall literacy level will thus reduce vulnerability by increasing people's capabilities and access to information and this in turn, increases their ability to cope with adversity. In this study, human and social capital is represented by adult literacy rates and female literacy (Adger, 2006; van der Land and Hummel, 2013).

Irrigation potential was selected based on the assumption that places with more potentially irrigable land are more adaptable to adverse climatic conditions (Gebrehiwot and van der Veen, 2013). The irrigation rate is measured by looking at the net irrigated area as a percentage of the net sown area. Developed irrigation systems are accordingly assumed to reduce farmers' vulnerability to erratic rainfall as agriculture in the study region is all nearly rain-fed.

Since each of the sub-components is measured on a different scale, it was first necessary to standardize each as an index. We used the Eq. (1) for this conversion was adapted from that used in the Human Development (UNDP, 2007):

$$index_{s_d} = \frac{S_d - S_{min}}{S_{max} - S_{min}} \tag{1}$$

Where S_d is the original subcomponent for community s and $S_{max} - S_{min}$ are the minimum and maximum values respectively, for each subcomponent prepared utilizing data from all the five regions. For variables that measure recurrences such as the percentage of farmers who have changed their crop types, the minimum value was set at 0 and maximum value set at 100. Subcomponent values for each indicator have been mentioned in Table 1. After each was standardized, the subcomponents were averaged using the Eq. (2) to calculate the value of each component.

$$C_x = \frac{n_{i=1 indexi}}{n} \tag{2}$$

Where C_x is one of the three components of the region exposure, sensitivity and adaptive capacity, *indexi* represents the sub- components, indexed by i, that make up for each major component, and n is the number of subcomponents in each major component. Once the values

for the exposure, sensitivity and adaptive capacity for a region were calculated, the three contributing factors were combined using the Eq. (3) to obtain the r-level vulnerability index (VI) (Panda, 2016).

$$VI_d = (e_d - a_d)^* s_d \tag{3}$$

Where VI_d is the climate VI score for region d using the IPCC vulnerability framework, e is the calculated exposure score for region d, a is the adaptive capacity score for region d and s is the sensitivity score for region d. We scaled the VI from 0 (minimum vulnerable) to 0.8 (maximum vulnerable).

For the physical characteristics of the environment, land cover or a green environment are desirable for most rural households and should form a major consideration in farming community's vulnerability assessment (Frank et al., 2003). Ecosystem stress and destruction can increase the physical vulnerability of settlements. Deforestation and ecosystem fragmentation can increase a region's ecological vulnerability to climate change. Greenness (in the form of vegetation cover) is thus believed to be a good replacement for socioeconomic conditions and is measured in the form of a vegetation index.

The normalized difference vegetation index (NDVI) is the most commonly used vegetation index for assessing vegetation cover (Tucker and Choudhury, 1987). The temporal variations in the NDVI reflect the change of vegetation as a response to the weather (Potter and Brooks, 1998). As a result, this index has been commonly used to monitor crop yield assessment/forecasting, ecosystem dynamics to detect the spatial extent of drought episodes and their impact (Groten and Ocatre, 2002).

However, the literature reported that the spatial and temporal variability of NDVI values is closely related to the contribution of geographical resources to the amount of vegetation cover. This contribution fluctuates considerably depending mainly on, soils, vegetation type, and topography, as well as the climate of the region (Groten and Ocatre, 2002). Accordingly, in tropical rainforest areas, high NDVI values could result from the tropical forest vegetation, whereas, in deserts, the low NDVI values are to be anticipated. For this reason, Vicente-Serrano et al. (2006) confirmed that the NDVI is not comparable in space, especially in the heterogeneous region. Also, surface moisture and aerosol signals may limit the accuracy of the observed NDVI in arid or semi-arid regions (Funk and Brown, 2006). Hence, in this study, the long-term (decadal) Average Vegetation cover index (VCI) is used as an indicator of the available natural resource, which is

widely used to monitor drought.

Since the study investigated droughts caused by water insufficiency in the rainy season from June till September, only data of the rainy months were applied for the analysis. Using maximum and minimum NDVI maps for every monsoon season, analysis was done for the duration 2008–2013. Using Eq. (4) VCI combined images were made for each year's rainy season using NDVI images to produce the multi-temporal drought maps and decide the connections between monthly precipitation and vegetation indices. About 300 decadal images were processed. VCI classification threshold was used to produce the maps of annual vegetative drought, which is presented by Eq. (4) (Kogan, 1995).

$$VCI(\%) = \frac{NDVI_{max} - NDVI}{NDVI_{max} - NDVI_{min}} \times 100 \qquad (4)$$

Where NDVI, $NDVI_{min}$ and $NDVI_{max}$ NDVI, are the smoothed ten days of NDVI, its absolute minimum over multi-year, and its multi-year maximum NDVI respectively for every pixel. The VCI, that is recommended by Kogan (1995), has been utilized to assess the climate effect on vegetation cover. The technique is valuable to separate the short-term weather signal in the NDVI from the long-term ecological signal and in this sense, it is a better indicator of NDVI than the water shortage condition. Kogan (1997) provided VCI for accurate drought information, he showed that VCI ranges from 0 to 100 comparing the effect of the vegetation condition from tremendously unfavorable to an optimum condition.

The classification threshold of VCI showed that values of 35% or less are an indicator of drought. Whereas VCI values of around 50% are considered as a fair vegetation condition, and VCI values between 50 and 100% are a sign of optimal or exceeding normal conditions. The data of NDVI was acquired from http://www.vito-eodata.be

Exposure describes the degree of climate stress upon a particular unit of analysis. It refers to the exposure of a system to stimuli that affect that system. This can be easily imagined as climate variability and the various changes in the climate system that are often of concern to stakeholders: increase in temperature, changes in rainfall or changes in drought frequency.

In this study, exposure is expressed by the frequency of climate extremes in temperature, rainfall, and droughts as a proxy to describe exposure at the household level in comparison with other studies (Jamir et al., 2013; Panda, 2016; Shukla et al., 2017). The frequency of climate extremes reflects the level of climate change to which districts are exposed. It is commonly agreed that in regions with a high frequency of climate extremes, increasing temperature and decreasing precipitation are expected to have negative impacts on farm production (Gornall et al., 2010; IPCC, 2014; Kang et al., 2009).

Sensitivity applies to the degree to which a system is affected by climate-related incentives, both positively or negatively. Gbetibouo et al. (2010a) described that the responsiveness of a system to climatic influences is shaped by both socio-economic and ecological conditions. This, in turn, determines the size to which a group will be affected by an environmental stressor. In this study, four indicators were considered that might influence the sensitivity of the farming community in a district: the share of subsistence farmers, rural population density, landless population, and part of the dependent population (Population that does not work in the agriculture sector).

Since the quality of the residential home doesn't play a significant role on drought because most farmers use Grass Sorghum to build their houses as this type of grass has a fast regrowth period, superior disease and pest resistance and can tolerate drought conditions (Zhu et al., 2017). Therefore we excluded the indicator of the quality of the residential home.

Agricultural dependency is determined by the percentage of the area workforce engaged in agriculture. It is assumed that high levels of agricultural dependency will increase a farming communities' vulnerability to drought. The vulnerability of the agricultural labor force is measured with the percentage of landless laborers used and this provides an indication of inequality in landholding. A region with a larger part of landless laborers in the agricultural workforce is more vulnerable to social and economic separation due to drought or other climate pressure (Galdino et al., 2016). This study contends that places with a high occurrence of droughts, a greater share of subsistence farmers, and agricultural dependency are more sensitive to drought and climate variability.

The vulnerability of food production to climate change is examined at the regional level; the impacts at farm level are not necessarily relevant for studies looking at regional and bigger aggregation levels. The way the farm level influences the local level is very relevant. However, as reported by Reidsma and Ewert (2008), we analyzed the impact of regional farm diversity on the impacts of drought on regional sorghum yield variability. Important here is to show sorghum yield variability at farm level and sorghum yield variability at the regional level and what this implied for climate impacts.

The diversity in farm type yield variability (SD), demonstrates the difference in the responses of farm types in a region. This measure indicates per region the variation among farm types in their inter-annual sorghum yield variability. SD was measured as the standard deviation in the relative yield anomaly per year of all farm types in a region, averaged over the study period (1989–2013) as shown in the below formula:

$$SD = \sum_{t=1}^{N} \frac{sd(Y_{A.1}, Y_{A.2}, \ldots, Y_{A.f})_t}{N} \ with \qquad (5)$$

$$Y_{A.i} \ \frac{100*\left(y_{it-}\sum_{t=1}^{N} y_{it}/N\right)_t}{\sum_{t=1}^{N} y_{it}/N} \qquad (6)$$

Where SD is the standard deviation of relative yield anomalies (YA, i) of farm types i (i = 1, 2… f) per year t(t = 1,2,…,N). Yield anomalies per farm type and year were calculated from the actual yield (y_{it}) related to the average of the study period. Relative yield anomalies were considered, as absolute yields differ per farm type within a region and therefore relative anomalies can be better compared than total anomalies. The second measure, the regional farm diversity, demonstrated the diversity in the abundance of farm types. Farm diversity was based on the Shannon–Weaver index and expressed by intensity diversity, size diversity and land use diversity. Regional effects of inter-annual climate variability on sorghum yields were measured by the Pearson correlation coefficient (r) between sorghum yield anomalies from a linear trend and growing average season precipitation r (yield, precipitation). Both diversity measures were related to r (yield, precipitation) in a regression model, to assess the relationship between farm diversity and regional effects of climate variability on crop productivity.

2.4. The limitations

Our above analysis demonstrates the importance of diversified livelihoods in managing risks associated with drought events. However, the limitations to the methods and results do need to be considered. Firstly choosing of indicators for building the VI is based on the availability of data and the situation in the particular study regions. Secondly, a significant limitation of our approach is the assumption that all the indicators are equally important and that is not possible as demonstrated by Eakin and Bojórquez-Tapia (2008). Also, Wiréhn et al. (2015) stated that due to the multiple dimensions, vulnerability indices on weighting methodologies for agricultural vulnerability assessment should not be treated and shown as a complicated method. Thirdly It is important to be aware of the study's limitations in assessing flood and traditional agriculture practices such as using wide level disk, which can mainly be attributed to lack of data. Hence, the results, especially

Table 2
Values of Subcomponent indicators.
Source: Author's calculation.

Subcomponents	Major components	Unit Measurement	Alfaw	Alfushqa	Algadaref	Alrahad	Algalabat
	temperature Change	%	0.97	0.94	0.91	0.74	0.72
	Change in precipitation	%	0.98	0.96	0.95	0.75	0.75
	Rural population density	%	0.96	0.97	0.83	0.85	0.64
	Frequency of drought	Number of occurrence of droughts from 1989 to 2013 %	0.94	0.90	0.93	0.45	0.60
	Long-term average VCI for 25	%	0.25	0.26	0.31	0.36	0.32
	irrigated land	%	0.58	0.31	0.35	0.43	0.47
Total exposure			0.78	0.72	0.71	0.63	0.61
	Landless population	%	0.90	0.78	0.80	0.30	0.29
	Dependent population	%	0.94	0.66	0.43	0.52	0.44
	Livestock ownership	%	0.70	0.77	0.47	0.51	0.49
	Crop diversity index	%	0.76	0.73	0.60	0.23	0.27
Total sensitivity			0.83	0.74	0.58	0.39	0.37
	income	population who own Farm holding size %	0.30	0.26	0.26	0.30	0.18
	Adult literacy rate	%	0.50	0.62	0.90	0.75	0.78
	Adult female literacy rate	%	0.43	0.39	0.45	0.33	0.24
	Insecticide and pesticide	%	0.89	0.86	0.85	0.54	0.43
	Hectares supply sources	population within km to supply sources %	0.25	0.22	0.17	0.44	0.57
	Fertilizer supply	population within km to supply sources %	0.66	0.54	0.26	0.41	0.47
	Change crop variety	%	0.93	0.89	0.76	0.60	0.45
	Changing planting date	%	0.89	0.85	0.93	0.43	0.33
	Crop insurance	%	0.61	0.62	0.62	0.59	0.60
	Crop market	population within 1–4 km to supply sources %	0.64	0.57	0.52	0.53	0.54
	Micro finance	population within 1–4 km of %	0.30	0.44	0.95	0.87	0.93
Total adaptive capacity			0.58	0.57	0.61	0.53	0.50
Vulnerability index			0.1635	0.1133682	0.0615076	0.0404182	0.0388077

values of overall vulnerability, must take these limitations into consideration.

3. Results and discussion

3.1. Exposure and sensitivity

Among the five regions, the average highest value of total exposure was recorded in the Alfaw area (0.78) and lowest in the Algalabat (0.61) (Table 2). A look at the different subcomponents exposure shows that the decreasing rainfall is highest in the Alfaw region (0.98) and lowest in the Algalabat region (0.750). In the index showing the average number of the disasters experienced in the last 25 years, Alfaw has the highest index value and Algalabat has the lowest value (see Fig. 4). In a drought-prone region, the extent of dryland can potentially create a high level of exposure to climate variability among farmers (Jamir et al., 2013). Our results show that Alfaw, Alfushqa and Algadaref have larger areas of dry land when compared to Alrahad and Algalabat. On the perception of the increasing frequency of droughts in the area, Alfaw has the highest index value (0.94). One of the main indicators for exposure in our case study was the number of times households have faced droughts affecting agriculture. We found that the households of Alfaw and Alfushqa have experienced nearly the same average number of drought disaster in the last 25 years as compared to the other two regions as reflected in the vulnerability index values. However, the overall level of exposure to the climatic risks is highest for the Alfaw followed by Alfushqa as the variability in the projected rainfall and temperature are highest for this region (Table 2). Investigations were done by Solomon (2007), Kumar et al. (2011) and Elagib (2015) stating that arid and semi-arid regions are more vulnerable due to high marginality and fragility.

The sensitivity indicator in Alfaw region showed the highest total sensitivity (0.83), followed by Alfushqa (0.74), Algadaref (0.58), Alrahad (0.39) and Algalabat (0.37) (Table 2). The households in the Alfaw and Alfushqa regions have a low level of income diversification when compared to other regions of the study area. Observation in the field shows that while the households in the other three regions

Algadaref, Alrahad and Algalabat are involved in other income-earning activities such as raising animals, collecting forest products, small business and government jobs, while households in Alfaw depend highly on agriculture as the major source of income. The crop diversity index in Table 2 shows the variety of crops among households in the region. The average crop diversity index is highest in Alfaw (0.76) and lowest for the Alrahad (0.23) followed by Algalabat (0.27). It has been observed that while farming households in Alfaw, Alfushqa and Algadaref are mostly being utilized for single crop cultivation, farmers in Algadaref region have diversified their crop cultivation by including Sorghum farming over the last decade and thus spreading the risk of crop failure and reducing sensitivity to climate variability. Zimmerman and Carter (2003) indicated that due to high relative risk aversion, poorer households are often impacted more by climate change. In line with this report, our result showed that the majority of the farming communities living in the southern and eastern zones of Gadaref are the most exposed to effects of climate variability. The Long-term average VCI % for 25 years of Gadaref regions in the map (Fig. 2) shows Alfaw and Alfushqa have low values 25 and 26 respectively. These regions are prone to repeated cycles of drought (Fig. 3).

A study by Booysen et al. (2008) showed that many parts of Sub-Saharan Africa face risk of a 10–40% probability in failed seasons during the major cropping time. Recently, around 10 million people across the Horn of Africa went hungry due to death of livestock as a result of prolonged drought (Shiferaw et al., 2014). There is also a key issue of desertification as a consequence of soil erosion that needs to be researched to achieve the right management via restoration and rehabilitation (Cerdà et al., 2017; Sharma et al., 2017).

The result of the overall sensitivity analysis also revealed that Alfaw, Alfushqa and Algadaref are the most sensitive areas. This is basically due to the relatively large landless population, the enormous proportion of small-scale subsistence farmers, the application of very low technology, low irrigation potential, and significant dependence on rain-fed agriculture. A fast-increasing population in combination with deforestation and soil erosion have been partially responsible for increasing this sensitivity in the Gadaref region (Blaikie, 2016; Homer-Dixon, 2010). Furthermore, a small landless rural population and a
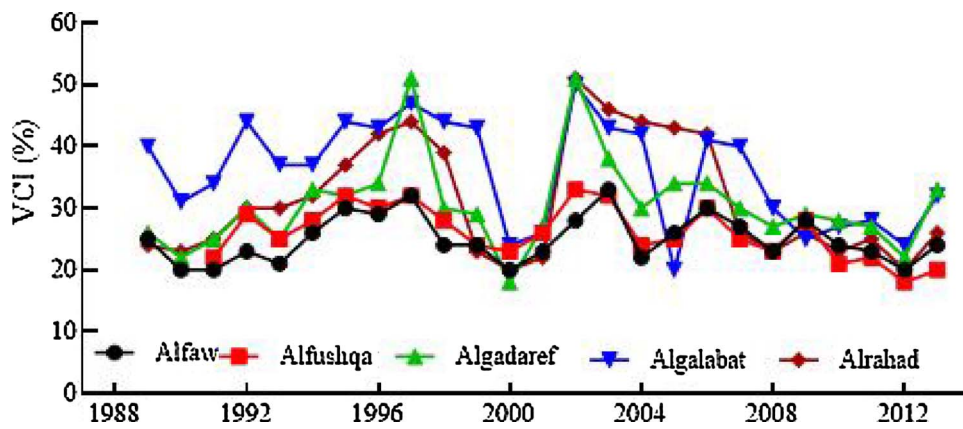
Fig. 2. Average Vegetation Cover Index of Gadaref regions.

general low population in the Western Zone of the region, makes it less susceptible to social and economic disruption and thus to climate change and variability (Kartiki, 2011). A general feature of these regions are that they have the least populated rural areas and a low percentage of subsistence farmers and landless laborers.

The combined consequence of the sensitivity and exposure indicator produce the potential influence of climate change and variability on the different regions. The north and central parts of the region which
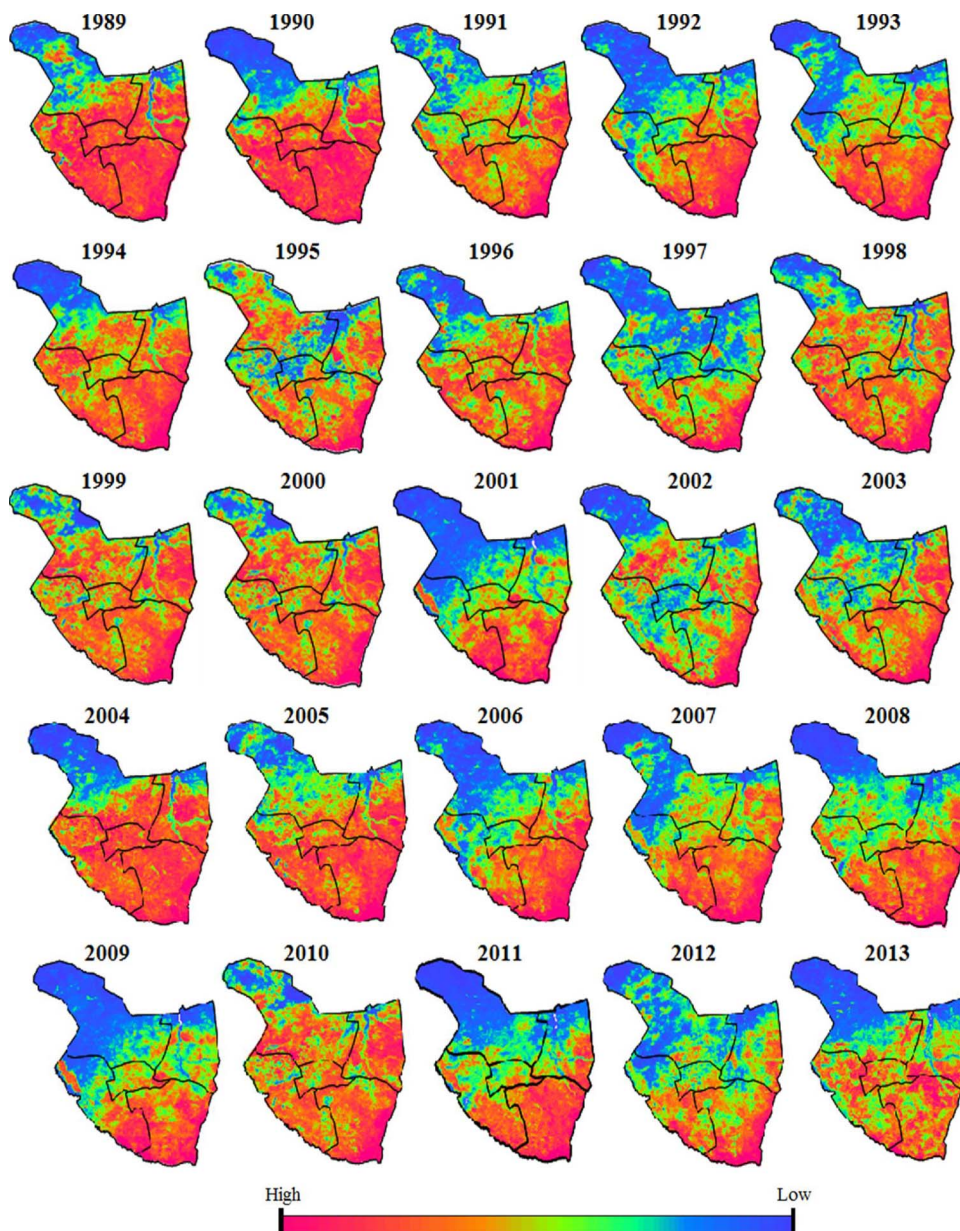
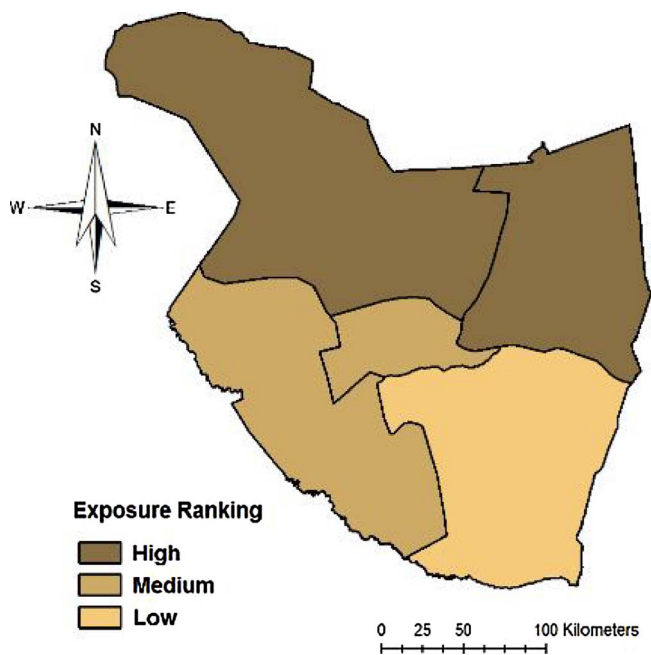**Fig. 3.** Maps of Average Vegetation Cover Index of Gadaref regions.

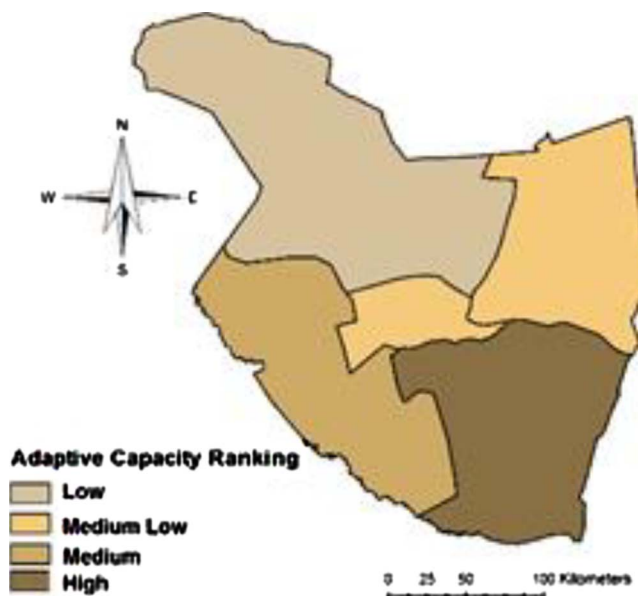**Fig. 4.** Exposure indices over the rural districts of Gadaref.
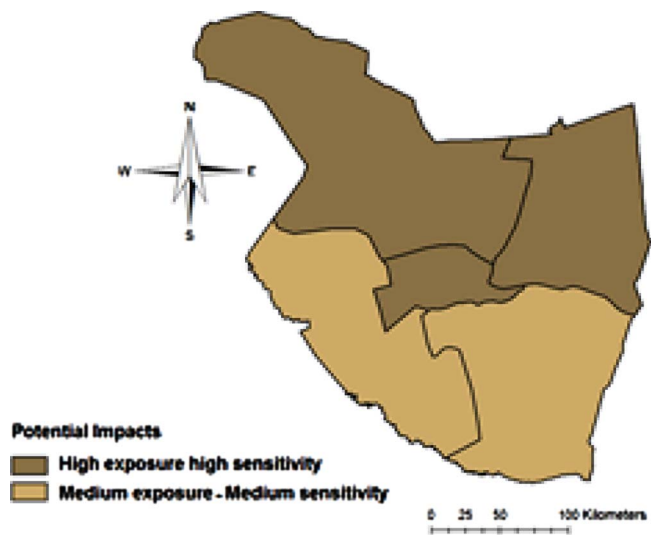

Fig. 5. Exposure-sensitivity indices over the rural district.

includes Alfaw, Alfushqa and Algadaref have both the highest exposure and the highest sensitivity while the rest of the regions show medium exposure and sensitivity. Fig. 5 shows the Gadaref region with the greatest potential impact.

3.2. Adaptive capacity

Farmers in all the regions reported undertaking different types of adaptation actions to deal with climate variability and drought. Changing planting dates, resorting to more non-farm income and using early maturing varieties of seeds were reported among the important adaptation actionsbeing used by the farmers (Araya et al., 2010a). In Alrahad and Algalabat, households indicated that they had changed their crop variety, having an index score of (0.60) and (0.45). However, Alfaw has the highest value, where around 93% of the households have changed their crop variety. Using herbicide, insecticide and fertilizers were mentioned as one of the most significant adaptation actions to deal with climate variability and drought. Around 93% of households in

Fig. 6. Ranking of adaptive capacity across the rural districts of Gadaref.

the Algadaref reported changing their planting times, having an index score of 0.93. In the Alfaw however, 89% of households reported changing their planting times, the lowest in the entire region. Using insecticide and pesticide were other important adaptation actions among farmers in all the five regions, while 89% of the households in Alfaw region reported using insecticide and pesticide followed by Al-fushqa (86%). In Algalabat around 43% of households reported using insecticide and pesticide, which is the lowest among the five regions (Fig. 6).

Crop insurance was found to be an important strategy in the Gadaref region households to cope with drought risks. Agricultural insurance has been recognized as one of the important adaptation measures for farmers to insure crops in case of unexpected crop failure and to increase their adaptive capacity (Jamir et al., 2013; Panda, 2016; Peterson, 2012). All the studied regions have a low number of households with the national traditional crop insurance. In Algadaref and Alfushqa around 62% of households had access to crop insurance, highest among the five regions, followed by Alfaw (61%).

The analysis of the total adaptive capacity showed great variation across the five rural regions. Algadaref and Alfushqa have the necessary adaptive capacity because of the combined effects of a relatively well-improved infrastructure network, access to institutions and high levels of literacy (Table 2). Alrahad is an exhibition of a mid-range coping ability. while in Algalabat region which is close to urban areas, the farming population is in closer proximity to sources of agricultural inputs and have excellent access to infrastructure and agricultural institutions. Furthermore, this area has a relatively high literacy standard.

The region with a lowest adaptive capacity is Alfaw as it has incredible needs to cope adequately with the potential impact of climate variability and drought. The area has comparatively limited access to the most important socio-economic factors such as asset ownership, access to agricultural technologies and institutions, infrastructural assistance (such as irrigation and road networks) or services (micro-finance, veterinary) and human resources. Similarly, Kirshen et al. (2015) indicated that countries with well-developed social institutions are considered to have greater adaptive potential than those with less effective institutional arrangements. Therefore highly sensitive regions such as Alfaw need more attention in the form of access to all-weather roads, better technology, health services, microfinance and sustainable agricultural practice.
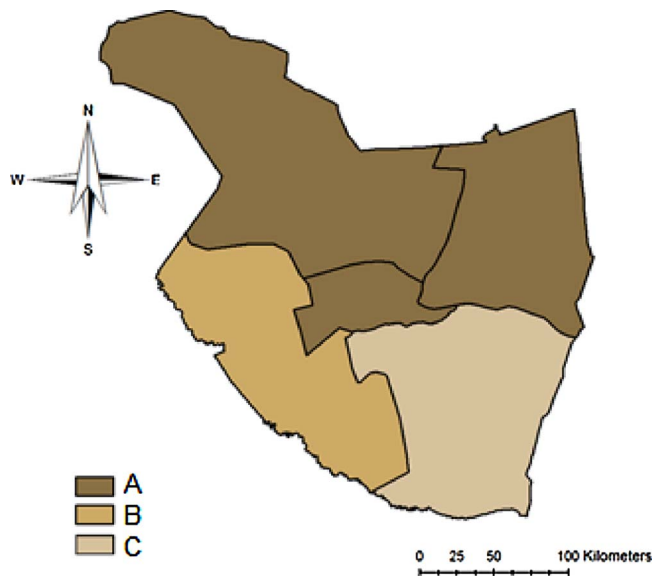
Fig. 7. Overall vulnerability indices across the rural districts of Gadaref.
A = High Exposure, High sensitivity and low adaptive capacity.
B = Medium Exposure, Medium sensitivity and Medium adaptive capacity.
C = Low Exposure, Low sensitivity and Low adaptive capacity.

3.3. The estimation of overall vulnerability

Despite maps of individual component scores being helpful, it is vital to evaluate the overall vulnerability in the region by linking the different components into a particular measure. Therefore, we measured the overall vulnerability based on the Intergovernmental Panel on Climate Change (IPCC) standards. Regions with high vulnerability (High Exposure, High sensitivity and low adaptive capacity) (Fig. 7), which include Alfaw, Alfushqa and Algadaref are extremely food insecure and prone to repeated cycles of drought (Table 2). Thus, the current limited human and infrastructural capacity will undermine their capability to react to the direct and indirect influences of drought. Campbell et al. (2016), Wright et al. (2014) and Kabubo-Mariara (2009) confirmed that it is becoming increasingly difficult for farmers to bounce back from ever-changing, incompatible weather affecting their livings, and many have been forced to adopt other livelihoods and coping mechanisms that only extend the period of vulnerability. These sequences further indicate the apparent relationship between vulnerability, agro-ecological contexts and the level of adaptive capacity (Araya et al., 2010b).

Due to the large variety of farms, not only in size, intensity, and land use but also in objectives and perspectives, adaptation strategies are difficult to generalize at a farm level (type). The most vulnerable regions are those with a high percentage of farmers who rely on rain-fed agriculture for their livelihood, significant levels of climate extremes, and a higher percentage of landless laborers in the agricultural workforce. These regions have repeatedly been hit by drought and are known to have chronic food deficit. Moreover, these regions are marked by inadequate resources, limited sources of income, low human capital, and high levels of deforestation. Davies et al. (2009) claims that the regions that have a high dependence on subsistence agriculture experience a greater impact of stresses and shocks (such as droughts) and these impacts are more keenly felt by rural poor people who directly depend on food system outcomes for their livelihoods. Tesfaye et al. (2011) and Mohammed and Inoue (2013) similarly stated rural farmers at the local level with a dependency on agriculture and other natural resources are more vulnerable. In general, our results show that vulnerability is highest in the regions with the high level of exposure, high level of sensitivity and low adaptive capacity. The continuing drought occurrence is expected to lead to increased poverty, vulnerability, loss

of livelihoods and conflict (IPCC, 2014; Scheffran et al., 2014).

3.4. Impact of rainfall variability on sorghum yield at farm level

The effect of precipitation on agriculture is mainly reflected in the reduction of crop yields (Potopová et al., 2016). In order to analyse the contribution of climate change on yield losses, it is important to calculate the incidence and magnitude of rainfall during the season and then to quantify the yield losses in response to these rates. The relative yield losses for the sorghum crop in response to the rainfall amount are presented in Fig. 8. The Severe decrease in rainfall in early the 1990s, caused the high sorghum yield losses as crop yield anomaly index (YAI) results show. For example, the highest YAI recorded in the whole Gadaref region (below −2) was when high rainfall occurred during the crop risk period of 2012 which made small farmers most vulnerable. Yu et al. (2014) reported that the regional mean precipitation during the crop-growing season in Northeast China had decreased significantly from 1960 to 2009 due to climate variability. Our results confirm the reduced precipitation, and the YAI results suggest a province-wide increase in yield losses over the past five years in the region, with a good correlation coefficient (Fig. 8). This result is in line with similar findings of Bannayan et al. (2010) who found that rainfed crop production is very vulnerable to climate variability and usually suffers from its occurrence. This climate variability implies serious production risks, which will have a higher impact on small landholders with lower capacity to get the required resources to overcome these circumstances. Khan et al. (2009) agreed with this result. At long term, the droughts results in a low vegetation cover and then in higher soil and water losses due to the positive effect of the plants to control the soil erosion (Keesstra et al., 2014) and this is very relevant in agriculture land were plants are managed by humans (Rodrigo-Comino et al., 2016; Kirchhoff et al., 2017).

4. Conclusions

This paper investigated farmers' vulnerability to drought and climate variability at the local level. Based on the results obtained for the overall vulnerability index using the most vulnerable regions, it was shown that most were located in the northern region which include Alfaw, Alfushqa and Algadaref, with the gradual decrease in vulnerability towards the southern and eastern parts of the Gadaref region. The least vulnerable regions are those with low drought occurrence in southeastern parts, the northern regions are classified as highly vulnerable, while the region with the irrigated areas such as Alrahad region is moderately vulnerable. The high vulnerability of the Alfaw, Alfushqa and Algadaref to future climate change is not only due to high climatic exposure but also to very high sensitivity and inadequate adaptive capacity. The essential ecological fragility of these regions is linked to high incidences of drought due to rainfall shortage.

It was concluded that the present adaptive capacity and expanded environmental stress are a result of current human-environment interactions (sensitivity), are the primary determinants of vulnerability in the most vulnerable regions, rather than the degree to which these regions are endangered to significant climatic differences. Given the significant spatial differences in vulnerability across the rural districts, policy-makers should, therefore, tailor policies to local conditions. A stronger focus should be given on adapting agriculture to future drought and climate variability. Notably, farm-level adaptation practices can incredibly decrease vulnerability to drought and climate variability by improving rural communities' ability to adapt to the changing climate.
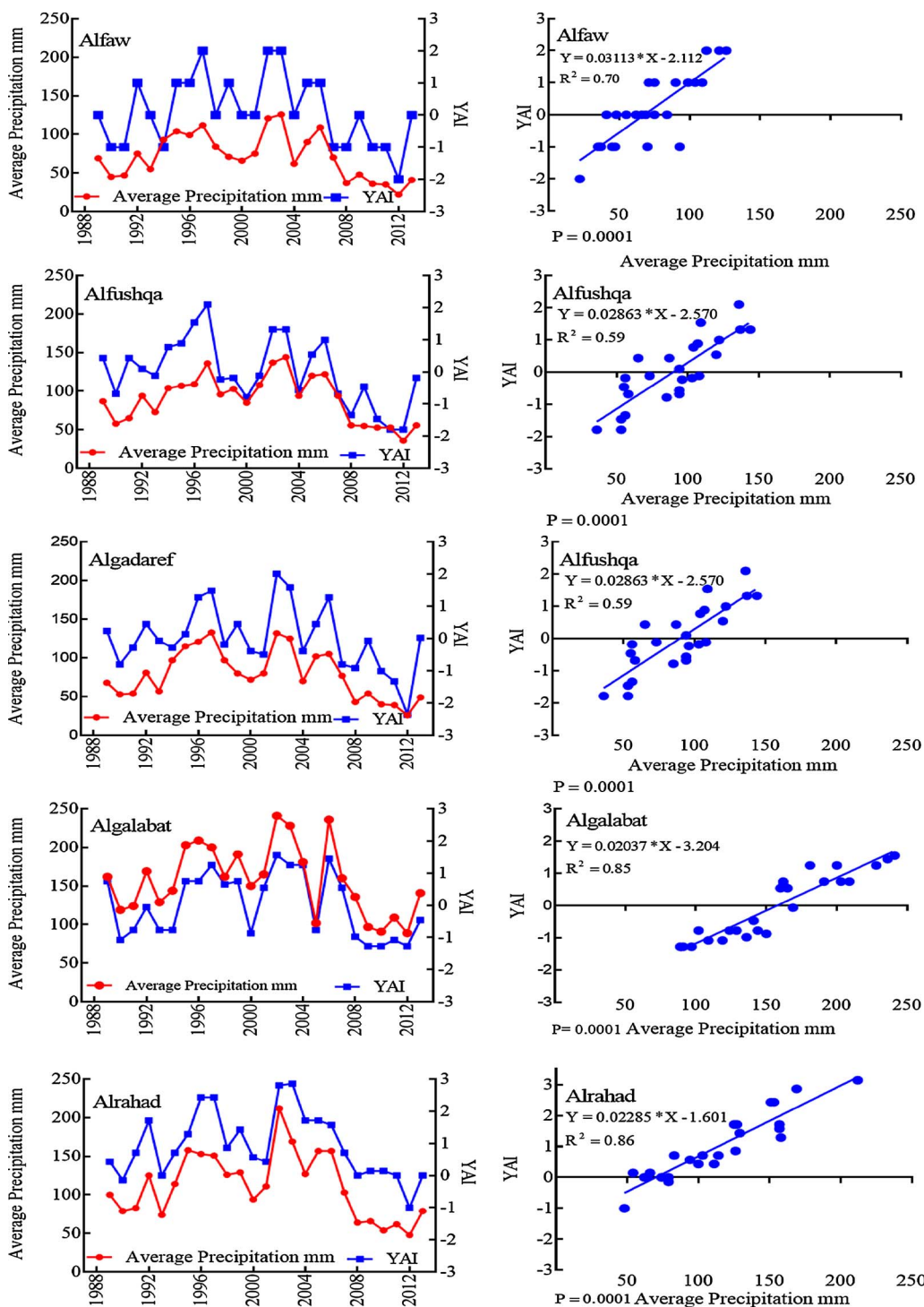
Acknowledgments

Fig. 8. Rainfall Variability on Sorghum Yield Anomaly Index (YAI) at farm level.

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