

Characterizing agricultural drought in the Karamoja subregion of Uganda with meteorological and satellite-based indices

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Abstract Karamoja is notoriously food insecure and has been in need of food aid for most years during the last two decades. One of the main factors causing food insecurity is drought. Reliable, area-wide, long-term data for detecting and monitoring drought conditions are critical for timely, life-saving interventions and the long-term development of the region, yet such data are sparse or unavailable. Due to advances in satellite remote sensing, characterizing drought in data-sparse regions like Karamoja has become possible. This study characterizes agricultural drought in Karamoja to enable a comprehensive understanding of drought, concomitantly evaluating the suitability of NDVI-based drought monitoring. We found that in comparison with the existing data, NDVI data currently provide the best, consistent, and spatially explicit information for operational drought monitoring in Karamoja. Results indicate that the most extreme agricultural drought in recent years occurred in 2009 followed by 2004 and 2002 and suggest that in Karamoja, moderate to severe droughts (e.g., 2008) often have the same impact on crops and human needs (e.g., food aid) as extreme droughts (e.g., 2009). We present in a proof-of-concept frame, a method to estimate the number of people needing food assistance and the population likely to fall under the integrated food security phase classification (IPC) Phase 3 (crisis) due to drought severity. Our model indicates that 90.7% of the variation in the number of people needing aid can be explained by NDVI data and NDVI data can augment these estimates. We conclude that the biggest drivers of food insecurity are the cultivation of crops on marginal land with insignificant inputs, the lack of irrigation and previous systematic incapacitation of livestock (pastoral) alternatives through government programming. Further research is needed to bridge empirical results with social–economic studies on drought impacts on communities in the region to better understand additional factors that will need to be addressed to ensure livelihood resilience.

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1 Introduction

Current socioeconomic conditions in pastoral (agro-pastoral) East Africa bring into question the worthiness of aid programs and policies in marginalized and poorly understood regions. Pastoralists in Africa are still considered the continent's most vulnerable group. To this day despite continued inflow of aid and poverty alleviation programs, extreme vulnerability due to entrenched poverty is vividly manifested during recurrent droughts that continue to have severe detrimental impacts on communities (Little et al. 2008; Juma 2009).

Although droughts are often labeled as the cause of food insecurity in the Karamoja subregion of North Eastern Uganda, the evidence is inconclusive (Nakalembe et al. 2017; Ayoo et al. 2013; Stark 2011; Ferreri et al. 2011). Agriculture in the region is primarily for subsistence, mainly characterized by small fields with minimal to no agricultural inputs such as fertilizer. Through systematic government programs, crop cultivation has taken precedence over livestock keeping; yet, the contribution of crop cultivation to food security remains meager (Nakalembe et al. 2017). Droughts stress livelihoods in Karamoja, often with devastating consequences. However, the reasons for near stagnant and declining resilience to drought in the region are complex. It is evident that the effects of droughts such as famine, escalating conflict, displacement, migration, and the loss of livestock and human lives remain of significant concern in Karamoja (Gelsdorf et al. 2012; FEWSNET 2005).

The characteristics and impacts of drought vary within Karamoja (Egeru et al. 2014). On the ground, it is evident that small amounts of rainfall in one village, which lead to complete crop failure, can coincide with sufficient amounts for a decent harvest in another village within a few kilometers distance (Fig. 1). Before the completion of the government's disarmament campaigns that started in 2001, drought-induced food insecurity and its impacts were also escalated by conflict and vice versa in the region (FEWSNET 2005). Irrespective of the long history of drought being blamed for famines and social unrest, there is currently no monitoring system in place.

Uganda has no nationally run drought early warning and monitoring system; currently, there is no basis to measure the relative severity of individual drought occurrences. Furthermore, early drought detection, tracking, mapping, and severity assessment are

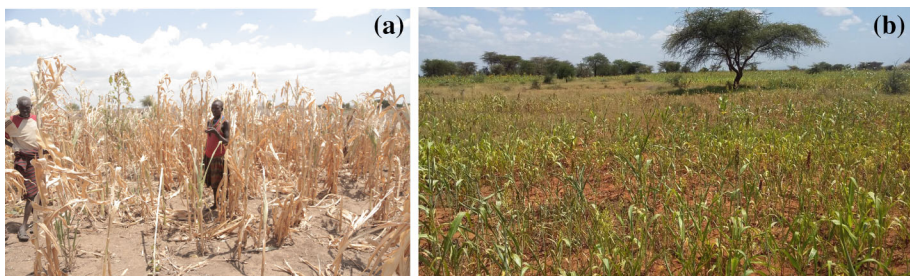


Fig. 1 **a** A failed sorghum field in Rupa sub-county, August 13, 2015. **b** A moderately impacted field in Nadunget sub-county, August 14, 2016. These two fields are within 10 km distance

considerably constrained by the lack of meteorological data, and very few empirical studies quantitatively assess drought at the subregional level, particularly assessing drought and its impacts on agriculture. This scarcity of data and information has led to the lack of consensus on the characteristics of drought in Karamoja today. Except for a few empirical studies such as Egeru et al. (2014), the vast majority including Gelsdorf et al. (2012), Stark (2011), DanChurchAid (2010) and Stites et al. (2007), focus primarily on the social and economic impacts of drought with minimal empirical backing. These studies, however, remain the primary source of information for policy-making. FEWSNET (2005), for example, reported that droughts that used to occur every 5 years now occur every 2–3 years. Based on Normalized Difference Vegetation Index (NDVI) analysis (FEWSNET 2005) concluded that severe droughts were experienced in 1992, 1994, 1998, 2000, 2001, 2002, and 2004. On the other hand, Stites et al. (2007) note that droughts occur every 3–4 years in Karamoja, with multi-year droughts every 10 years, while (Ayoo et al. 2013) indicate that Karamoja experiences cyclical droughts every 2–3 years. Using such information can mislead decision making and planning.

There are several drought monitoring systems developed by development partners including the Famine Early Warning Systems Network (FEWS NET) created by US Agency for International Development (USAID) that provides early warning and analysis on food insecurity and World Food Program's (WFP) Vulnerability Assessment and Mapping (VAM) Seasonal Explorer (World Food Programme 2017). FEWS NET's system provides objective and evidence based information. Combining satellite data, the expertise of researchers from National Aeronautics and Space Administration (NASA), National Oceanic and Atmospheric Administration (NOAA), US Department of Agriculture (USDA), US Geological Survey (USGS), and field information from regional scientists (FEWSNET 2017). To date, these data provide some of the best information about food insecurity and drought in East Africa (FEWSNET 2017). Both websites are rich resources, particularly the FEWS NET website that provides tools, data, assessments, and reports, but to the best of authors knowledge, these are not mainly used by government departments in Uganda for their reporting and monitoring.

There is also a general lack of empirical studies of drought and its impacts on agriculture in Karamoja. This void remains an obstacle to agricultural development in Karamoja. This information is now more critical with the current and projected rates of extreme events (McSweeney et al. 2015). The goal of this study is to demonstrate the opportunity for a nationally run operational drought monitoring for Karamoja, using readily available remote sensing data to derive spatially explicit drought information in combination with historical climate station data to empirically characterize agricultural drought at the subregional level. This information is essential in the design and implementation of emergency response programs as well as food security and social safety net programs.

1.1 Defining and characterizing drought

Drought remains one of the most complex and devastating, but also least understood natural disaster (Wilhelmi and Wilhite 2002). Drought intensity, variability, duration, and impacts differ from drought to drought and from region to region; hence, no single universal drought definition exists (Edwards 1997). Drought definitions should identify regional differences including specific climatic conditions, physiological characteristics, economic development, and traditions to understand the potential impacts on livelihoods (Kogan 1995). However, in many resource and data scarce regions droughts are poorly

defined, which calls into question the suitability of drought management programs (Alley 1984; Wilhite 1985; Heim 2002; Vicente-Serrano et al. 2010).

According to Palmer (1965), a meteorological drought is an interval (generally spanning several months or years) during which the actual moisture supply at a given place consistently falls below the expected or climatically adequate moisture supply. However, the climatically adequate moisture supply is difficult to determine, and average rainfall alone does not provide an appropriate statistical measure to determine drought, particularly in drier areas (Palmer 1965; Vicente-Serrano et al. 2012). Moreover, the same precipitation deficit could have different impacts depending on other meteorological factors, vegetation types, farming practice, and the socio-political situation of the affected area. Therefore, droughts are grouped into four main types and are defined according to disciplinary perspectives (Heim 2002; Wilhite 1985).

In addition to meteorological drought defined above, drought types include agricultural, hydrological, and socioeconomic. Moisture deficits (meteorological drought) that occur at critical growth stages for crops leading to dryness in the root zone can lead to an agricultural drought that severely reduces crop yields (Heim 2002; Palmer 1965). A hydrological drought occurs when precipitation deficits affect surface or subsurface water supply, thus reducing stream flow, groundwater, reservoir, and lake levels, while socioeconomic drought associates the supply and demand of some economic good with elements of meteorological, agricultural, and hydrological droughts. Hence, though difficult, drought characteristics and impacts are not impossible to identify and quantify plus, recent advances in land remote sensing make possible spatially explicit drought studies even in the most data scarce regions (Wilhite 1985).

To date several meteorological drought indices have been used to study droughts systematically. These include the Palmer Drought Severity Index (PDSI) (Palmer 1965), Precipitation Anomaly Percentage (PAP) (Yang and Wu 2010) and the Standardized Precipitation Index (SPI) (McKee et al. 1993), based on the cumulative probability of a given rainfall event at a given meteorological station (Vicente-Serrano et al. 2010; National Drought Mitigation Center 2015). These indices are often location-specific, and although they provide accurate point-based estimates of drought conditions, they are limited when climate data are lacking or incomplete and limited in providing spatially continuous drought information across large areas (Quiring and Ganesh 2010; Brown and DeBeurs 2008). Moreover, in semiarid regions, the spatial heterogeneity of rainfall events makes the use of point-based rainfall estimates to calculate these indices highly questionable since these data are extrapolated over large distances between rain gauge stations (Flitcroft et al. 1989).

The Normalized Difference Vegetation Index (NDVI) remains the most commonly used satellite-based index used to monitor greenness of land surfaces, plant vigor, density, and growth conditions (Atzberger 2013; Quiring and Ganesh 2010; Karnieli et al. 2010; Tucker 1979). The Vegetation Condition Index (VCI) (Kogan 1995) and Standardized Vegetation Index (SVI) both derivatives of NDVI and the Normalized Difference Water Index (NDWI) (Gao 1996) are the most commonly used in drought studies. VCI is per-pixel normalized NDVI to enhance the weather-related component in NDVI time-series data by reducing the influence of environmental conditions and has been used to characterize drought at various spatial and temporal scales (Jain et al. 2009; Ji and Peters 2003; Anyamba et al. 2001; Kogan 1995). The SVI is the probability of vegetation conditions diversion from the average (Peters et al. 2002). These satellite-based indices have an advantage over station-based indicators since spatial details on vegetation condition are inherent (Kogan 1995).

Combinations of various multi-source, multi-sensor, and multi-index information capitalizing on the advantages of individual indices to conduct multi purpose, multi-temporal and multi-spatial scale studies tend to produce more reliable drought information (Xu et al. 2011; Suwanprasert et al. 2013). Several studies have investigated the relationship between satellite and meteorologically based indicators of drought to provide more accurate information. Liu and Kogan (1996) showed that drought patterns delineated by NDVI and VCI agree well with rainfall anomalies observed from rainfall maps, providing useful information to analyze the temporal and spatial characteristics of regional drought and crop production quantitatively. Moreover, high correlations between satellite indices and crop yield have been demonstrated, particularly during the critical periods of crop growth (Franch et al. 2015; Lotsch et al. 2003; Kogan 1997). Franch et al. (2015) proved that timeliness of reliable forecast of winter wheat production before the NDVI peak could be improved when growing degree information from climate data is added to the (Becker-Reshef et al. 2010a) method that combined NDVI, officially reported crop statistics and crop type masks. Lotsch et al. (2003) demonstrated a high degree of association between NDVI and SPI time series. Kogan (1997) also showed that VCI could be used to identify vegetation stress even in the early growing season and proved to be useful for real-time assessments, diagnosis of vegetation condition, and weather impacts on vegetation. Besides, Peters et al. (2002) indicated that SVI, when used with other indicators, is a good indicator of short-term weather conditions and can be used as an indicator of onset, extent, intensity, and duration of stress.

Several factors including rainfall regime, vegetation, and soil types affect the time response of NDVI to available rainfall amount (Quiring and Ganesh 2010; Liu and Kogan 1996). Rainfall and moisture availability in particular influence the lagged relationship between NDVI and meteorological indices. For example, Quiring and Ganesh (2010) show that in Texas the growing season VCI responds to prolonged moisture stress and is less sensitive to short-term precipitation deficiencies. Ji and Peters (2003) similarly demonstrated the lagged relationship between weather and NDVI, showing that the lagged 3-month SPI had the highest correlation with NDVI, but significant variability existed between months. The highest occurred during the middle of the growing season, and lowest at the beginning and end of the growing season (Ji and Peters 2003). Their regression model revealed significant relationships between NDVI and SPI in grasslands and croplands, the best occurring in areas with low soil water-holding capacity (Ji and Peters 2003). Similarly, Liu and Kogan (1996) showed that NDVI responded quite well to water deficiency with a 1-month time lag. This delayed response implies that seasonality and vegetation type must be taken into account when assessing and monitoring drought with NDVI (Quiring and Ganesh 2010; Vicente-Serrano 2006; Ji and Peters 2003). Also, care has to be taken to account for errors due to data aggregation and interpolation across large areas when using satellite data (Kogan 1997).

Taking the above into account, in this paper focuses on characterizing agricultural drought in Karamoja using SPI and assess the suitability of an NDVI-based index in supporting spatially explicit drought monitoring.

1.2 Study area

The Karamoja subregion (Fig. 2) falls within the semiarid region of East Africa in North Eastern Uganda between Latitude 1° and 4° North and Longitude 33° and 35° East. The broader East Africa region is described to have the most ‘impressive climate anomalies in all of Africa’ (Trewartha 1961). According to Baker (1974), the causes of rainfall

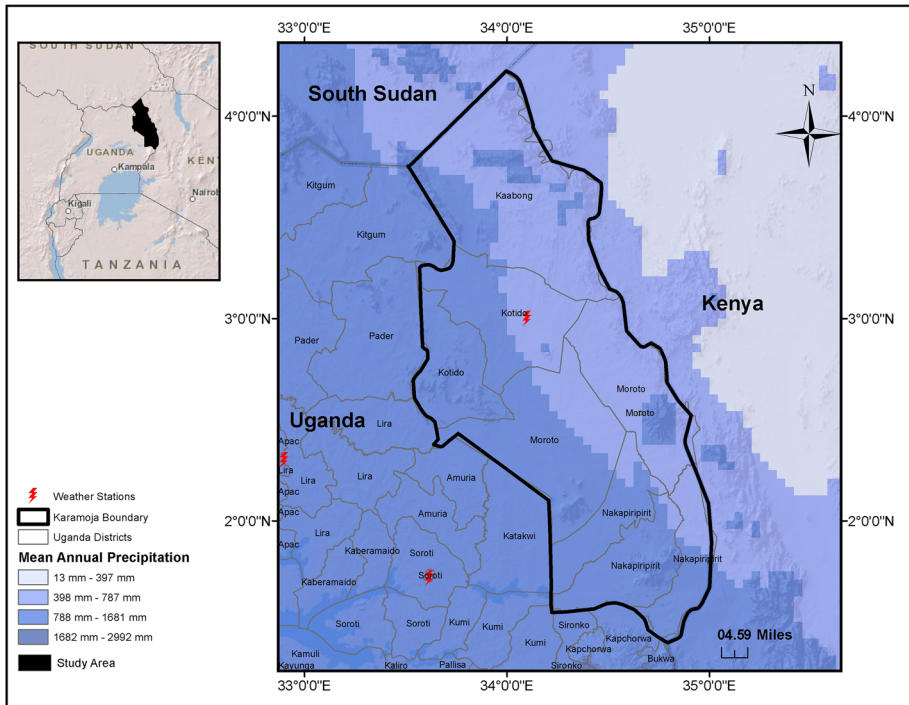


Fig. 2 Location of Karamoja subregion, showing meteorological stations with fairly complete records. The rainfall gradient decreasing annual average rainfall from west to east. [Rainfall data source: Hijmans et al. (2005)]

variability in East Africa include diverging and subsiding air streams that tend to flow parallel with the East African coast and the failure of cloud formation when dry, stable air caps the moist lower air. Rainfall in the region is highly erratic resulting in recurring droughts that impact livelihoods, resulting in famine, migration, and loss of lives (Stark 2011; Gartrell 1985; Baker 1974).

Most parts of Uganda have bimodal rainfall. Peak rainfall occurs both during March to May and October to December with annual rainfall close to 1345–1500 mm (McSweeney et al. 2015). Karamoja, however, has a uni-modal regime with peak rainfall occurring June to August. The region's total annual rainfall is estimated at 500–773 mm with long dry spells and high spatial variability (Egeru et al. 2014; Uganda-Government 2007). The rainfall gradient is consistent with the vegetation transition from the east (driest) to the west (greenest). The wetter and hence most productive areas include parts of western Kaabong, Moroto, Nakapiripirit, and the entirety of Abim (OPM 2009).

2 Data and methods

2.1 Standardized Precipitation Index

The data used in this study including the MODIS NDVI, land use, and standard rainfall are summarized in Table 1. Historical daily rainfall data obtained from the Uganda National

Table 1 Datasets used in this analysis include rainfall data from Kotido Station and Karamoja District boundaries subset from the national dataset

Data	Resolution (period)	Source (reference)
MODIS/NDVI time series	250 m (2000–2011)	GLAM (Becker-Reshef et al. 2010a)
Kotido climate station data	Daily (1960–2011)	Uganda National Meteorological Authority (UNMA)
Croplands mask	2 m (2012)	(Nakalembe et al. 2017)
Uganda districts shapefile	Subregional (2014)	Uganda Bureau of Statistics (UBOS)

Meteorological Authority (UNMA) were used to calculate SPI for the Kotido Station which had at least 30 years of continuous rainfall data, which is a requirement for calculating SPI following the method outlined by McKee et al. (1993). Satellite-derived rainfall data such as the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al. 2015) or WorldClim (Hijmans et al. 2005) are not used since these data are calibrated by and interpolated from meteorological station data. Moreover, satellite measurements are area-averaged quantities with different spatial distribution and do not capture the variations that may occur (Hijmans et al. 2005; Flitcroft et al. 1989).

To preserve continuity and minimize inaccuracies resulting from missing data¹ in the monthly precipitation time series, linear gap filling was necessary before aggregating to monthly rainfall time series. To calculate SPI historical data are used to compute the probability distribution at set time-frames (1, 2, 3 months, etc., i.e., monthly and seasonal) observed precipitation totals, and then the probabilities are normalized using the inverse Gaussian function (McKee et al. 1993; Heim 2002). Thus, SPI allows an analyst to measure the rarity of a drought event at a particular time scale, e.g., 1, 2, 3, 6, 9, 12, or 18 months (McKee et al. 1993). Prior to drought identification and categorization, derived SPI values at 1, 3, 6, 9, and 12 months (SPI-1, SPI-3, SPI-6, SPI-9, and SPI-12) timescales data were correlated with NDVI data to determine the most suitable timescale for looking at drought impacts on agriculture in the region. Short-term SPI (SPI-1) is used to measure meteorological drought, while SPI-3 and SPI-6 are a good measure of agricultural drought (Zhang and Jia 2013). The droughts are categorized based on SPI values as: mild (0 to -0.99), moderate (-1.00 to -1.49), severe (-1.50 to -1.99), and extreme when values fall below 2.00 (McKee et al. 1993).

2.2 Normalized Difference Vegetation Index

District level (Abim, Amudat, Kaabong, Kotido, Moroto, Nakapiripirit, and Napak) 16-day NDVI maximum value composites (MVCs) for Karamoja were downloaded from the Global Agriculture Monitoring System (GLAM) for East Africa for 2000 to 2012. GLAM East Africa is an online system for automated processing of MODIS satellite image time-series and graphs for vegetation condition monitoring and crop condition monitoring when non-cropland areas are excluded (Becker-Reshef et al. 2010a). These data were used to calculate Vegetation Condition Index (VCI) (Liu and Kogan 1996), NDVI Anomaly and the Standardized Vegetation Index (Table 2). The MODIS NDVI MVCs were retrieved from daily, atmosphere-corrected, bi-directional surface reflectance using MODIS-specific

¹ Data for September to December 1991, May to December 1997, and January to April 2006 were incomplete.

Table 2 NDVI-based indices used in the analysis

Index	Equation
Vegetation Condition Index (VCI) (Kogan 1995)	$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$
NDVI anomaly (Anyamba et al. 2001)	$\Delta NDVI = NDVI - NDVI_{mean}$
Standardized vegetation condition (SVI) (Ji and Peters 2003)	$SVI = \frac{NDVI - NDVI_{mean}}{\sigma_{NDVI}}$

Each index was calculated from NDVI maximum value composite in 14-day time steps from 12-year (2000 to 2012) time-series data

compositing methods, based on product quality assurance metrics to remove low-quality pixels² (Vermote et al. 2009). The MVC pixels contain the best possible observations selected based on high-observation coverage, low-view angle, the absence of clouds or cloud shadows, and aerosol loading, retaining the highest-quality NDVI value for each pixel within each 16-day period. The images are spatially continuous and relatively cloud-free (Becker-Reshef et al. 2010b; Holben 1986). The data were subset using district polygons from Uganda National Bureau of Statistics (UBOS) 2014 to obtain values for each district from the larger MODIS NDVI image. Finally, the 16-day data were converted to monthly data by averaging two consecutive values from each month.

2.3 Agricultural land use data

Crop production data were not considered for this study due to data scarcity, poor quality, and inconsistency in reporting for this region. However, in-season and end-of-season NDVI data combined with cropland spatial extent were used as a proxy for crop condition and crop failure, i.e., agriculture drought. Average NDVI values within cropland areas identified using a 2012 croplands mask shown in Fig. 3 (Nakalembe et al. 2017). The croplands mask was developed from very-high resolution WorldView 1 and 2 data acquired between 2010 and 2012 and obtained from the National Geospatial-Intelligence Agency (NGA) archive through an agreement with NASA under the NextView License³ (Nakalembe et al. 2017). The crop mask enabled investigation of drought within agricultural areas by eliminating misleading results from other land cover types such as pasture and scrub land. Updated and higher resolution land use data that would provide more accurate results were not available for this study.

To account for seasonality analysis focused at the peak of the growing season during the months of June, July, August, and September (JJAS) when crops and other vegetation are most sensitive to water availability in Karamoja, and the strongest correlations between NDVI and SPI occur (Fig. 4). Time-series plots and spatial maps were derived for the most severe drought years between 2000 and 2012 at 250 m resolution. Drought years identified through this analysis were cross-referenced with documentation in official government documents, news, and food aid assistance reports.

² More information available at <http://modis-land.gsfc.nasa.gov/vi.html>.

³ For information about the NextView License, please visit: <http://cad4nasa.gsfc.nasa.gov/>.

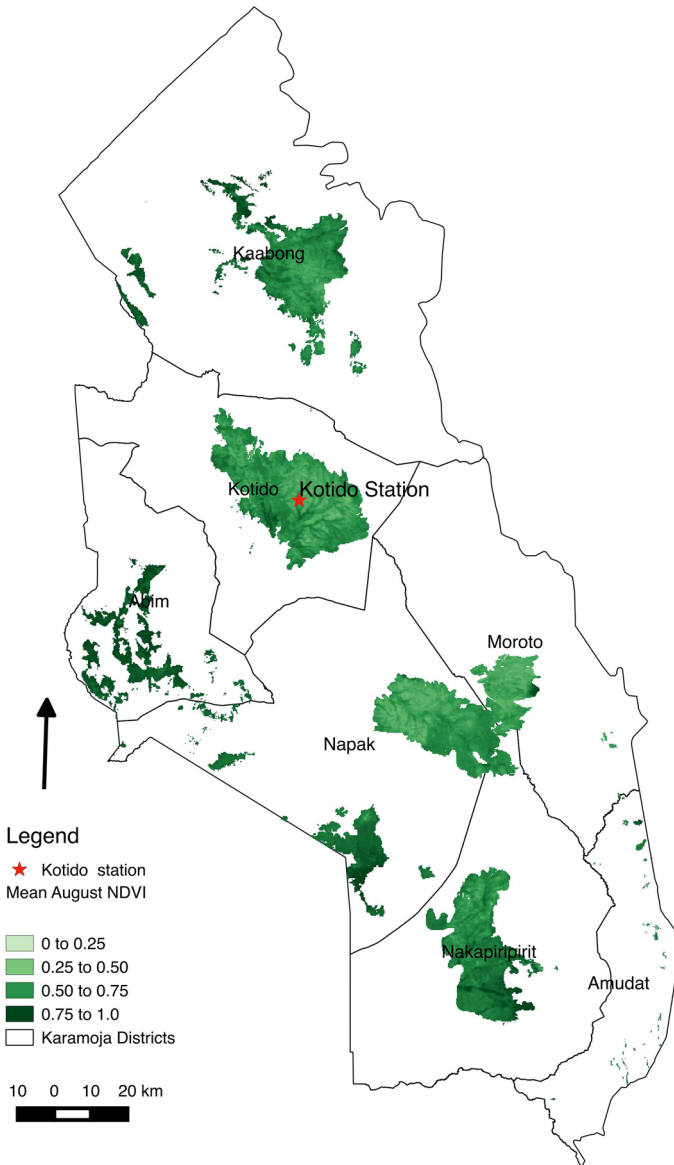


Fig. 3 The 2012 croplands map used in this analysis (Nakalembe et al. 2017). These data show the extent of agricultural land use in Karamoja and the mean NDVI values within the masked croplands during the month of August

2.4 NDVI and SPI relationships

The relationship between NDVI-derived indices (SVI, VCI, and ANDVI) and at different time steps is assessed using simple linear regression. Using a model similar to Ji and Peters (2003), linear regression with dummy variables (Eq. 1) was also done on ANDVI and SPI-

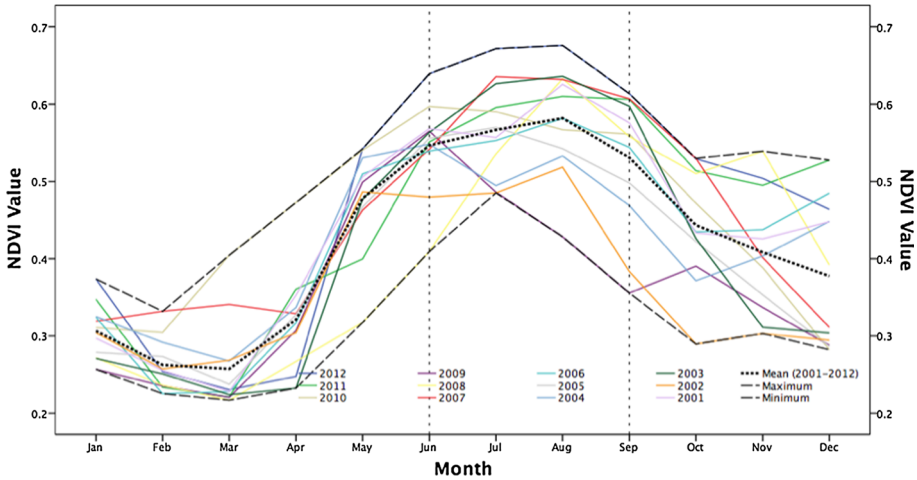


Fig. 4 NDVI temporal profile at Kotido Station (2000–2012). The rain season is April to September and NDVI values are moderate (0.4–0.5) during the planting months of April and May. The highest NDVI values (peak greenness) are during the months of June, July, August, and September (0.55–0.6)

3 to account for the effect of each individual growing season month. However, in this study the dummy variables are four levels assigned to each of the four growing season months. Therefore, the regression model containing monthly dummy variables is expressed as:

$$ANDVI = \beta_0 + \beta_1(SPI3) + \beta_2D_1 + \beta_3D_2 + \beta_4D_3 + \beta_5D_1(SPI3) + \beta_6D_2(SPI3) + \beta_7D_3(SPI3) + \epsilon \tag{1}$$

where ANDVI is the average NDVI anomaly value within croplands in Kotido District, SPI-3 is the 3 months SPI at Kotido station ending in June, July, August, or September, $D_1 - D_3$ are the dummy variables, $\beta_0, \beta_0, \dots, \beta_{11}$ are regression coefficients, and ϵ is random error. Dummy variables $D_1 - D_3$ are assigned binary values as shown in Table 3.

The regression models corresponding to each of the 4 months are:

$$\begin{aligned} \text{June ANDVI} &= \beta_0 + \beta_1(SPI3) + \epsilon \\ \text{July ANDVI} &= \beta_0 + \beta_1(SPI3) + \beta_2 + \beta_5(SPI3) + \epsilon \\ \text{August ANDVI} &= \beta_0 + \beta_1(SPI3) + \beta_3 + \beta_6(SPI3) + \epsilon \\ \text{September ANDVI} &= \beta_0 + \beta_1(SPI3) + \beta_4 + \beta_7(SPI3) + \epsilon \end{aligned} \tag{2}$$

Table 3 Dummy variable assignment

D_1	D_2	D_3	
0	0	0	If June NDVI observation
1	0	0	If July NDVI observation
0	1	0	If August NDVI observation
0	0	1	If September NDVI observation

2.5 Investigating the relationships between NDVI anomaly and food insecurity in Karamoja

As a proof-of-concept, the relationship between growing season crop conditions and food insecurity in Karamoja is investigated. ANDVI (Minimum, Maximum, and Average ANDVI) data are compared with the reported number of people needing food aid and the population in the different phases of the Integrated Food Security Phase Classification (IPC) each year. The IPC set of protocols classifies the severity of food insecurity by drawing from all available information and allows for comparability. Food production is one of the key inputs determining food availability.⁴ The IPC standardized scale categorizes the severity of acute food insecurity into five levels of food security (called phases): minimally food secure, crisis, stressed, emergency, and famine. Figure 5 is an example of the summary assessment for Karamoja, while Fig. 6 is the summary report for Uganda. The underlying assumption is that in Karamoja crop failure is linearly correlated with food insecurity. Therefore, the number of people needing food aid will increase with drought severity due to consequent production losses. Each month's recorded ANDVI values were used to estimate the percent of Karamoja's population needing food aid. The percent of the population needing food aid each year summarized in Nakalembe et al. (2017), while the population in each IPC phase were obtained from IPC reports.

3 Results and discussion

3.1 Correlation between rainfall and crop/vegetation conditions

The relationship between NDVI-derived indicators with SPI at 1, 3, 6, 9, and 12 months time steps at the Kotido Station is summarized in Table 4 for cropland areas during the growing season months of JJAS. Each ending month was correlated separately, for example, average June SPI is correlated with June NDVI. Overall, SPI-3 had the highest correlations with NDVI data. The ANDVI had the highest and significant correlation with R^2 values between 0.26 and 0.29 for JJAS for all land cover (results not shown) and improved further to range between 0.31 and 0.32 when non-cropland areas were excluded.

Figure 7 indicates that correlations also vary by month that crop conditions are most influenced during the growing season in Kotido by cumulative rainfall of up to 3 months. The highest correlations occurring during the month of August with a R^2 of 0.516. Hence, the 3-month timescale is better when using SPI to monitor drought impacts on crops and vegetation in Kotido, because vegetation response is insufficient at the shorter timescales of 1 or 2 months and the covariation of NDVI anomaly and SPI reduces after 3 months. August is also the best month for assessing agricultural drought when using both cumulative rainfall data and ANDVI. It is interesting to note that (Ji and Peters 2003) reached a similar conclusion in a study assessing vegetation response to drought in the northern Great Plains of the USA.

Table 5 summarizes the results of the simple regression and regression with dummy variables tested using ANOVA. Both models were very significant with the p value <

⁴ For more information visit <http://www.ipcinfo.org/>.

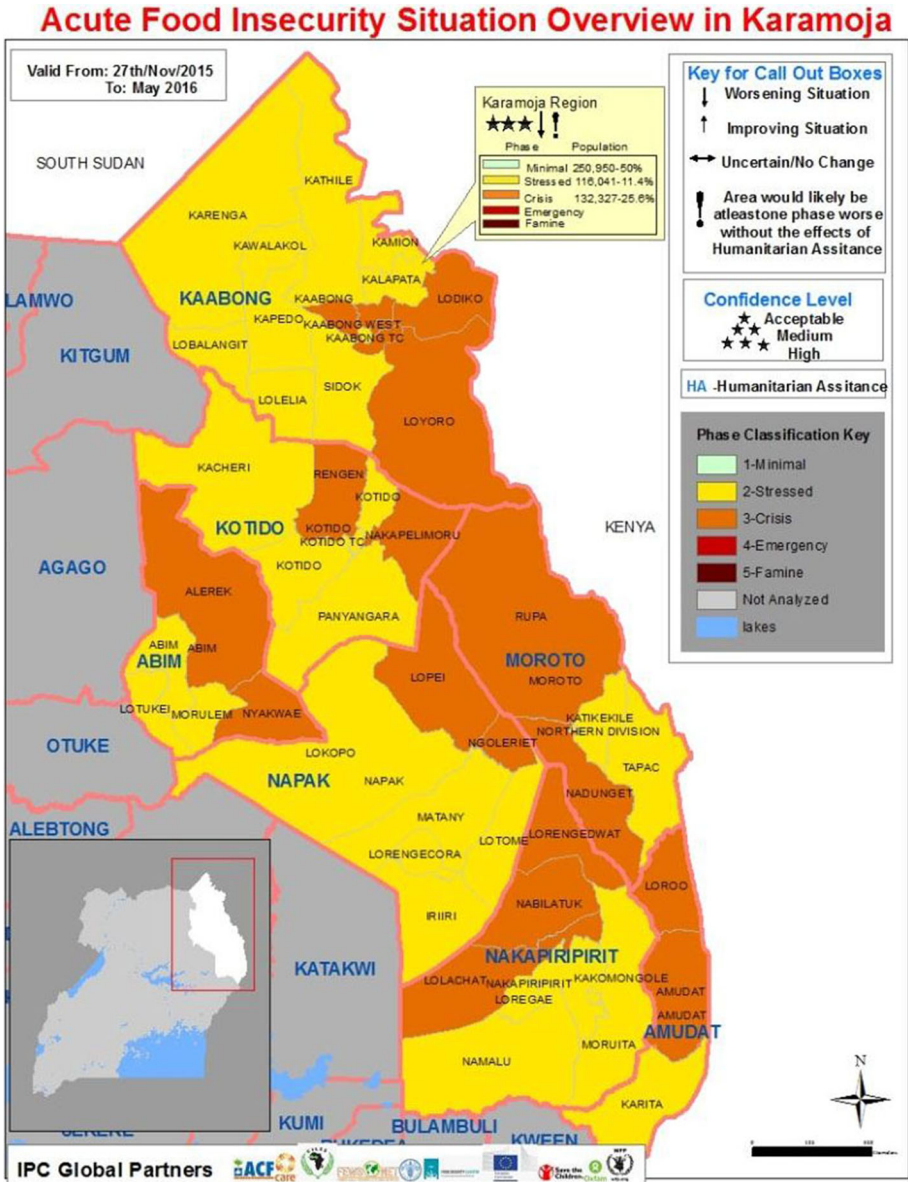


Fig. 5 IPC assessment summary map for Karamoja (valid November 2015 to May 2016). Full report available here: <http://www.ipcinfo.org/ipcinfo-detail-forms/ipcinfo-map-detail/en/c/446708/>

0.0001. After eliminating nonsignificant values, only predictor variables SPI3, D1, D2, and D3 are included in the model and the regression models corresponding to each of the 4 months are:

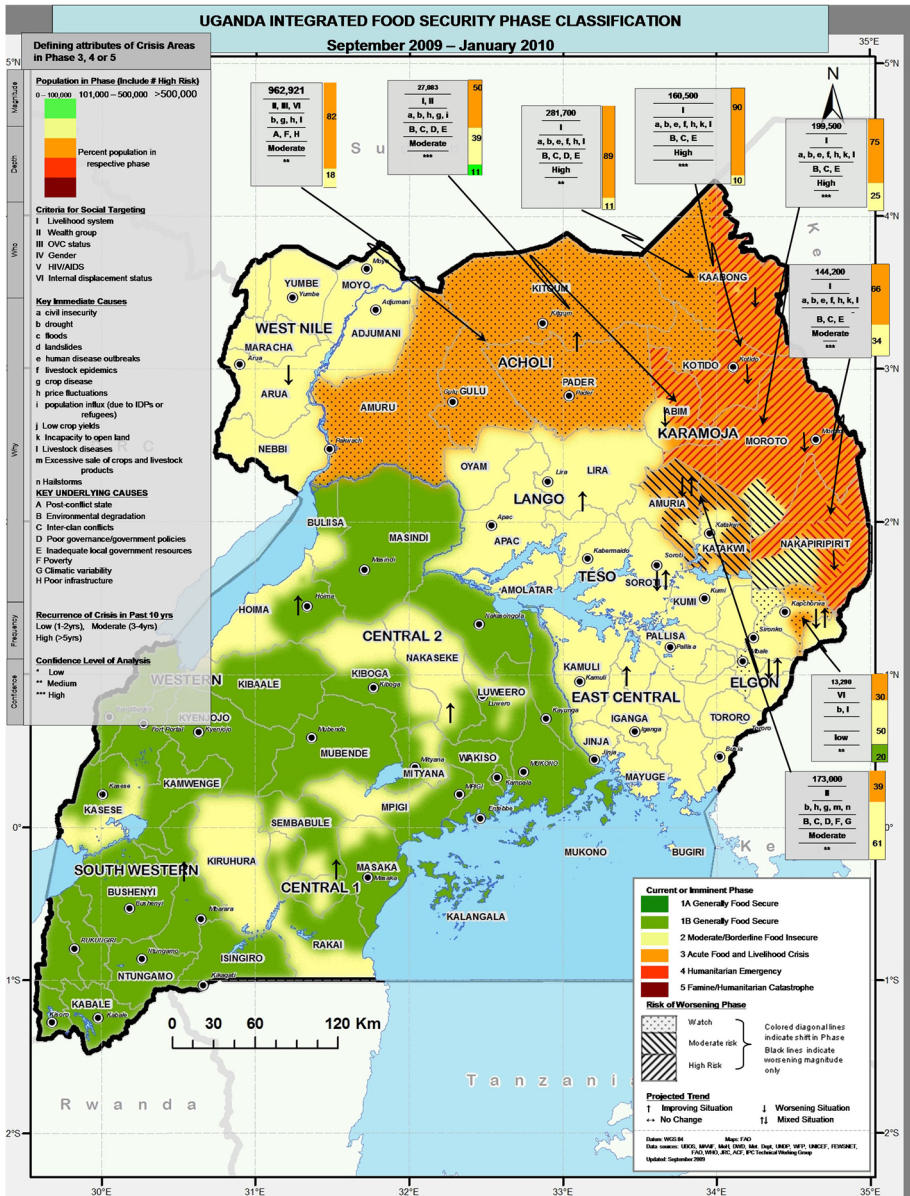


Fig. 6 IPC assessment summary map for Uganda (valid September 2009 to January 2010). Full report available here: <http://www.ipcinfo.org/ipcinfo-detail-forms/ipcinfo-map-detail/en/c/141532/>

Table 4 SPI timescales 1, 3, 6, 9, and 12 months and NDVI-based indices at Kotido Station within cropland areas $N = 48$

	SPI-1	SPI-3	SPI-6	SPI-9	SPI-12
NDVI anomaly	0.078	0.324**	0.235**	0.231**	0.187**
VCI	0.103*	0.308**	0.254**	0.241**	0.182**
SVI	0.060	0.316**	0.240**	0.237**	0.196**

$N = 48$

The highest R^2 values are shown in bold for each NDVI index. Overall, ANDVI data had the highest correlation with SPI-3

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

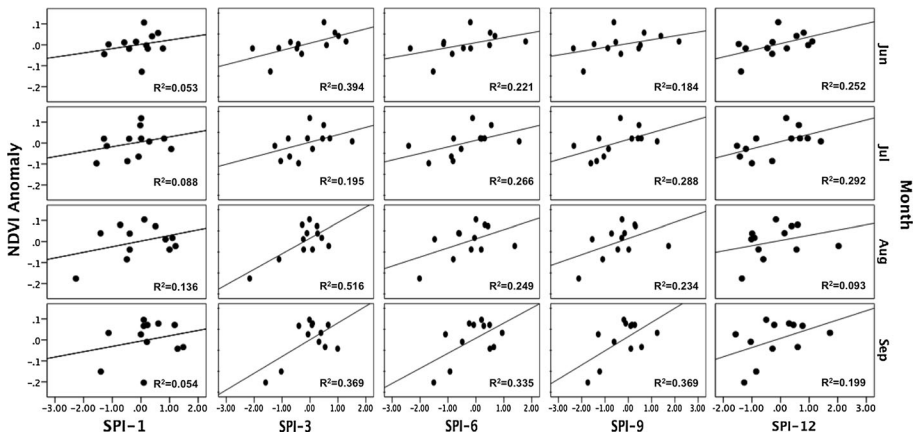


Fig. 7 Relationship between SPI (at different time steps) at Kotido Station and NDVI anomaly data for crops only data 2001–2012 ($N = 12$)

Table 5 Regression analysis on ANDVI and SPI-3 Kotido

Variable	Coefficient	SE	t value	Sig.
1. Simple regression ^a				
Intercept	0.006	0.009	0.689	0.494
SPI3	0.050	0.011	4.692	0.000
2. Regression with dummy variables ^b				
Intercept	0.006	0.009	0.691	0.493
SPI3	0.034	0.017	2.007	0.051
D1	0.002	0.028	0.054	0.957
D2	0.037	0.028	1.284	0.206
D3	0.046	0.030	1.517	0.137

^a $F = 22.012$, p value < 0.0001 , $R^2 = 0.324$, adjusted $R^2 = 0.309$

^b $F = 6.457$, p value < 0.0001 , $R^2 = 0.375$, adjusted $R^2 = 0.317$

$$\begin{aligned}
 \text{June ANDVI} &= 0.0061 + 0.034(\text{SPI3}) \\
 \text{July ANDVI} &= 0.0401 + 0.034(\text{SPI3}) \\
 \text{August ANDVI} &= 0.0426 + 0.034(\text{SPI3}) \\
 \text{September ANDVI} &= 0.0520 + 0.034(\text{SPI3})
 \end{aligned}
 \tag{3}$$

The scatter plot in Fig. 8a demonstrates the relationship between observed and predicted ANDVI from SPI-3 with simple regression (2001–2012). By accounting for the month effect using regression with dummy variables the relationship between ANDVI and SPI improved slightly from $R^2 = 0.324$ ($p < 0.0001$) to $R^2 = 0.375$ (Fig. 9b).

Figure 9 shows the temporal relationship of ANDVI and the predicted ANDVI from SPI with both regressions. There is a clear and significant association between SPI and ANDVI with clear degradation of vegetation conditions or recovery in response to rainfall. It is important to note that the predicted values for 2010 remain above zero, while the observed values dropped in August. When the two datasets (ANDVI and SPI) are further analyzed, extreme rainfall at the beginning of 2010 seems to be the cause of this disparity. Observed 3-month cumulative rainfall in 2010 was almost 400% above normal by the end of February and remained above 100% above normal by the end of June. It appears extreme rainfall negatively impacted crop conditions leading to below average crop conditions by the end of August.

The main conclusion is that NDVI response is most influenced by cumulative moisture up to 3 months and NDVI anomaly and not deseasonalized NDVI (SVI or VCI) having the better relationship at the peak of the growing season during the month of August.

3.2 Drought identification from rainfall (SPI-3) data

Since the highest and significant correlations between SPI-3 and NDVI data occur during the month of August, in this section droughts in Karamoja are classified based on the August SPI-3. Between 1960 and 2012 (52 years) extreme agricultural droughts (shown in

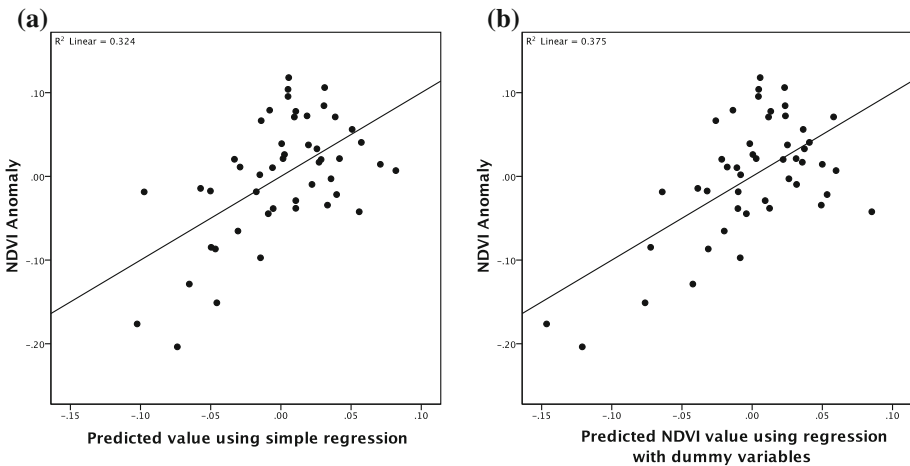
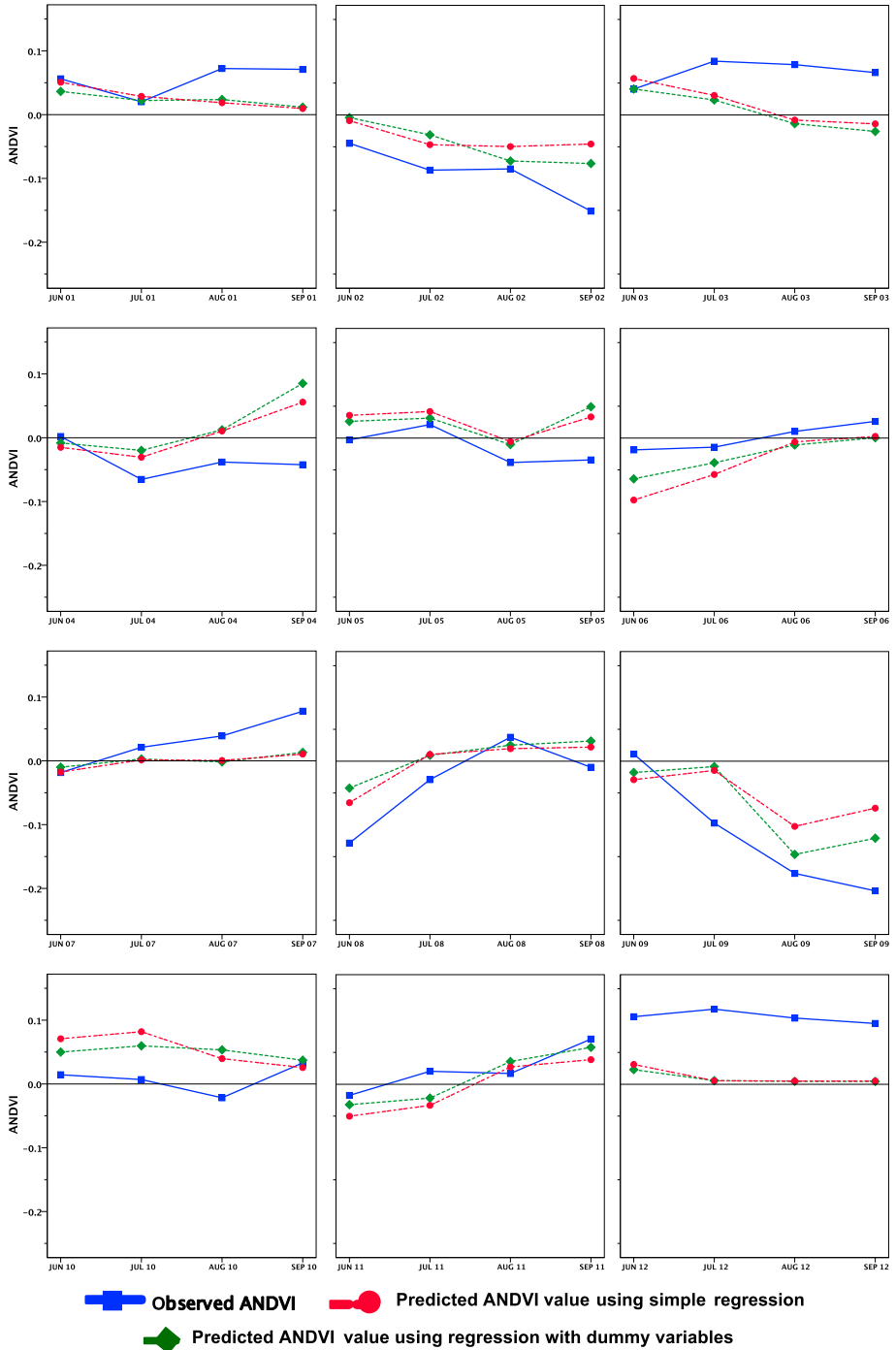


Fig. 8 Relationship between SPI-3 at Kotido Station and NDVI anomaly data for crops only data 2001–2012. **a** Simple regression, **b** regression with dummy variables ($N = 48$)



◀ **Fig. 9** June to September (JJAS) crops only observed ANDVI and predicted ANDVI using simple regression and regression with dummy variables time-series data for 12 years at the Kotido Station (2000–2012)

red) occurred only in 1965 and 2009, when SPI-3 for the month of August fell below -2 . 1980 was the only severe drought year in the record (orange), and moderate droughts occurred in 1963, 1979, and 2002 (beige). Mild droughts (yellow) occurred more frequently (every 2–3 years) and occurred in 1960, 1966, 1967, 1968, 1969, 1972, 1982, 1983, 1984, 1985, 1986, 1987, 1988, 1990, 1996, 1997, 1999, 2003, 2005, 2006, and 2007 (Fig. 10).

By averaging all growing season months SPI-3 values, 1965 was found to be the worst year on record, with the driest August in the 52-year period followed by 1963 and 2009. August 1979 to August 1988 period marks the longest consecutive period when drought occurred in the month of August (i.e., when SPI values for the month of August remained below zero). The period from 1973 to 1978 marks the longest non-drought period when SPI values remained above average. August 1994 was an exceptional month with the SPI-3 value above 2, evidenced by exceptional harvests reported during this year. 1994 is named *Apamulele* by Moroto district residents, which translates as intact, complete, full or filled up, or good harvest.

Focusing on the period 2000–2012 (12 years) when SPI and NDVI data overlap in the study area, 2009 was an extreme drought year followed by 2002 a moderate drought year. While in 2003, 2005, 2006, 2007, and 2012 mild drought conditions were experienced during the month of August. Taking a closer look at 2009, the SPI reached a record -3.92 low in April at the start of the season (data not shown), improving slightly before dropping to -2.16 by August. The next section presents spatially explicit NDVI data from 2000 to 2012 to explain drought impacts in agriculture beyond the Kotido Station and to show the differences in spatial severity across the region.

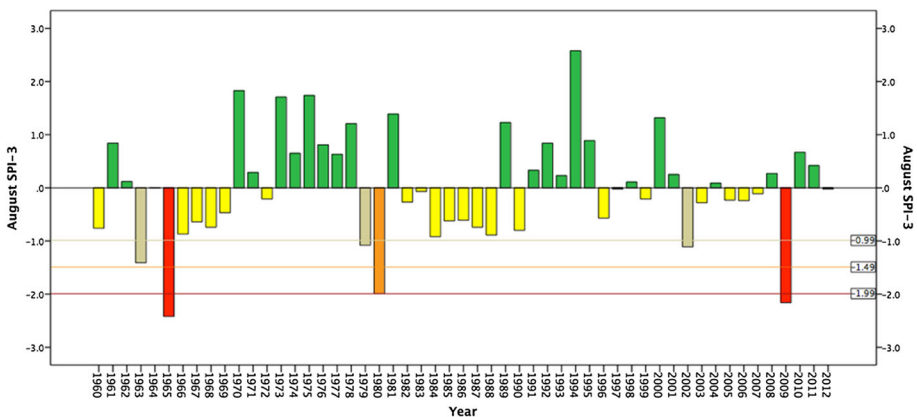


Fig. 10 August SPI-3 values 1960–2012. The droughts are categorized based on SPI values as: mild (0 to -0.99) in yellow, moderate (-1.00 to -1.49) in beige, severe (-1.50 to -1.99) in orange, and extreme in red, when values fell below -2.00 . [Reproduced with permission from McKee et al. (1993)]

3.3 Spatial and temporal patterns of agricultural drought 2000–2012 from NDVI data

Given the relationship between NDVI-derived indicators and SPI, ANDVI data time-series for cropland areas in all other districts in Karamoja are shown in Fig. 11. It can be observed in these data that there are subtle variations in ANDVI between districts. However, the major patterns are similar. Overall, Abim District showed the least variation and is the least impacted, while Moroto District had the highest inter-annual variability and often the most severely impacted. The differences between the two districts (indicated with blue arrows) are clear in 2002, 2004, 2007, 2009, 2011, and 2012. 2012 was a year with well distributed and above average rainfall during all growing season months.

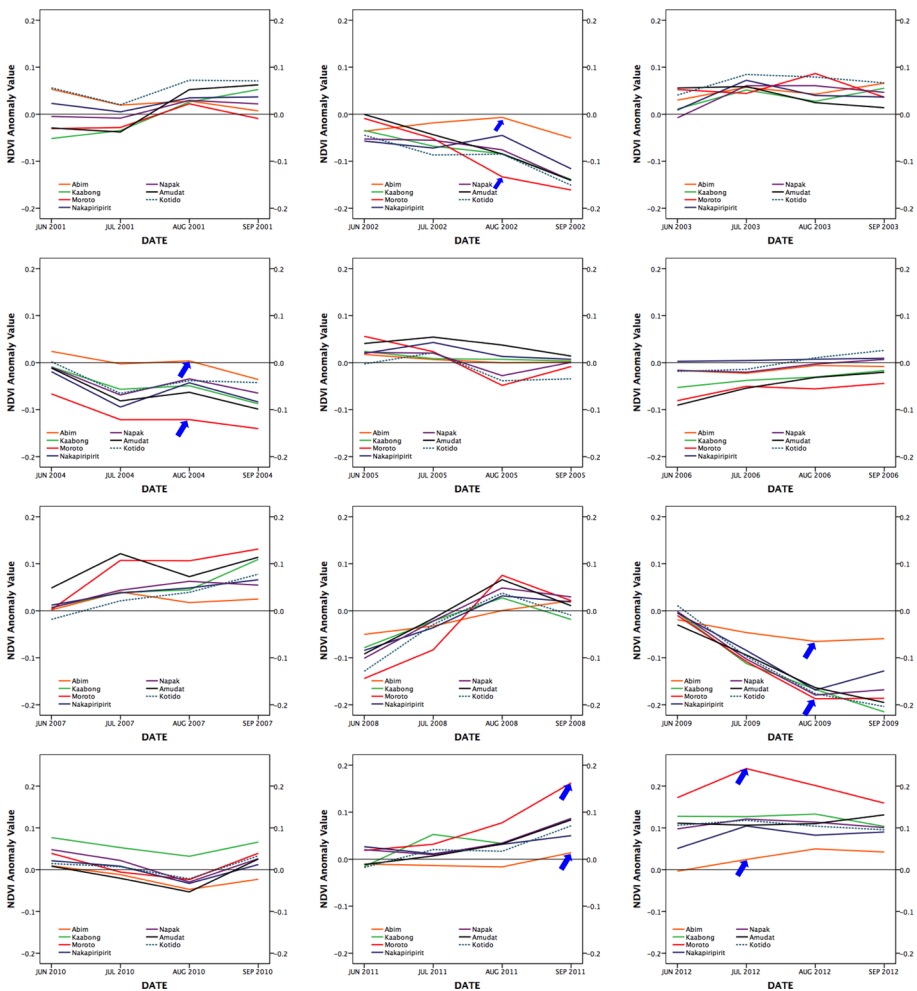


Fig. 11 The June–September NDVI anomaly crops only time-series data for Abim, Amudat, Kaabong, Kotido, Nakapiripirit, Napak, and Moroto Districts from 2000 to 2012. The blue arrows highlight the difference in severity between Moroto and Abim districts

The NDVI anomaly data also indicate that August 2004 crop conditions were poorer than August 2006 conditions, which was not captured by the August SPI-3 analysis. We anticipate the extremely low June SPI-3 value (−1.16) had severe impacts on crops and rainfall in late July was too late to significant ensure recovery of the crops by the end of August. Therefore, 2004 is re-classified as a moderate agricultural drought.

The derived spatially and temporally explicit NDVI anomaly maps within cropped areas at the end of August are shown in Fig. 12 and further support this finding. Within cropland areas at least 30% of cropland areas were severely impacted in 2004, 2005, and 2010, over 75% in 2002 and 100% in 2009.

To demonstrate the usefulness of high frequency and spatially explicit data in monitoring droughts in the region we show in Fig. 13 the development of drought conditions in Karamoja from April at the start of the season to September for 2009, the worst drought in 12-year NDVI data record, and 2002. The record lows found in the SPI values during April 2009 at the start of the season were not evident in ANDVI data until July 2009 (3 months later) given the slow response of vegetation to water deficits. During the 2002 growing season, SPI-3 data indicated moderate drought conditions which prevailed to the end of the season which resulted in crop failure evidenced by extreme poor crop conditions at the end of the growing season across the region seen in the ANDVI data.

We also show data for 2008 that we consider a phenomenal year based on the supplementary data that indicated severe food insecurity. The start of the 2008 season was poor, but SPI-3 values remained above zero. Improvement in vegetation conditions can be seen in the NDVI data but, as indicated earlier this recovery might not have been sufficient to see crops to maturity since more than 50% of the population required food aid (Nakalembe et al. 2017). We conclude that the August 2008 ANDVI data are simply an indicator of general vegetation conditions (grass rather than crops) since crops are likely not to have survived the poor rainfall during April to June. Moreover, there are no other data to explain the extreme food insecurity in 2008 except for heightened insecurity in the region during the time. Insecurity could have resulted in poor production during 2008 and explains the documented food insecurity more than drought severity. From 2008 to 2011 marks the peak period of the government’s disarmament campaigns that started in 2004 (OPM 2010). Official reports indicate that between 2008 and 2010 more than 50% of the



Fig. 12 NDVI anomaly data for the end of August (2001–2012)

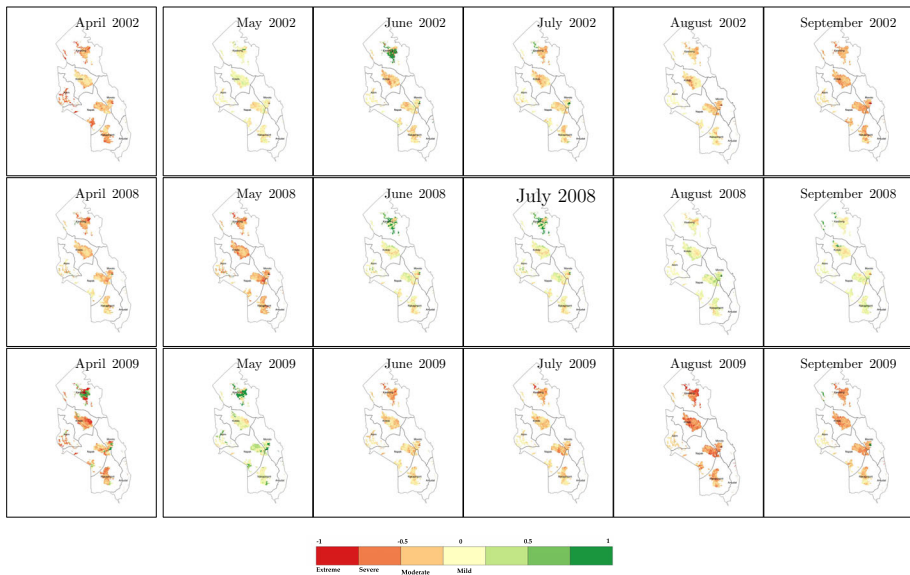


Fig. 13 End of month 16-day NDVI anomaly maps from May to September for 2002, 2008, and 2009

population required food aid. The assumption is that heightened insecurity disrupted day-to-day activities; crop cultivation was perilous in vast areas of the region and irrespective of good rainfall, harvests were very poor.

The observations above demonstrate part of the usefulness of combining meteorological and satellite-based indices when understanding drought severity for better drought monitoring (Zhang and Jia 2013). Without the spatially explicit NDVI information classification of droughts, only analyzing rainfall anomaly would not provide the extent and differences in severity of drought across the region. For example, without the NDVI information, extreme rainfall would indicate a good year. However, this is not necessarily the case since heavy rainfall often leads to flooding that physically damages crops (e.g., in 2010). This information, where, when, and how severe drought impacts are, is important when planning response, e.g., when determining if, where and when to begin providing humanitarian assistance.

3.4 Relationship between NDVI and number of people requiring food aid

The primary goal of this section was in a proof-of-concept frame use ANDVI data to estimate the impact of agricultural droughts on food security in Karamoja. It is important to note that the relationships presented below are derived from a small sample, and it assumes there is a relationship between vegetation condition, crop production, and domestic food supply. Nevertheless, this would be a quantitative, easily reproducible, and quick method to estimate food aid need in this region. This straightforward model used area-averaged seasonal $ANDVI_{min}$, $ANDVI_{mean}$, and $ANDVI_{max}$ to calculate the percent of the population likely to need food aid each year (Eq. 3) and the percent of the population likely to fall in the IPC Phase 3 (crisis) by the end of the year (Eq. 4).

The regression model equations are shown below. Future studies will continue to evaluate this model as more data become available for more years.

$$\text{IPC Phase 3 (percent of population)} = 87.47 - 358 * \text{ANDVI}_{\text{max}} \quad (4)$$

$$\text{Food aid need (percent of population)} = 55.17 - 476 * \text{ANDVI}_{\text{max}} \quad (5)$$

In spite of the current limited sample size ($n = 5$), correlations between ANDVI and food aid need were high. $\text{ANDVI}_{\text{max}}$ had the highest correlation with $R^2 = 0.907$ (Table 6) implying that 90.7% of the variation in the number of food aid needed can be explained by seasonal $\text{ANDVI}_{\text{max}}$. Similarly, correlations with ANDVI and population in IPC Phase 3 ($n = 8$) were high. Irrespective of seasonal ANDVI value used (min, mean or max), at least 50% of the variation in the population in IPC Phase 3 can be explained by ANDVI.

From this proof-of-concept estimate, at least 72% of the population in Karamoja (about 759,240 people⁵ will require food aid to make through to the 2017 harvest Fig. 14a. The model also estimated that at least 30% (316,350 people) of the population would fall in the IPC 3 (crisis phase) by December 2016 (Fig. 14b).

Similarly, the model demonstrated that it possible within a reasonable margin of error (less than 10%) to estimate the population that will likely need support as early as August (at the peak of the growing season). As more monitoring data on food security for Karamoja become available, better early warning leading to informed decision making can be realized.

4 Concluding remarks

The lack of clarity concerning occurrence, boundaries, and possible impacts of drought on agriculture remains an obstacle to agricultural development in the region. This information is now more critical with the current and projected rates of extreme events in this region (Cervigni and Morris 2016).

Agriculture in Karamoja is nearly 100% rain-fed, and the soils have poor water-holding capacity resulting in the high sensitivity of crops to drought conditions (Nakalembe et al. 2017). As a result, and with no irrigation, consistent rainfall during the growing season is necessary for above average production in the region. Rainfall is often poorly distributed and hence sorghum a drought-tolerant crop is widely grown in Karamoja. However, its performance has not been sufficient to ensure food security as unpredictable shocks often decimate the crop sometimes causing complete crop loss.

The majority of farmers in Karamoja maintain their cropping calendar, and once seeds are sowed, many are not in a position to replant if rains fail at the start of the season. Extended dry periods often result in extreme crop failures irrespective of a good start of the rainy season.

This study demonstrated the suitability of MODIS NDVI data for monitoring and characterizing agricultural drought in Karamoja and shows that the satellite-derived data provide sufficient details for spatially explicit drought assessment. The SPI provides good point measurements average, but in this region it is of limited use due to the scarcity of climate station data, leading to the lack of spatial information.

Though without extensive testing, we have shown that it is possible to predict the number of people who require food aid during the lean season in Karamoja (December to March) within a reasonable margin of error at the peak of the growing season. With the

⁵ Estimated from UBOS 2016 population projection.

Table 6 Pearson correlation coefficients (r) between ANDVI (min, mean, and max) values and food aid need ($n = 5$), and IPC Phase 3 ($n = 8$)

ANDVI _{value}	Food aid need	IPC Phase 3
ANDVI _{min}		
r value	0.724	0.724*
R^2	0.524	0.524
RMSE (%)	9.9	19.3
ANDVI _{mean}		
r value	0.881*	0.730*
R^2	0.777	0.533
RMSE (%)	6.8	19.1
ANDVI _{max}		
r value	0.952*	0.708*
R^2	0.907	0.501
RMSE (%)	4.4	19.7

Bold r values indicate cases with highest correlation coefficient

* Indicate values significant at the 0.05

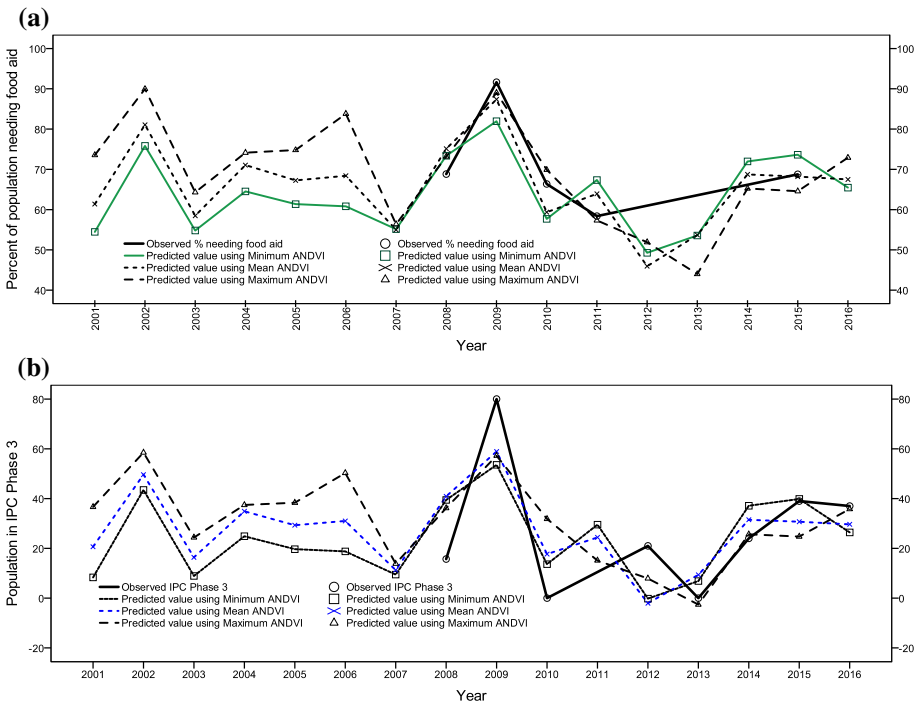


Fig. 14 **a** Observed and projected (from ANDVI) number of people needing food aid and **b** reported and projected (from ANDVI) number of people in IPC Phase 3

sparsity of information, this method could help improve timeliness and appropriateness of response plans.

This study also highlights the need for continued detailed assessment of drought to minimize over generalization and misleading information. Assessments that lack empirical backing have to be used with extreme caution in decision making. Apart from detailed

spatial and temporal drought information, more research is needed regarding drought impacts in Karamoja. Human perceptions of drought in the region are necessary to help understand additional underlying causal factors of severe crop failure (e.g., agricultural practices). Besides, other factors including pests, flash floods, and wind erosion can cause substantial crop damage from year to year; these need to be considered when examining the suitability and sustainability of agricultural production.

There is a general lack/poor distribution of meteorological data that would otherwise form the basis for the design of crop insurance programs to enable a timely and appropriate response to help farmers (Turvey and McLaurin 2012; Rowley et al. 2007). There is some indication that NDVI data can fill this gap which has been demonstrated in Kenya using VCI (Klisch and Atzberger 2016)'s hard to determine and similarly, Uganda is in the process of implementing its Disaster Risk Financing Program using MODIS NDVI data.⁶

There is also a strong need to educate farmers, and to provide early warning/forecast information to support decision making. Most importantly there is a need for behavioral change. If farmers receive timely information, positive and informed change can be realized.

The Intergovernmental Panel on Climate Change (IPCC) projects an increase in extreme events such as drought in the subregion. Observations of rainfall for Uganda (1960–2010) show significant decreasing rainfall trends for March, April, May (MAM) and June, July, August (JJA) a period that covers the entire growing season in Karamoja (McSweeney et al. 2015). Decreased rainfall projected to coincide with an increase in temperature at an average rate of 0.28 °C per decade (McSweeney et al. 2015). Uganda is already experiencing the negative impacts of climate change witnessed in the reduced in rainfall amounts, and according to Funk et al. (2012) Karamoja is projected to experience further decrease in June to September rainfall of 20 mm and temperature increase of greater than 1.5 °C from 2010 to 2039. These projections indicate that drought frequency; severity and impacts are likely to increase making it paramount to have a functioning drought monitoring system to minimize negative impacts on the people of Karamoja.

This study shows that satellite data can provide the much-needed data to fill the data gap that inhibits long-term drought monitoring at a significantly lower cost than traditional climate station-based monitoring in data scarce regions like Karamoja. With more spatial details, satellite data provide a baseline for understanding long-term food insecurity in the region. Satellite-derived data from decision support systems such as the GLAM system used in this study can also be used for near real-time drought monitoring enabling proactive assessment, planning, and response, and would limit incidences where information gets to the decision maker too late. The country would be able to avoid events such as the 2015 drought when the Karamoja region experienced famine, and no action was taken until the food security situation had deteriorated in September (NewVision 2015); yet, extreme crop failure was eminent earlier and was evident in MODIS NDVI by early July 2015 (OPM 2015).

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⁶ As per NUSAF 3 Disaster Risk Financing Handbook.

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