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RESEARCH ARTICLE

CHARACTERIZATION, FORECASTING AND ASSESSMENT OF AGRICULTURAL DROUGHT IMPACTS IN THE SUDANO-SAHELIAN CLIMATE OF GOURMA PROVINCE IN BURKINA FASO

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ABSTRACT

Natural hazards such as agricultural droughts impact negatively on crop yields and economic activities. Characterization of agricultural droughts provides precise and accurate information for decision making processes during agricultural drought events. Planning and responding to the hazards by government, and non-governmental organizations in the Sudano-Sahelian belt has been limited in the past due to knowledge gap on the nature and impact of the hazard. This study seeks to characterize historical agricultural droughts, assess their impact on crop yields and people's susceptibility to undernourishment and through forecasting, unravel what the future holds. Annual effective reconnaissance drought index values are computed using mean monthly potential evapotranspiration and effective precipitation data. To assess the impact of agricultural drought, the index's values are compared to crop yields and prevalence to undernourishment data. Results show that agricultural drought events of 1983 and 2008 are mild and ephemeral while the 1999 – 2006 event is severe and protracted. While there is 26% chance of materialization of an agricultural drought in Gourma, the chance of being ephemeral and of moderate category is the highest (8%). It has been determined that an ephemeral and moderate agricultural drought would trigger below average yields for maize, sorghum and millet. Mild, moderate and severe events increase prevalence to undernourishment by 2.9 %, 4.3 % and 5.8 % respectively. From 2020 to 2030, a continued materialization of agricultural droughts is expected.

KEYWORDS

Agricultural drought characterisation, Drought indices, Effective Reconnaissance Drought Index.

1. INTRODUCTION

In 2014, about 4 million Burkinabés that is a quarter of the entire population were reported to have been affected by drought in the country (Guha-Sapir, 2019). In 2018, the United States Agency for International Development (USAID) reported that more than 954,300 Burkinabés faced food insecurity and malnutrition caused by environmental shocks such as drought, floods and insecurity (USAID, 2018). The Burkinabé government has promised to prepare a national drought management plan in accordance with the structure of the United Nations Convention to Combat Desertification (UNCCD) ratified in Paris (1974) (Global Water Partnership-West Africa, 2019; UNCCD, 2019). National drought plans are living documents and characterisation of agricultural drought is key for the preparation and implementation of the drought plan (Berbel and Esteban, 2019).

An agricultural drought event is a naturally occurring phenomenon during which there are long periods of consistently "below normal" supplies of soil moisture required for crop growth (Iglesias et al., 2007). The use of drought indices for the identification and description of intensity, severity, duration and aerial extent of drought events is referred to as drought characterisation (Iglesias et al., 2007). Agricultural drought characterisation is valuable for the assessment of future agricultural drought risk, determination of the impact of drought on agriculture as a sector, preparation and implementation of drought preparedness plans and for the establishment of an agricultural drought monitoring mechanism (Rossi et al., 1992). Understanding the characteristics of drought is vital for the sustainable development of the agricultural sector and economic development (Han et al., 2021).

As of 2011, there were 34 Agricultural drought indices used world over for characterisation of agricultural droughts with varying strengths and weaknesses from one region to another (Sivakumar et al., 2011; Agutu et al., 2020). The effective reconnaissance index (eRDI) was developed in 2017 in Greece by modifying the Reconnaissance drought index (RDI) (Tigkas et al., 2017). This index has been used most prominently in the semi-arid climate of the Mediterranean countries for purposes of characterization of agricultural droughts in the process of designing and implementing drought management plans (Tigkas et al., 2016). Other Agricultural drought indices include: Normalised Difference Vegetation Index, Palmer Drought Severity Index (PDSI), Crop Moisture Index (CMI) and the Standardized Precipitation Evapotranspiration Index (SPEI) (Rokni and Musa, 2019; Tian et al., 2018; Chitedze and Chikabvumbwa, 2020; Chen et al., 2020). A group researcher while evaluating the performance of drought indices for monitoring agricultural drought concluded that SPEI was the most suitable index for monitoring agricultural drought in South Central USA (Tian et al., 2018). SPEI is computed in a similar manner as the eRDI and also takes into account precipitation and potential evapotranspiration data. A group researchers used the Agricultural Drought Frequency Change and Agricultural Drought Area Change indices to quantify the impact of anti-drought measures in China so as to enable the government and other entities in adjusting their response mechanisms owing to the massive agricultural and economic losses caused by droughts (Wu et al., 2020).

Preceding studies in the Sudano-Sahelian and Sahelian belts suggest that understanding the nature of hazards such as agricultural drought forms a basis upon which risk reduction policies and programs could be established as it could be key in assessment and prioritization of interventions thus alleviating impacts of hazards and enabling timely recovery of victims (Roncoli et al., 2001; Traore and Owiyo, 2013). However, in cases such as the 1997 drought in the Central Plateau (Region within the Sudano-Sahelian belt of Burkina Faso), the Government and Non-Governmental Organisations (NGOs) were not capable of mobilising adequate aid to alleviate the stress on households food insecurity arising from the 1997 agricultural drought in the region (Roncoli et al., 2001). Review by some researchers on level of preparedness for flood and drought disasters established that governments and other stakeholders in many countries are more prepared for floods as compared to droughts (Raikes et al., 2019). This informs the need to comprehend the nature and impact of agricultural droughts on crop yields and human health in the region so as to establish a basis upon which planning and response to these hazards is adequate.

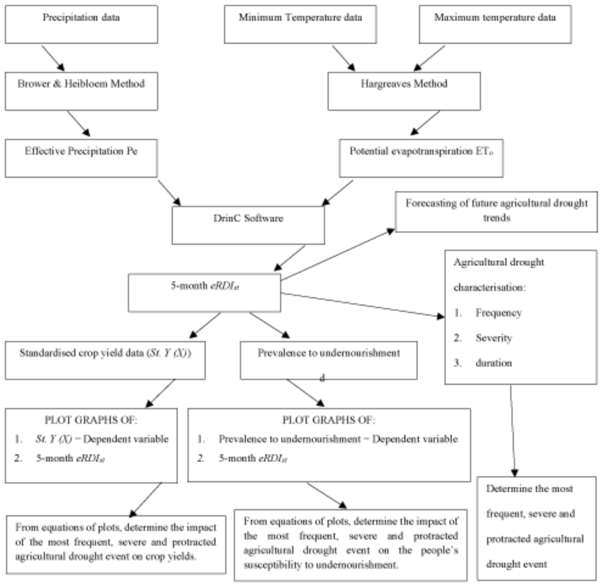
A relied on both qualitative and quantitative methods to establish the impact of the 1997, 2004 and 2010 droughts in the Sahelian belt region and identified loss of crops and livestock resulting in food insecurity as the major impacts (Traore and Owiyo, 2013; Roncoli et al., 2001). However, the approach employed in both studies, does not make it possible to quantify losses and thus put up adequate mitigation strategies. Developing future agricultural drought scenarios is also not possible since the focus was on three events that were also never characterised. The relationship between the agricultural drought characteristics and quantity of losses cannot therefore be established as well. The use of index-based methods to analyse historical agricultural drought events enables the characterisation of previous events, development of future agricultural drought scenarios and the ability to develop monitoring mechanisms for agricultural drought indicators which are key in planning for Governments and NGOs (Liu et al., 2020). A group researchers further argues that monitoring agricultural drought with reliable and coherent drought indices together with Geographic Information System (GIS) is crucial in mapping, and monitoring agricultural drought dynamics as well as reducing the impacts of climate change (Li et al., 2016; Sandeep et al., 2021). Similarly, emphasize the need to monitor agricultural drought combined with satellite imageries such as Sentinel-3A SLSTR (Sea and Land Surface Temperature Radiometer) in order to improve food security noting that globally agricultural drought is one of the highly destructive natural hazards that cause substantial agricultural production losses and water scarcity (Hu et al., 2019).

Some researchers working on impact and response of local communities to drought in the region established that local strategies such as diversification in agriculture and migration were inefficient in mitigating drought impacts and thus suggested an in-depth study of the nature and impact of droughts in the region so as to provide precise and accurate information for decision making (Gautier et al., 2016; Mertz et al., 2011). Other studies in the Nigerian Sudano-Sahelian region characterised meteorological drought but failed to link the characteristics of the droughts to the impact on crops and human health quantitatively (Abaje et al., 2013). The state of research on agricultural drought in the Sudano-Sahelian belt thus gives the impetus to carry out research that explicitly specifies the drought hazard being studied and quantifies the impacts of the events on agriculture and residents in such a manner that Government and NGOs can adequately plan for interventions. Given that this study is index based, historical agricultural droughts can be characterised and future agricultural drought scenarios can be developed through forecasting which is fundamental to establishing a preventive, precautionary and adaptive drought monitoring mechanism through further research work (Kisi et al., 2019).

2. MATERIALS AND METHODS

2.1 The conceptual framework

For the purposes of achieving the objective of this study, the below conceptual framework was used.



2.2 Location and Climate

Burkina Faso lies within latitudes 9º and 15º N and longitudes 6º W and 3º E in Western Africa with a total area of about 274,200 km². Burkina Faso is surrounded by Mali, Niger, Cote d'Ivoire, Ghana, Benin and Togo. Fada N'Gourma is the administrative headquarters of Gourma Province which is situated in the East region of Burkina Faso. Gourma covers a total area of 11,217 km² (see location in Figure 1 below) with an average altitude of 280m. The province receives an average annual rainfall ranging between 800mm and 900 mm within a period of four to five months in a year (Abdoulaye et al., 2017). Between 1963 and 2003, Gourma is reported to have received an average of 818 mm of precipitation and registered a mean temperature of 28.3 °C (Some et al., 2014).

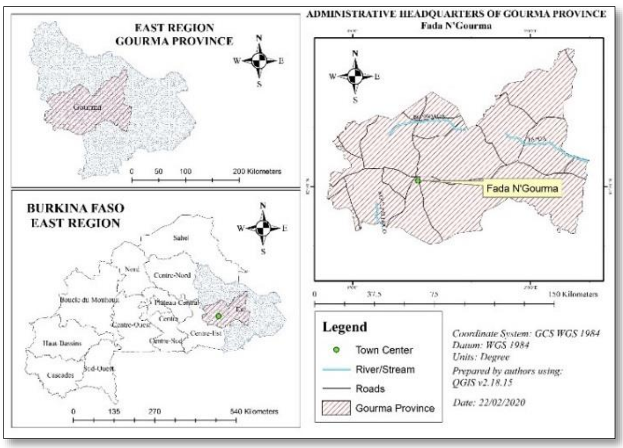


Figure 1: Administrative map of Gourma Province (SOURCE: Prepared by authors in QGIS v 2.18.15)

2.3 Agriculture in Gourma Province

As of 2017, the population was estimated at about 429,709 people with majority of them depending on agriculture for subsistence (INSD Burkina Faso, 2018). Majority of farmers in Gourma province practice rain-fed agriculture where the most commonly cultivated crops are: sorghum, millet, rice and maize. The rainy season begins in June with light showers and continues to October/November during which crops are grown. Planting season begins anytime between mid-May into June depending on the onset of the rains and lasts 5 months on average (ending in November/October) depending on the crop (Gyga and Ouattara, 2014).

2.4 The effective reconnaissance drought index (*eRDI*)

The effective reconnaissance drought index (*eRDI*) was introduced by Tigkas, Vangelis and Tsakiris (Tigkas et al., 2016). It is an agricultural drought index that is calculated by dividing the cumulative effective precipitation (P_e) and potential evapotranspiration (ET_O) for a particular time series depending on the purpose of its determination (Tigkas et al., 2016). Data needed to calculate the index includes temperature and precipitation data. The results obtained from calculating effective reconnaissance index include the initial ($a_{e(k)}$) and standardized ($eRDI_{st}$) forms for various time series (12, 6, 3 or 5 months) depending on objectives.

2.5 Data

Climate data was obtained from The National Center for Environmental Prediction-Climate Forecast System Reanalysis (NCEP-CFSR) research data archives in a Soil Water Assessment Tool (SWAT) file format. The NCEP-CFSR archives contain global and high-resolution daily climate data [precipitation data (mm), minimum and maximum temperature (°C)] for 35-years (1979 to 2014) which is accepted for drought characterisation (Svoboda and Fuchs, 2017; (National Centers for Environmental Prediction, 2016). For the purpose of this study, data files from the Fada N'Gourma weather station (coordinates: Longitude 0.367°E and Latitude 12.033°N) were used to represent the climate data of Gourma province.

The minimum and maximum daily temperature data was converted into minimum and maximum mean monthly temperature data for the determination of the Potential Evapotranspiration (ET_O) using the Hargreaves method as shown by equation (1) below. Equation (1) was established by replacing R_S in equation (2) with its equivalent as demonstrated in equation (3) and taking the empirical coefficient K_{RS} to be 0.16 (Hargreaves & Allen, 2003).

$$ET_O = 0.0023R_a(TC + 17.8)TR^{0.50} \tag{1}$$

$$ET_O = 0.0135R_s(TC + 17.8) \tag{2}$$

$$R_s = K_{RS}.R_a.TR^{0.50} \tag{3}$$

Where: ET_O is the Potential Evapotranspiration in mm month^{-1}

R_a is the extra-terrestrial radiation in mm month^{-1} evaporation equivalent

TC is the mean monthly temperature in °C

TR is the mean monthly temperature range in °C and $TR = T_{max} - T_{min}$ in °C

The Potential Evapotranspiration (ET_O) was determined using the Drought Indices Calculator (Tigkas et al., 2015). Hargreaves method was selected due to its simplicity, low data requirements, reliability and ease of computation as compared to the Thornwaite and Blaney-Criddle methods (Vangelis et al., 2013). The Brouwer & Heibloem method illustrated below by equations (4) to (6) was applied for the estimation of effective precipitation (Brouwer and Heibloem, 1986). This method was chosen due to its simple structure and low data requirements.

$$P_e = 0 \quad for\ P \leq 17\ mm \tag{4}$$

$$P_e = 0.6 \times P - 10 \quad for\ 17mm < P \leq 70\ mm \tag{5}$$

$$P_e = 0.8 \times P - 25 \quad for\ P > 70\ mm \tag{6}$$

Where: *Pe* is Effective precipitation (mm) and *P* is Precipitation (mm)

2.6 Drought index computation and forecasting

The initial value ($a_{e(k)}$) of the effective reconnaissance index (*eRDI)* was calculated for each year and for a reference period of 5-months starting June of every year. June was taken as the starting month since in Gourma province, the rainy season mostly begins with light showers in mid-June and crop planting in rain-fed agriculture starts towards the end of June and continues in July (Gyga and Ouattara, 2014). This is intended to capture the impact of initially available soil moisture that is critical for seed germination and emergence. The 5-month reference period was chosen since the goal of this study is targeting agricultural drought and this period covers the crop development period of the major crops grown in Gourma Province (Tigkas et al., 2017). The values of the initial form ($a_{e(k)}$) of $eRDI_{st}$ were calculated as illustrated in equation (7) below and their frequency of distribution fitted to the gamma probability density function in equation (8).

$$a_{e(5)} = \frac{\sum_{j=1}^{j=5} P_{ej}}{\sum_{j=1}^{j=5} PET_j} \tag{7}$$

Where: P_{ej}-the monthly effective precipitation of the jth month (mm)

PET_j-the monthly potential evapotranspiration of the jth month (mm)

k-reference period (Number of months) June to October

$$g(x) = \frac{1}{\beta^{\gamma}\Gamma(\gamma)} x^{\gamma-1} e^{-x/\beta}, for\ x > 0 \tag{8}$$

Where:

γ – is the shape parameter

β – is the scale parameter

x - is the precipitation amount

$\Gamma(\gamma)$ - is the gamma function.

The parameters γ and β vary spatially and temporally and are estimated by equations (9):

$$\gamma = \frac{1}{4A}\left(1 + \sqrt{1 + \frac{4A}{3}}\right), \beta = \frac{\bar{x}}{\gamma}\ , where\ A = ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{9}$$

n = number of observations

To take care of the possibility of months with zero cumulative precipitation in the 5-month reference periods, the number of occurrences of zero precipitation was divided by the total number of observations and thus, the probability of zero precipitation, q, in equation (10) below, was determined. The probability of zero precipitation was then used to transform the cumulative probability, $H(x)$ in equation (10), of the initial form ($a_{e(5)}$) of $eRDI_{st}$ into a standard normal random variable with a variance of one (1) and a mean of zero (0) which gave the values of $eRDI_{st}$ for the 5-month reference periods for every year i.e. 5-month $eRDI_{st}$.

$$H(x) = q + (1 - q)G(x) \tag{10}$$

Where:

q - is the probability of zero precipitation

$G(x)$ - is the cumulative probability of the incomplete gamma function.

The agricultural droughts were classified as shown below in Table 1.

Table 1: Drought characterisation (severity) based on eRDIst values (adopted from (Tigkas et al., 2017) for this study)

$eRDI_{st}$ values	Drought class
> 2.00	Extremely humid
1.50 to 1.99	Severely humid
1.00 to 1.49	Moderately humid
-0.49 to 0.99	Normal conditions
-0.99 to -0.50	Mild drought
-1.49 to -1.00	Moderate drought
-1.99 to -1.50	Severe drought
< -2	Extreme drought

To forecast the future agricultural drought trends, the values of the 5-month $eRDI_{st}$ characterizing the historical agricultural droughts were used. The 35-years of 5-month $eRDI_{st}$ values calculated previously were firstly divided into two portions for the purposes of validation in the ratio of training data (51%) : testing data (49%) i.e. training data was 1979 to 1997 while testing data was from 1997 to 2013. The plot of training data exhibited seasonality and thus the forecasts had to start earlier than 2013 (hindcasting) in order to visualize how well the predictions matched the known values. The forecasts were then done starting the year 1997 to 2030.

The year 2030 was chosen since it marks the target year up on which all the Sustainable Development Goals and targets are to be achieved. This includes goal 2 targeting to end all forms of hunger and malnutrition as well as goal 15 that is focused on combating impacts of desertification and droughts (UNITED NATIONS, 2019). A plot of the known 5-month $eRDI_{st}$ values (starting 1997 to 2013) against the forecasted values (starting 1997 to 2013) was made and the mathematical model responsible for the prediction was established from a polynomial trendline with its R-Squared (R^2) value also determined. This procedure was repeated with increments of 2 years every time until the highest value of R^2 was attained. To select the best performing forecast, both the value of R^2 and the shape of the forecasted 5-month $eRDI_{st}$ plot were considered i.e. $0 < R^2 < 1$ and the forecasted plot must show seasonality (polynomial) like observed from known 5-month $eRDI_{st}$ values.

2.7 Validation

Results of characterization of the agricultural drought events in Gourma were firstly validated by comparing the 5-month $eRDI_{st}$ values to reported crop yields (t/ha) of major crops in Gourma province (Gyga and Ouattara, 2014). The 3-year averages of the 5-month $eRDI_{st}$ values were also compared to the 3-year averages of reported prevalence to undernourishment (%) (FAO, 2016).

2.7.1 Crop Yields and the 5-month $eRDI_{st}$

To assess impact of agricultural drought on crop yields, crop yield data and 5-month $eRDI_{st}$ values were used. Crop yield data for the major rainfed crops in Gourma province starting 2002 to 2011 were obtained from the Global Yield Gap Atlas (GYGA), available at: www.yieldgap.org. The downloaded data was the reported average actual yield (Y_a) in tons per harvested hectare (t/ha) at standard moisture content i.e. 13 % to 15.5 % for grains (Gyga and Ouattara, 2014). The average actual yield (Y_a) values were 10-year averages of rainfed maize, sorghum and millet grown by farmers in Gourma under similar farming practices (cultivar, sowing dates, plant density) and soils (Gyga and Ouattara, 2014). In order to be able to compare the crop yields for three of the four major crops and the agricultural drought index, the crop yields data were standardised using equation (11) below:

$$St.Y\ (X) = \frac{Y(X)_i - \overline{Y(X)}}{\sigma_{Y(X)}} \qquad (11)$$

Where: $St.Y\ (X)$ is the standardised crop yield for crop X i.e. Rice, Maize, Sorghum or Millet

$Y(X)_i$ is the crop yield in tonnes/hectare for the i^{th} year.

$\overline{Y(X)}$ is the mean of the 10 years of crop X yield data.

$\sigma_{Y(X)}$ is the standard deviation of the 10 years of crop X yield data.

The 5-month $eRDI_{st}$, which is a standardised form of the effective reconnaissance drought index and the $St.Y\ (X)$ were graphed as dependent variables against the time series from 2002 to 2011 as the independent variable. The crop yields (t/ha) and the 5-month $eRDI_{st}$ values were then compared by graphing as dependent and independent variables respectively.

2.7.2 Prevalence to undernourishment and the 5-month $eRDI_{st}$

For the purposes of understanding the impact of agricultural droughts on the people's susceptibility to undernourishment, prevalence to undernourishment data which is given as 3-year averages by FAO starting 1999 to 2013 and the 5-month $eRDI_{st}$ values were used. Values of the 5-month $eRDI_{st}$ starting 1999 to 2013 were used to compute their 3-year averages starting 1999 to 2013 (FAO, 2016). The 3-year averages of the 5-month $eRDI_{st}$ values were directly compared to the 3-year averages of the prevalence to undernourishment (%) by graphing as independent and dependent variables respectively.

3. Results and Discussion

3.1 Characteristics of historical agricultural droughts in Gourma

Outcome of calculating the 5-month $eRDI_{st}$ reveals the occurrence of three agricultural drought events between the years 1979 and 2013 with varying characteristics. From these results, the suggestions by Hagenlocher on being able to develop drought monitoring models after assessing enough historical data are therefore a possibility (Hagenlocher et al., 2018; Tigkas et al., 2015). From the assessment it is possible to characterise the historical events as compared to previous studies in the country (Roncoli et al., 2001; Traore and Owiyo, 2013). See détails in Figure 2 (standard error ± 0.1).

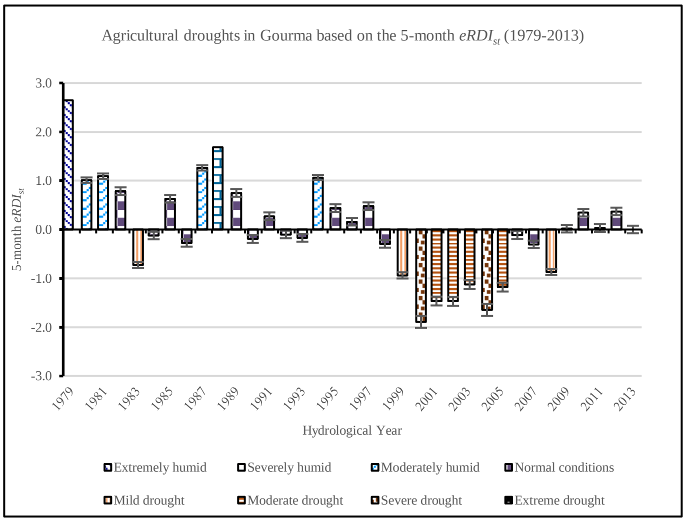


Figure 2: The Agricultural drought events that have historically manifested in Gourma (1979-2013) based on the 5-month $eRDI_{st}$ values i.e. bars with negative values < -0.49. - The events show varying characteristics in terms of severity, frequency and duration.

3.1.1 Frequency

Results of this study reveal that between 1979 and 2013, there have been agricultural droughts in 26% of the crop growing seasons with moderate agricultural droughts being the most recurrent while the extreme agricultural droughts never manifesting in Gourma Province. From Table 3.1 below, moderate agricultural droughts were the commonest at 11% frequency while mild and severe agricultural droughts were experienced at a frequency of 9% and 6% respectively. Extreme agricultural droughts were never experienced. Table 3.1 below also illustrates that while there have been moderately humid conditions with a frequency of 11%, there have also been extremely and severely humid conditions with a frequency of 3% each. Based on the history, there is 26% chance of reoccurrence of an agricultural drought in Gourma.

Table 2: 5-month eRDIst Frequency in percentages (%). Moderate agricultural droughts have the highest frequency.

Drought category	5-month $eRDI_{st}$ Frequency (%)
Extremely humid	3
Severely humid	3
Moderately humid	11
Normal conditions	57
Mild drought	9
Moderate drought	11
Severe drought	6
Extreme drought	0
Total	100

3.1.2 Duration

From this study, out of the three agricultural drought events in Gourma province, the 1983 and 2008 events were ephemeral while the 1999-2006 event was protracted. In Figure 2 above, climatic conditions during the 1983 and 2008 agricultural drought events change from normal to mild agricultural drought and back to normal conditions within one season. However, for the 1999-2006 event, the climatic conditions change from normal to mild, moderate and severe agricultural droughts incessantly for 7 seasons before changing back to normal conditions. Therefore, ephemeral agricultural drought events have a higher probability of reoccurrence (67 %) in future compared to protracted events. Table 3.2 summarises the durations of historical agricultural drought events in Gourma.

Table 3: Duration of agricultural drought Events in terms on annual crop growing seasons i.e. annually and the severity level at which the agricultural drought commenced.

Year (s)	Start (Drought class [5-month $eRDI_{st}$])	End (Drought class [5-month $eRDI_{st}$])	Duration (Crop growing Seasons)
1983 - 1984	Mild drought [-0.73]	Normal conditions [-0.12]	1
1999 - 2006	Mild drought [-0.94]	Normal conditions [-0.11]	7
2008 - 2009	Mild drought [-0.87]	Normal conditions [-0.02]	1

3.1.3 Severity

According to the study, the "severe" category of agricultural drought was the harshest that ever materialised in Gourma between 1979 and 2013. While there is 26% chance of materialisation of an agricultural drought in Gourma, the chance of it being extreme, severe, moderate or mild is 0 %, 22 %, 45 % and 33 % respectively (see Figure 3).

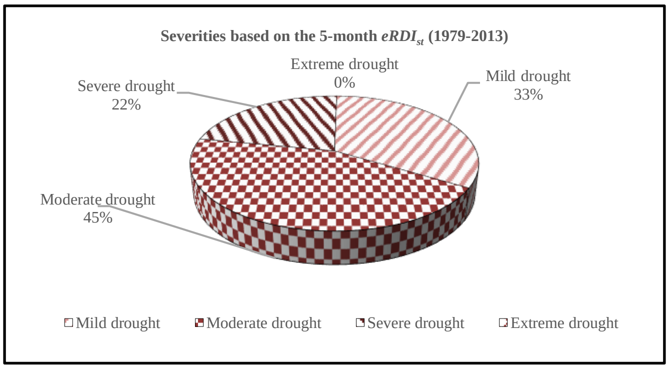


Figure 3: Pie chart of Severity of Historical agricultural droughts in Gourma based on the 5-month eRDIst. The Severe drought category is harshest severity level ever experienced in the study area while no extreme drought has manifested.

Since the three properties of the agricultural drought events are independent, an overall probability for the characteristics of future events is as presented in Table 4 below. Therefore, as much as the next agricultural drought to materialize is most probably moderate (probability = 45 %), the chances of the event being the harshest ever experienced before i.e. severe, is 4 %.

Table 4: Probable characteristics of future agricultural droughts that could manifest in Gourma province

Drought category *(X)*	*P(X)*	*P(R)*	*P(E)*	*P (O) = P(X).P(R).P(E)*
Severe	0.22	0.26	0.67	0.04
Moderate	0.45	0.26	0.67	0.08
Mild	0.33	0.26	0.67	0.06
Extreme	0.00	0.26	0.67	0.00

Where:
P(X) is the probability of a particular agricultural drought category *(X)* reoccurring
P(R) is the probability of an agricultural drought event reoccurring
P(E) is the probability of the event being ephemeral
P (O) is the overall probability

3.2 Impact of historical agricultural droughts on Crop yields

General trend of the standardised crop yields is found to be in harmony with the 5-month $eRDI_{st}$ trend between 2002 and 2011. Figure 4 below shows the graph of standardised crop yields and the 5-month $eRDI_{st}$ [i.e. mean of zero (0) and a standard deviation of one (1)] thus enabling their comparison. Crop yields of maize, sorghum and millet are found to be below average in 2004, 2005, 2008 and 2009 while the 5-month $eRDI_{st}$ values for these years infer severe (-1.6), moderate (-1.2), mild (-0.9) and normal conditions (0.02) respectively. As the agricultural drought severity declines during the following time series: 2002-2003, 2004-2006 and 2008-2010, crop yields of maize, sorghum and millet show an increasing trend. The time series:2003-2004 and 2006-2008, show an increase in agricultural drought severity which coincides with a decreasing trend in crop yields. Thus, the trends reveal that crop yields decrease during agricultural droughts and they improve during normal and wet conditions inferring a direct relationship thus validating the assessment results (Birkmann et al., 2015; Feizizadeh and Kienberger, 2017).

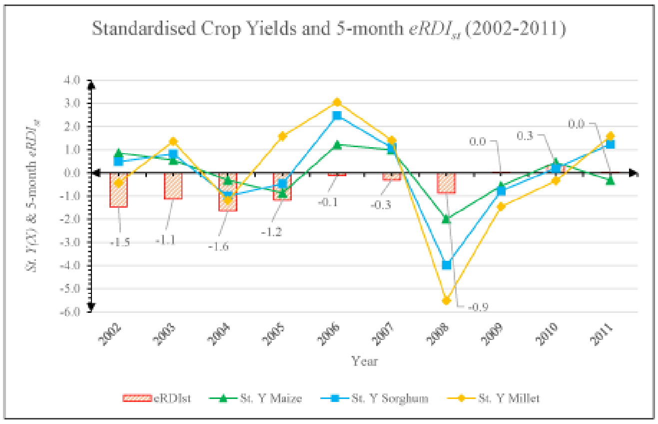


Figure 4: Plot of Standardised Crop Yields & 5-month eRDIst depicting how crop yields show a decreasing trend when effective rainfall reduces i.e. 5-month eRDIst values decreasing from one season to another while crop yields increase when the 5-month eRDIst values increase from one season to another.

Cumulative declines of the 5-month $eRDI_{st}$ over several seasons of magnitudes ≥ 0.4 ± 0.1 result in below average crop yield slumps. The rainy seasons normally occur within the 5-months as used to compute the index and if the 5-month $eRDI_{st}$ values continuously decline from one season to another, it infers continued decline in soil moisture available for crop growth and increased potential evapotranspiration, which directly affects crop yields. Crop yields exhibit sharp declines in the following time series: 2003-2004 and 2006-2007 and 2007-2008 during which the magnitudes of the cumulative declines are: 0.5 ± 0.1, 0.4 ± 0.1 and 0.8 ± 0.1

respectively (see details in Figure 4 above). Thus, the impact of persistent agricultural droughts however low their severity is from one season to another is crop yield slumps and hence the need for monitoring.

Although comparison of crop yield data and the index cannot perfectly elaborate the impact of agricultural droughts, it can be used to give an indication of the nature of their relationship. From Figure 4 above, in 2002 the 5-month $eRDI_{st}$ infers mild agricultural drought and yet maize and sorghum yields that are above average. In 2003 too, the 5-month $eRDI_{st}$ infers mild agricultural drought but all the yields are above average. In 2011, the conditions are drier as compared to the previous season but the millet and sorghum yields are above average. These deviations from the general trend could be attributed to other factors that influence yields such as soil fertility, floods, insects and harvested areas. The Figures 5, 6 and 7 below show the relationship between the crop yields (t/ha) and 5-month $eRDI_{st}$ with satisfactory values of the coefficient of determination (R^2), see Table 3.4 below. Since, the relationship between the two variables is strong, the 5-month $eRDI_{st}$ is a suitable tool for the demonstration of agricultural drought impact on crop yields in Gourma.

Figures 5, 6 and 7 Plots of standardised crop yields against the 5-month eRDIst showing R^2 value is the lowest for Maize then Millet and finally Sorghum but the relationship is very strong and can be employed in crop yield estimation and thus aid in planning.

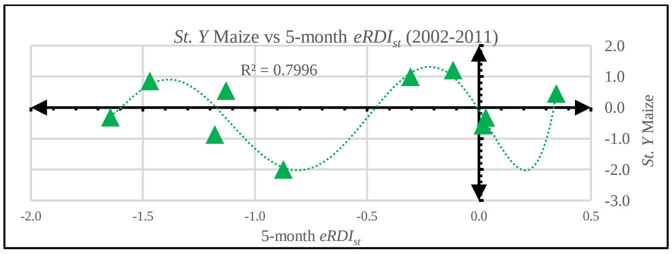


Figure 5: St. Y Maize vs 5-month eRDIst.

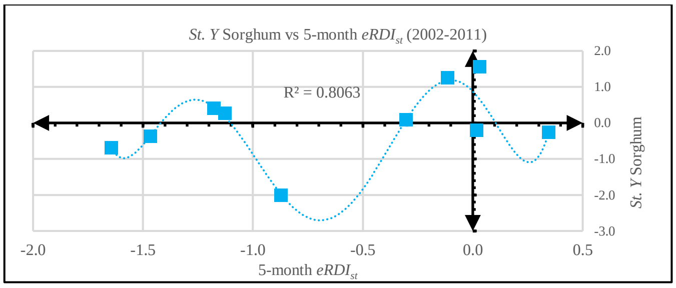


Figure 6: St. Y Sorghum vs 5-month eRDIst

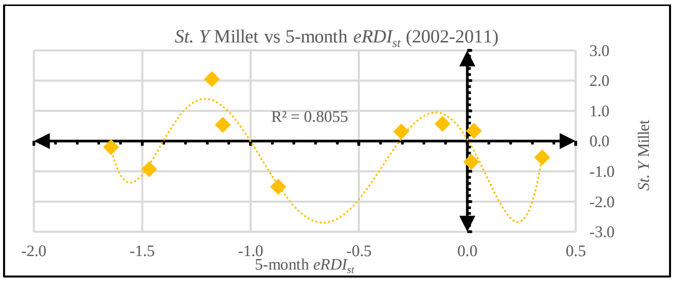


Figure 7: St. Y Millet vs 5-month eRDIst

Table 5: R^2 values between standardised crop yields and the 5-month $eRDI_{st}$

R^2	*St. Y* Maize	*St. Y* Sorghum	*St. Y* Millet
5-month $eRDI_{st}$	0.7996	0.8063	0.8055

Since an ephemeral agricultural drought of the moderate category has the highest chance of reoccurring at 8 %, its impact based on the above comparisons (Figures 5, 6 and 7 above) would be as shown in Table 3.5 below. Maize yields show the highest magnitude of decline followed by sorghum and finally millet (see Table 6 below). Thus, an ephemeral agricultural drought event of the moderate category would impact specific crop yields differently but all three would be below average.

Table 6: Impact of an ephemeral and moderate agricultural drought on crop yields

	St. Y Maize	*St. Y* Sorghum	*St. Y* Millet
Moderate agricultural drought (5-month $eRDI_{st}$ = -1)	-1	-1	-1
Crop yields: St. Y (X)	-1.32	-0.87	-0.01

3.3 Impact of historical agricultural droughts on the people's susceptibility to undernourishment

According to the results of this study, agricultural droughts have been found to result in an increased prevalence to undernourishment. From Figure 8 below, the 3-year average of prevalence to undernourishment shows a strong relationship with the 3-year averages of the 5-month $eRDI_{st}$ having the coefficient of determination, $\boldsymbol{R^2} = \mathbf{0.9306}$. The relationship between the independent variable (5-month $eRDI_{st}$) and the dependent variable (prevalence to undernourishment) is captured by the equation (13) below. Using equation (13) below, mild, moderate and severe agricultural droughts would result in increases of the prevalence to undernourishment by 2.9 %, 4.3 % and 5.8 % respectively. Thus, the impact of continuous agricultural droughts over 3-years on people's health is an increased susceptibility to undernourishment. This therefore establishes a direct link between the hazard (agricultural drought) and the victims which is vital for planning and interventions (Hagenlocher et al., 2019) .(see plotted data in Table 7 below).

$$Y = -2.8965X + 21.601 \qquad (12)$$

Where: -Y is a 3-year average of Prevalence to undernourishment (%)
-X is a 3-year average of 5-month $eRDI_{st}$ values.

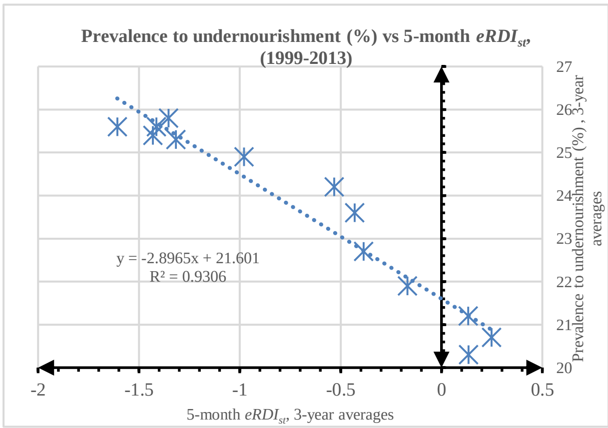


Figure 8: Plot of 3-year averages of Prevalence to undernourishment (%) against 3-year averages of the 5-month $eRDI_{st}$ showing a strong direct relationship between the two variables with R^2 = 0.9306.

Table 7: 3-year averages of Prevalence to undernourishment (%) & 5-month eRDIst, (1999-2013)

3-year period	Prevalence to undernourishment (%) (3-year averages)	5-month eRDIst (3-year averages)
1999-2001	25.4	-1.4
2000-2002	25.6	-1.6
2001-2003	25.8	-1.4
2002-2004	25.6	-1.4
2003-2005	25.3	-1.3
2004-2006	24.9	-1.0
2005-2007	24.2	-0.5
2006-2008	23.6	-0.4
2007-2009	22.7	-0.4
2008-2010	21.9	-0.2
2009-2011	21.2	0.1
2010-2012	20.7	0.2
2011-2013	20.3	0.1

3.4 Future trends of the 5-month $eRDI_{st}$

The 5-month $eRDI_{st}$ has a random probability distribution. While it can be statistically analysed, the 5-month $eRDI_{st}$ cannot be precisely predicted but a general trend of the future conditions can be established. The validation process used to develop the most reliable forecasting model showed that dividing the known values of the 5-month $eRDI_{st}$ into training data (74 %): testing data (26 %) produced the best performing forecasting model (polynomial of order 6) with an R^2 value of 0.9198 as shown in figure 9 below. Table 8 below shows the progressive validation process whereby the forecasting models were trained to forecast the future trends of the 5-month $eRDI_{st}$ using the known values of the index. Hindcasting starting 2005 produced the best performing forecasting model.

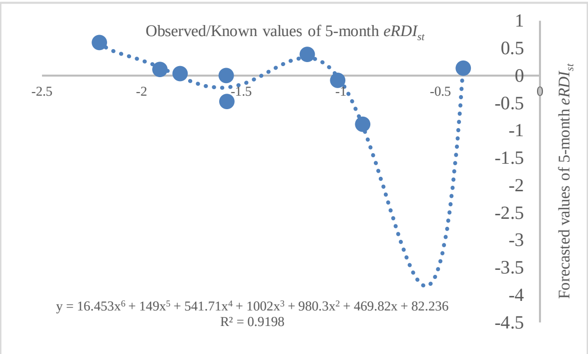


Figure 9: Plot of known values of the 5-month $eRDI_{st}$ against the known values of the 5-month $eRDI_{st}$ that produced the best performing forecasting model.

Table 8: Progressive training and testing of forecasting model for $eRDI_{st}$ future trends

Shape of forecasted curve	Start year of forecast	R^2 Value
Straight line	1997	0.356
Polynomial	1999	0.407
Straight line	2001	0.827
Polynomial	2003	0.818
Polynomial	**2005**	**0.920**
Polynomial	2007	1.000
Straight line	2009	1.000
Straight line	2011	1.000
Straight line	2013	*
*No observed (known) 5-month $eRDI_{st}$ values to compare with forecast		

A 25-year hindcast of the 5-month $eRDI_{st}$ starting 2005 to 2030 exemplifies a decreasing trend in the 5-month $eRDI_{st}$ values from normal conditions and with a negative slope as illustrated in Figure 10 below. The forecasted 5-month $eRDI_{st}$ values depict the frequent occurrence of mild, moderate and severe agricultural droughts in the next 11-years in Gourma Province. Subsequently, the mild, moderate and severe agricultural droughts are likely to result in crop yield slumps as well as increased prevalence to undernourishment by 2.9%, 4.3% and 5.8 % respectively. This enables the development of plans by Government, NGOs and Religious Organisations to put in place proactive intervention measures and avoid cases like the 1997 drought in Central Plateau (Roncoli et al., 2001) .

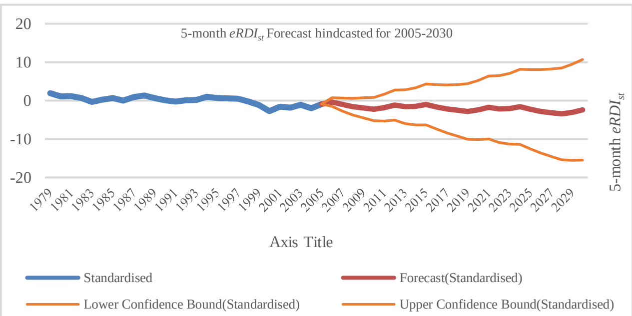


Figure 10: 5-month eRDIst future trend

3.5 Comparing the 5-month *eRDIst* and reported drought events

Other researchers such as Kasei et. al. who used climatic data to characterise meteorological drought events in the Volta basin (western part of Gourma is within the basin) revealed the occurrence of meteorological droughts in the years 1983, 1992, 1998 and 2001 in the basin (Kasei et al., 2010). They also stated that that the event of 2001 had a relatively higher chance of reoccurrence compared to the 1992 event (Kasei et al., 2010). The 5-month $eRDI_{st}$ in this study has inferred the occurrence of mild and moderate agricultural droughts in 1983 and 2001 respectively. Moderate category has also been found to have the highest probability of reoccurring in this study. The 5-month $eRDI_{st}$ shows a declining trend for the time series: 1991-1992 and 1997-1998 revealing a persistent decline in available soil moisture. Reports by Food and Agriculture Organisation (FAO) recorded the occurrence of droughts in Burkina Faso in the years 2004 and 2007 that resulted in a 16 % decline of production in 2007 (MAFAP, 2013). The 5-month $eRDI_{st}$ in this study infers the occurrence of moderate agricultural drought in 2004 and shows a decline from the season of 2006 into 2007. The 5-month $eRDI_{st}$ as an agricultural drought index is thus suitable for characterisation of agricultural drought in the Sudano-Sahelian climate of Gourma.

4. Conclusion

Using the effective reconnaissance drought index, this study has adequately revealed the occurrence and attributes of previous agricultural drought events in Gourma and subsequently, evaluated their impact on rainfed crop production and people's susceptibility to undernourishment. Based on historical events, the next agricultural drought will probably be ephemeral and of the moderate category and since this type of event has been found to result in below average yields, its impact needs to be further assessed and measures put in place to counter them. There's need for agricultural drought monitoring in Gourma so as to factor in the impact of the index's values declining while still in the "normal" category over successive seasons ($|\sum$5-month $eRDI_{st}| \geq 0.4 \pm 0.1$). Since over 30 years of climatic data has been used in this study, the necessary constants for the development of drought monitoring models specifically for Gourma can be determined. Combination of the index with other indices and remote sensing products as well as site-specific crop modelling can further be explored for the establishment of crop yield monitoring and prediction models. This study's outcomes can be employed in the design and implementation of drought management plans that will see a reduction in numbers of persons affected by drought in Burkina Faso at large. In terms of impact of this study, it has been shown that index-based methods enable researchers to learn from the past and thus predict what the future holds for the sole reason of being prepared for natural hazards such agricultural droughts. Further research work on index-based approaches on agricultural drought monitoring and preparedness in Gourma and the Sudano-Sahelian zone is therefore recommended.

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Authors' Contributions

JO: conceptualized the research, collected data, and wrote the draft manuscript. IC designed the methodology, analyzed the data, editing manuscript. JK supervised, organized the revision, editing, content supplementary of the paper. All authors have read and approved the final manuscript.

Conflict of Interests

The authors declared that they have no competing interests associated with this publication.

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