




# Assessing the effect of spatial–temporal droughts on dominant crop yield changes in Central Malawi

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Received: 15 September 2021 / Accepted: 23 December 2021 / Published online: 7 January 2022  
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**Abstract** Central Malawi has intensely been subjected to different climate-related shocks such as floods, dry spells, and droughts, resulting in decreases in crop yields. Due to their recurrence arising from the effects of climate change, drought characterization, monitoring, and prediction are crucial in guiding agriculture-water users and planners to prepare drought risk management plans and early warning systems. This research analyzed droughts, using multiple drought indices and their impacts on dominant crops over Central Malawi. Forty years of hydro-meteorological data (1977–2017) from nine rain-gauging stations and crop yield data from 1983 to 2017 from four districts were analyzed. The study discovered that drought events in the Agricultural

Development Division (ADD) are highly a function of rainfall deficit and high temperatures. The results highlighted that the rainfall patterns in the area are not dependable, calling for the utilization of climate-smart irrigation systems such as drip irrigation and rainwater harvesting technologies. Furthermore, we achieved that crops such as cassava and groundnuts must be promoted to withstand the long water stress duration. These crops also have a multiplier effect; hence, they can enhance food security in the region. This study recommends that using more robust variables in drought analysis studies is necessary for effective drought monitoring and early warning systems. In corroboration with disaster management NGOs, it is recommended that the government should be proactive in developing integrated drought management policies and planning strategies for drought adaptation and mitigation.

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**Keywords** Water management · Cassava · Palmer Drought Severity Index (PDSI) · Drought indices · Drought early warning systems

## Introduction

Drought is described as a complex phenomenon that is least understood yet has many adverse effects on the socioeconomic and agricultural sectors (Khalili et al., 2020). In addition to discussing on the impacts of droughts, Potop et al. (2012) further conferred

that droughts cause significant losses in agriculture-based economies. Rossi (2000) contended that deficiencies are generally associated with water unavailability over a large area. An analysis, therefore, of drought characteristics such as severity, duration, and frequency is crucial for water resource planning and management in a river basin (Dodangeh, 2017; Figueira Branco et al., 2019; Masud et al., 2019; Masupha & Moeletsi, 2020). Knowledge of drought duration and magnitude is vital in determining water demand for people, crops, and animals. Drought characteristics are also decisive in guiding water planners on the best water storage options, operational water management decisions, and planning drought monitoring (Palmer, 1965; Wu et al., 2021; Yu et al., 2021).

Mahapatra and Ratha (2016) argued that the poorest countries are the most vulnerable to climate change. Wossen et al. (2017) cemented the discussion and observed that Africa's agriculture sector is highly susceptible to climate change and droughts. As an example, Warnatzsch and Reay (2019) underlined Malawi as one of the highly exposed countries in sub-Saharan Africa with limited mitigation and adaptation strategies to the impacts of climate change. Chabvunguma et al. (2014) asserted that droughts are becoming recurrent with increased frequency, magnitude, and intensity in Malawi. The effects of these droughts are well observed in agriculture (NAPA, 2006; Esfahanian et al., 2017). As close to 90% of Malawi's agricultural production depends on rainfall (Khamis, 2006); any significant variation in rainfall decreases crop yields. Chabvunguma et al. (2014) further affirmed that Malawi has inadequate capacities and weak policies for drought monitoring and awareness of drought insurances to smallholder farmers, in addition to high vulnerability to climate change effects. Mahapatra and Ratha (2016) concur that many farmers in developing countries have inadequate adaptive capacity to climate change. Malawi has a Drought Recovery Strategy (DRS) that aims to promote drought recovery and encourage the adoption of risk-reducing measures that mitigate future drought events. However, this strategy has a gap in that it lacks partnerships with other sectors, such as irrigation. This agrees with Mahapatra (2012), who noted that most government policies lack coordination, cooperation, and consistencies hence are not sustainable to mitigate some disasters.

Although significant research has been done on disaster risk management, research on drought characterization

is still limited in Malawi. Despite the complexity of drought conditions (Hagman, 1984), it is possible to characterize and monitor droughts (dar & dar, 2021; Salehnia et al., 2017; Sheffield & Wood, 2007; Wu et al., 2001; Zhou et al., 2021) using parameters such as rainfall, temperature, evapotranspiration, land cover, soil moisture, and river flows. Of these parameters, rainfall is a significant parameter for monitoring meteorological droughts (Amirataee et al., 2018; Kwon et al., 2019; Wu et al., 2001; Zhao et al., 2020). Mwangi et al. (2014) assert that understanding droughts' occurrences are vital as it helps in early warning systems and provides management strategies to its effects.

There are multiple drought indices to aid drought monitoring, but they are massively underutilized in Malawi. Kamdonyo (1993) used percentiles to assess droughts in Malawi. The study observed that more indices are required to understand and monitor droughts adequately. The severity of a drought cannot be judged from the reduction in total rainfall only. Munthali et al. (2003) analyzed droughts in Malawi using percentiles. The study highlighted that more research that is rigorous was required to investigate other drought regimes in Malawi. Regionally, Wambua et al. (2015) used the Standardized Precipitation Index (SPI) to characterize the spatiotemporal drought characteristics in Upper Tana River Basin in Kenya. The study found that SPI is a helpful tool for detecting monthly drought severities and being used in drought severity studies. Mutsotso et al. (2018) applied the Standardized Precipitation Evapotranspiration Index (SPEI) and Normalized Difference Vegetation Index (NDVI) to investigate the drought severity and duration in Kenya. Lweendo et al. (2017) evaluated the characteristics of meteorological, agricultural, and hydrological droughts in the Upper Kafue River Basin of Zambia using a combination of SPEI, SPI, Standardized Soil Moisture Index (SSI), and Standardized Runoff Index (SRI).

Therefore, this research sought to characterize meteorological, agricultural, and hydrological indices, which have not been used in the past studies in Malawi. Furthermore, this study aimed to examine the relationships between spatial-temporal droughts and dominant crop yields in Central Malawi. By analyzing three different kinds of droughts, we want to answer this question: what is the optimized dominant crop for planting due to drought conditions over Malawi?

**Materials and methods**

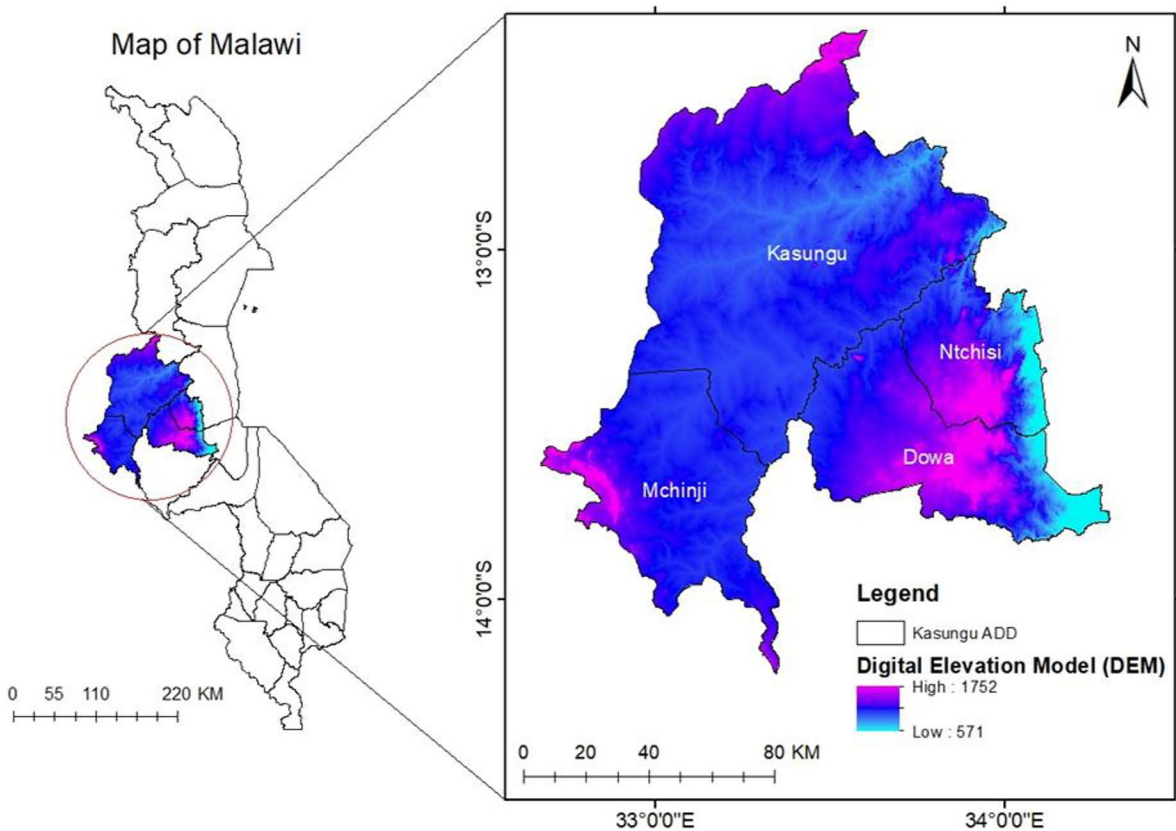
**Study region and software applications**

The study area spans between latitudes 13° S and 14° S, and longitudes 33° E and 34° E. Topographically, most parts of the study area are flat, especially the western part, while the eastern part is mountainous. About 80% of the study area is within 800–1200 m above mean seal level. The highest point is 1752 m and the lowest elevation is 571 m. The average minimum temperature in the area is 20.6 °C while the average maximum temperature is 22.8 °C. The mean annual rainfall varies from 781.1 to 1093 mm in the Agricultural Development Division (ADD). The eastern parts of Ntchisi and the western parts of Mchinji Boma receive higher amounts of rainfall than the other areas in the ADD. In terms of evapotranspiration, the average values range from 4.12 to 4.76 mm/day while the solar radiation ranges from 19.1 to

20.7 MJ/m<sup>2</sup>/day. Mchinji has the lowest evapotranspiration rate than the other three districts. The region is dominantly agro-based where crops such as maize, cassava, tobacco, groundnuts, beans, and soya beans are commonly grown. Figure 1 shows the location of the study area.

Daily hydrological (streamflow) data from 1977 to 2017 for Bua River was collected from the Ministry of Irrigation and Water Development. Meteorological data (monthly temperature and monthly rainfall) for 40 years was obtained from the Department of Climate Change and Meteorological Services ([www.metmalawi.gov.mw](http://www.metmalawi.gov.mw)). Crop yield data from 1983 to 2014 was sourced from the Ministry of Agriculture (<https://agriculture.gov.mw>). Dominant crops grown in the ADD were determined from a household survey, which involved interviewing farmers and critical personnel. This was validated with the 2015 Malawi Irrigation National Master Plan.

The Drought Monitor and Prediction (DMAP) tool (AgrimetSoft, 2018) was used to calculate drought



**Fig. 1** Maps showing the geographical location of Kasungu ADD in Malawi

indices, and ArcGIS 10.5 was used for spatial analysis using the Kriging technique. All the data collected were subjected to statistical analysis in Excel 2016 and SPSS software applications to determine descriptive statistics, analyze trends, and perform linear regression analysis.

### Drought indices and calculations

Table 1 summarizes the drought indices, data required to compute them, and their category of use. All the data needed for each drought index have been collected from the related center in Malawi (“Study region and software applications”).

#### SPI

The SPI is recommended as the standard indicator for categorizing meteorological droughts (Li et al., 2019; Svoboda et al., 2012). McKee et al. (1993) classified the SPI for short-timescale (1, 3, and 6) and long-term scale (12, 24, and 48) months with monthly rainfall for at least 20–30 years as input data. SPI is then calculated by fitting the long-term monthly rainfall data to a gamma probability density function, which is transformed to a normal distribution (Eqs. 1 and 2):

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \quad (x > 0) \quad (1)$$

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy \quad (2)$$

where  $\Gamma(\alpha)$  is the Gamma function;  $x$  is the rainfall (mm);  $\alpha$  is the shape parameter ( $\alpha > 0$ ); and  $\beta$  is the scale parameter ( $\beta > 0$ ), and the transformed probability gives SPI output values on a  $-2$  to  $+2$  scale. SPI-positive values indicate wet conditions, and negative values depict dry conditions. SPI values classify drought condition from  $\geq 2$  for an extremely wet condition,  $-0.99$  to  $0.99$  for near-normal condition,  $-1.0$  to  $-1.49$  for moderate drought,  $-1.5$  to  $-1.99$  for severe

drought, and  $\leq 2$  for extreme drought. Refer to McKee and Edwards (1997) for a more detailed explanation.

#### PDSI

The Palmer Drought Severity Index (PDSI) was developed to investigate the start and end of drought or wet period spell (Palmer, 1965). Using rainfall, temperature, and soil moisture as input data, this index applies a water balance model to generate different drought severity categories (Han et al., 2020).

The main calculations of PDSI are initialized as Eqs. (3) and (4), as below:

$$d = P - \hat{P} \quad (3)$$

$$\hat{P} = ET + R + RO - L \quad (4)$$

As denoted in Eq. (3), the value of  $d$  is the difference between the actual precipitation ( $P$ ) and precipitation ( $\hat{P}$ ) is an indicator of water deficiency or surplus. Moreover,  $ET$ ,  $R$ ,  $RO$ , and  $L$  are represented as evapotranspiration (mm), recharge of soil moisture, runoff, and loss of soil moisture, respectively. There are several equations to achieve the final PDSI ranges. More details can be found in Palmer (1965).

PDSI values are on a  $-4$  to  $+4$  scale. PDSI-positive values indicate wet conditions, and negative values depict dry conditions. SPI values classify drought conditions from  $\geq 4$  for an extremely wet condition,  $-0.49$  to  $0.49$  for near-normal condition,  $-1.0$  to  $-1.99$  for a mild drought,  $-2.0$  to  $-2.99$  for moderate drought,  $-3.5$  to  $-3.99$  for severe drought, and  $\leq 4$  for extreme drought.

Soil moisture data were obtained from the Agriculture department at Kasungu ADD while evapotranspiration was calculated using FAO CropWat software.

#### SMDI

The Soil Moisture Deficit Index (SMDI) is based on the total daily moisture during a year, and soil moisture is

**Table 1** Drought types and indices with the necessary input data

Drought indices	Data needed	Category of use
SPI, PDSI	Precipitation, potential evapotranspiration, temperature, soil moisture (available water content)	Meteorological, for monitoring and forecasting, effective in agriculture, used in historical analysis and risk analysis
SMDI	Soil moisture conditions	Agricultural, effective for crop planning
SWSI	Precipitation, stream flow	Hydrological, effective for water resources management

the only climatic factor used in this index. The following steps are used in the computation of the index on an incremental basis (Eqs. 5 and 6):

$$SD_{ij} = \frac{MWS_j - WS_{ij}}{MWS_j - minWS_j} * 100 \quad \text{if } (WS_{ij} = MWS_j) \tag{5}$$

$$SD_{ij} = \frac{MWS_j - WS_{ij}}{maxWS_j - MWS_j} * 100 \quad \text{if } (WS_{ij} > MWS_j) \tag{6}$$

where  $MWS_j$  is the median of total daily moisture  $j$ ,  $maxWS_j$  is the maximum of total amount of the moisture  $j$ , and  $minWS_j$  is the minimum of the total amount of moisture  $j$ .  $SD$  values range from  $-100$  to  $+100$ , indicating very dry to very wet conditions, respectively. Then, Eq. (7) calculates SMDI as follows:

$$SMDI_j = 0.5SMDI_{j-1} + \frac{SD_j}{50} \tag{7}$$

where  $SMDI_{j-1}$  represent the SMDI for the initial month and  $SD_j$  represents soil moisture deficit.

### SWSI

The Surface Water Supply Index (SWSI) was developed as an indicator of surface water or moisture levels (Shafer & Desman, 1982). Input data required for this index include streamflow, rainfall, and storage reservoir volume. Refer to Garen (1993) for the procedure of determining this index. The main equation of this index is presented as Eq. (8) (Shafer & Desman, 1982):

$$SWSI = (aP_{snow} + bP_{prec} + cP_{strm} + dP_{resv} - 50)/12 \tag{8}$$

where  $a$ ,  $b$ ,  $c$  and  $d$  are the weights for each hydrologic component.  $P$  is the probability of non-exceedance (percent); the indices snow, prec, strm, and resv are the snowpack, precipitation (mm), streamflow ( $m^3/s$ ), and reservoir storage hydrologic components (m), respectively.

### Drought severity

Drought characteristics such as duration, severity, and intensity are determined using the runs theory. Based on the duration, which is the number of months in drought conditions, the severity becomes the product

of the duration and the intensity of the drought event. The severity of a drought therefore defines the definite value of the sum of the index during a drought event.

### Statistical tests

#### Mann–Kendall test

The Mann–Kendall test is a non-parametric technique, which tests trends whether they are decreasing, increasing, or none (Li et al., 2021). The sum of increments and decrements gives a Mann–Kendall statistical trend value,  $S$ , calculated as Eq. (9):

$$S = \sum_{k=1}^{n-1} \left[ \sum_{j=k+1}^n \text{sign}(x_i - x_k) \right] \tag{9}$$

The right hand side of the equation is simplified as Eq. (10):

$$\text{sign}(x_i - x_k) = \begin{cases} 1 & \text{if } (x_i - x_k) > 0 \\ 0 & \text{if } (x_i - x_k) = 0 \\ -1 & \text{if } (x_i - x_k) < 0 \end{cases} \tag{10}$$

To determine the level of significance of the trend, the probability linked to  $S$  and selected  $n$ -data were established. The variance of the data sets  $\text{VAR}(S)$  and the normalized test statistic  $Z$  were both calculated using Eqs. (11) and (12):

$$\text{VAR}(S) = n(n - 1)(2n + 5) - \sum_t \frac{t(t - 1)(2t + 5)}{18} \tag{11}$$

where  $\text{VAR}(S)$  is the variance of the data sets, and  $n$  is the number of data points.

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{VAR}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{VAR}(S)}} & \text{if } S < 0 \end{cases} \tag{12}$$

Drought trend qualification as decreasing, increasing, or no trend was based on whether  $S < 0$ ,  $S > 0$ , and  $S = 0$ , respectively. Significance level at 95% was used to determine whether the drought trend was significant or insignificant.



## CV

In agro-meteorological studies, coefficient of variation (CV) is used to categorize the level of variation or dependability or unpredictability. If the CV value is high, it means there is greater dispersion around the mean, and if the CV value is low, it means the estimate is precise. Different studies (Gomez & Gomez, 1984; Nyatuame et al., 2014) concur that the higher the CV value, the higher the variability and the lower the reliability of that distribution and vice versa. These studies consider 0.3 as the benchmark such that for  $CV > 0.3$ , the distribution is highly variable, and for  $CV < 0.3$ , the distribution is less variable. It is calculated as Eq. (13):

$$CV = \frac{\sigma}{\mu} \times 100 \quad (13)$$

where  $\sigma$  is the standard deviation, and  $\mu$  refers to the mean of data.

## Skewness and Kurtosis

Skewness is a measure of symmetry or, specifically, the lack of symmetry. The data set is said to be symmetric if it is a mirror image of the other such that it looks the same to the left and right from the center point. The skewness for a normal distribution is zero, and any symmetric data should have skewness near zero. Negative values for the skewness indicate that data are skewed to the left, and positive values for the skewness indicate that data are skewed to the right. Skewness is computed as Eq. (14):

$$\text{Skewness} = 3 \times \frac{(\mu - \tilde{Y})}{\sigma} \quad (14)$$

where  $\sigma$  and  $\mu$  indicate the standard deviation and the mean of data.  $\tilde{Y}$  refers to the sample median.

$$\text{Kurtosis} = \frac{\sum_{i=1}^N (X_i - \mu)^4}{\sigma^4} \quad (15)$$

Kurtosis is a measure of how peaked or flat data is about normal distribution. Positive kurtosis indicates a peaked distribution and negative kurtosis indicates a flat distribution. It is computed as Eq. (15):

where  $N$  is the number of data points, and other parameters are the same as Eq. (14).

## Results and discussions

### Statistical analysis of annual rainfall in Kasungu ADD

The respective summaries of descriptive statistics, Mann–Kendall trend test, evapotranspiration, and soil characteristics in Kasungu ADD are illustrated in Table 2 through Table 4. Table 2 shows that Ntchisi and Mchinji received higher annual rainfall than Dowa and Kasungu. The results in Table 2 further demonstrated high and significant ( $p < 0.05$ ) variations in rainfall patterns in the ADD as evidenced by the high values of standard deviation and CV. Gomez and Gomez (1984) and Nyatuame et al. (2014) suggested that high fluctuations are determined from high values of CV. Tadeyo et al. (2020) further discussed that the rainfall patterns in Central Malawi are highly variable than in Southern Malawi. Both skewness and kurtosis showed that the data rainfall distribution is spread to the right of the mean value and peaked, respectively.

Table 3 shows that the annual rainfall in all ADD was decreasing with respect to the Mann–Kendall test and the Sen's slope estimator. This decrease in annual rainfall is responsible for the reduction of water availability in the soil, hence promote drought conditions in the ADD. Table 4 describes the evapotranspiration rates and soil parameters in the ADD. The

**Table 2** Summary of descriptive statistics for the study area

Station	Annual (mm)	Maximum (mm)	Minimum (mm)	Standard deviation	Skewness	Kurtosis	Coefficient of variation
Dowa	852.1	469.9	0.0	103.7	1.02	1.43	1.47
Kasungu	781.1	513.2	0.0	97.3	1.38	1.03	1.51
Mchinji	1071.9	552.9	0.0	116.5	1.10	0.30	1.32
Ntchisi	1093.0	878.5	0.0	130.0	1.40	1.20	1.43

**Table 3** Z value of the Mann–Kendall test and Sen’s slope estimator for annual precipitation (1977–2017)

Station	Mann–Kendall’s Z	Sen’s slope estimator	Remark
Dowa	-1.70+	-4.567	Decreasing
Kasungu	-1.00	-2.578	Decreasing
Mchinji	-0.64	-2.611	Decreasing
Ntchisi	-3.22**	-17.057	Decreasing

\*\*If trend is significant at  $\alpha=0.01$ ; \*if trend is significant at  $\alpha=0.05$ ; + if trend is significant at  $\alpha=0.1$

evapotranspiration rate guides in determining crop water requirements for crop production. The results indicate that Dowa and Ntchisi have higher ETo values than Mchinji and Kasungu. This is crucial in determining better crops to grow in the districts to respond to the high variability of rainfall patterns in the region.

Crop yields analysis in Kasungu ADD

The yields of maize, cassava, and pulses in Kasungu ADD are highlighted in Fig. 2a–c, respectively. Figure 2 a indicates negative trends in maize yields; Fig. 2b indicates positive trends in pulses, while Fig. 2c indicates positive trends for cassava. The maximum pulses yield was 1157 kg/ha in Ntchisi in 2009, and the minimum was 178 kg/ha in Dowa in 1988. The average pulses yield was 559 kg/ha. Pulse yields were below the ADDs’ average in Dowa (473 kg/ha) and Kasungu (432 kg/ha), whereas the averages in Ntchisi (710 kg/ha) and Mchinji (619 kg/ha) was higher than that of the ADD. The trend lines of pulse yields displayed positive slopes showing an increase in the yields. This could be attributed to the fact that many farmers diversified crop production as a drought insurance strategy. There were low patterns in 1993, 1995, and 2001 in cassava yields. In all the districts, there was an increase in 1994 following the low crop yields observed in 1993; hence, there was a

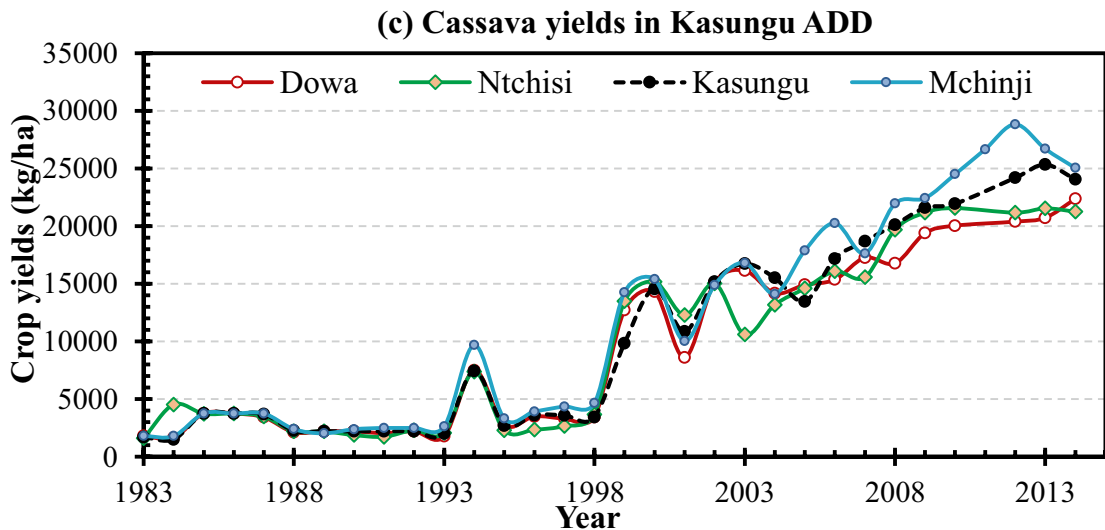
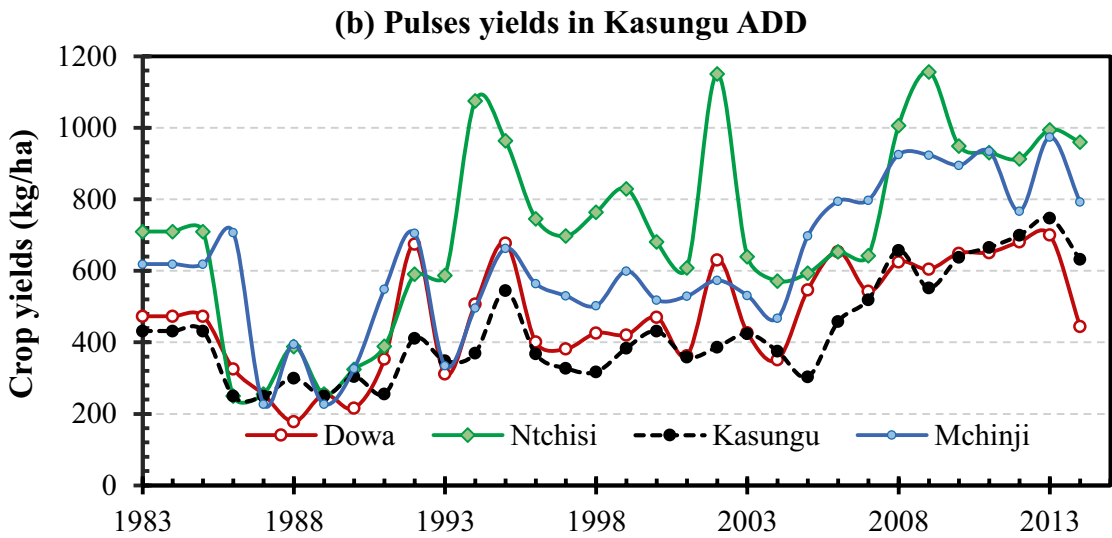
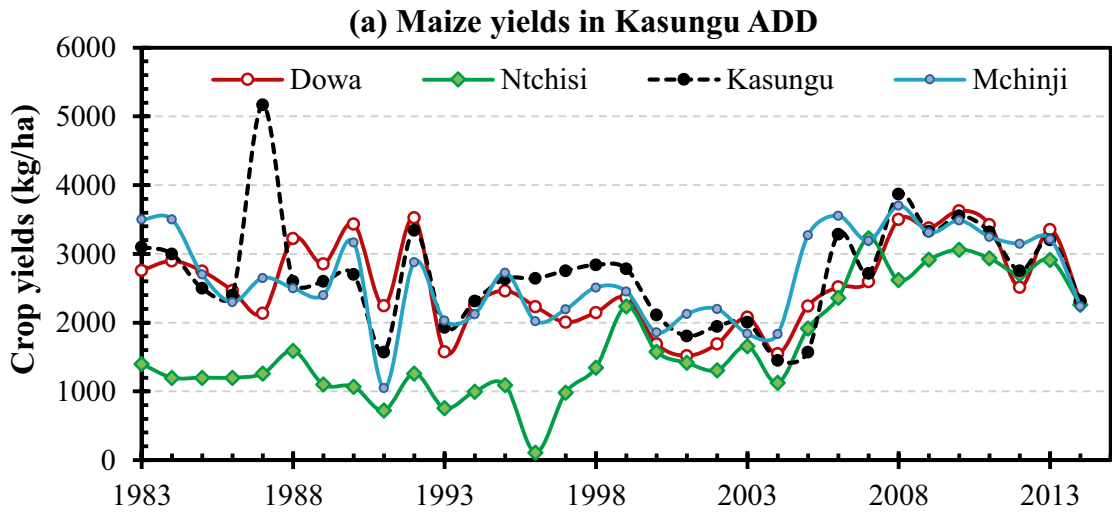
promotion of cassava production in that year. Except for Mchinji, the yields in the other three districts were low than the average cassava yields.

The results indicated very high correlations between reduced crop yields and high variations in rainfall dependability. Similar trends were shown when crop yields were compared with the different drought indices in Figs. 5, 6, 7 and 8. These findings suggested that less rainfall was available for full crop production in the ADD which subsequently reduced yields in maize and pulses. Furthermore, districts on lower elevations such as Kasungu some parts of Dowa were affected significantly as compared to Mchinji and Ntchisi. Interesting trends were observed in cassava as compared to maize and pulses in relation to rainfall variability and drought conditions. The cassava yields were significantly higher in the region during all the drought regimes. The increase in the cassava yields in the face of drought regimes in the area supports the initial finding that cassava requires fewer amounts of water for its production, making it a viable crop to be grown in drought prone areas. These trends highly correlated with the patterns of the drought indices.

The spatial–temporal variation in rainfall distribution in the ADD reduced maize and pulse yields, as there was a low amount of rainfall sufficient for production. This concurs with Abdullahi et al. (2006) and Salehnia et al. (2020), who established that low rainfall often reduces crop yields, thereby affecting food security. This suggested that the anomalies in the rainfall regimes reduce the contribution of water into the root zone and in the river system. These reductions, therefore, affected the distribution of water in the region. However, the increase in cassava yields was due to the drought-tolerant characteristics of cassava. Since agriculture contributes significantly to the gross domestic product (GDP) of a country and that crop yields are highly correlated to rainfall patterns,

**Table 4** Evapotranspiration and dominant soil type characteristics in Kasungu ADD

District	ETo (mm/day)			Thickness of surface soil layer (SS, mm)	Available water capacity (AWC, mm)
	Max	Min	Average		
Dowa	7.41	3.83	4.76	180	200
Kasungu	6.10	3.40	4.30	180	200
Mchinji	5.87	3.08	4.12	180	200
Ntchisi	6.31	3.95	4.62	180	180





◀**Fig. 2** Crop yields in Kasungu ADD (a Maize. b Pulses. c Cassava)

the crop yield configurations cement the discussion of Gray and Sadoff (2004) that there is a correlation between rainfall variability in a watershed and GDP of a country. The GDP of Malawi within the study period was below USD\$500. In 1990, the GDP was US\$199.99, while in 1994, the GDP decreased to US\$121.26. Even though it increased in 1999 to US\$163.61, the GDP further decreased to US\$156.39 and US\$150.15 in 2000 and 2001, respectively. The GDP decrease significantly correlated with the drought conditions.

#### Temporal and spatial analysis of droughts based on different indices

The drought frequencies within Kasungu ADD based on different indices are computed (Fig. 3a–e). Drought frequency was determined from the temporal variations of drought indices. It is apparent that most drought indices illustrate similar trends with differences in their characteristics in terms of severity and duration. Based on SPI-3, the frequency of mild droughts in the ADD was dominant over the other regimes. Similar patterns were observed in SPI-6. These characters suggested that the ADD is prone to mild droughts, which have adverse impacts on agriculture yields. The frequencies in PDSI and SMDI showed that the ADD is vulnerable to mild and severe droughts, whereas SWSI exhibited higher occurrences of severe droughts.

Drought frequency regimes indicated that Kasungu ADD experiences mild meteorological droughts, moderate agricultural droughts, and extreme hydrological droughts. This could be due to uneven rainfall distribution, which reduced water contribution in the riverine system and groundwater. These scenarios are constructive to guide farmers in terms of water management.

Figures 4, 5, 6 and 7 exhibit the severity of the drought regimes in Kasungu ADD based on the drought indices. As shown in Fig. 4, PDSI revealed that Kasungu was the most prone district to droughts than the other three districts in the ADD. The index further ascertained that the severity regimes were least expected in Mchinji and Ntchisi districts. This could be because these districts receive considerable significant amounts of rainfall that enhance crop growth and yields.

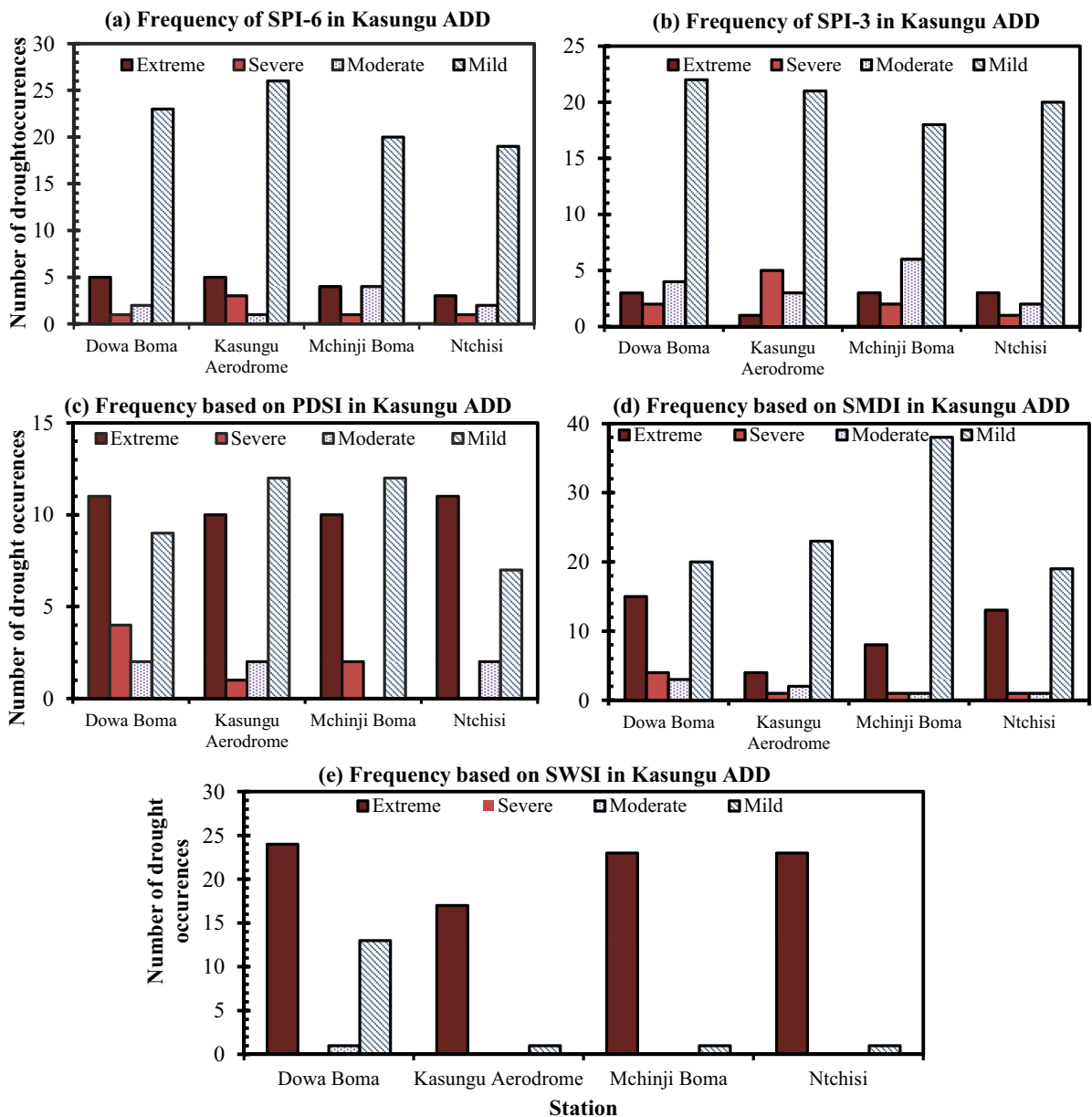
The severity regimes in terms of SMDI have been presented in Fig. 5. The SMDI established that the Mchinji district had the lowest drought severity. In contrast, Kasungu and Ntchisi districts displayed a considerably increasing drought trend suggesting that these areas of the ADD are more vulnerable to droughts than Mchinji and Dowa. In the ADD, periods of the driest years (1994, 1999 and 2015) highly correlated with reduced maize crop yields. The temporal dynamics of the SMDI severities in Kasungu and Ntchisi districts unveiled the excellent need for best management practices in agriculture to combat these droughts' impacts.

Figure 6 displays the temporal variations of SPI-3 in Kasungu ADD. The characterization of the drought indices showed that indices on a 3-month and 6-month moving average had low drought duration and severity compared to those on a 12-month moving average. SPI-3 suggested that meteorological droughts are short yet frequent in the ADD, with more experience in Kasungu, Dowa, and Ntchisi. This indicated that drought events in the ADD are highly a function of rainfall deficit and high temperatures.

The reductions in crop yields, especially maize and pulses, mirrored the impact of drought regimes with low timescales in the ADD. This indicated that a 3-month drought was very crucial as it affected crop development. This showed that maize and pulse yield reduction also depended on the intensity and duration of the drought.

Figure 7 shows the temporal SWSI regimes in Kasungu ADD. The oscillating SWSI index indicated that Kasungu was the most vulnerable to severe hydrological drought than the other districts. This could be because most rivers in the district are not perennial since the district receives less rainfall. This suggests the need for water harvesting strategies and irrigation water management in the district. Mchinji, Dowa, and Ntchisi revealed that they mostly experience mild hydrological droughts. This could be because these areas have rich networks of rivers, which are perennial and receive reasonable amounts of dependable rainfall.

The spatial distribution of drought severity conditions was assessed using the Kriging interpolation technique in ArcGIS 10.5. SPI-3 with different severities for the driest years (1994, 1999 and 2015),



**Fig. 3** The amounts of drought frequencies over Kasungu ADD based on different drought indices (from a to e). **a** Frequency of SPI-6 in Kasungu ADD. **b** Frequency of SPI-3 in

Kasungu ADD. **c** Frequency based on PDSI in Kasungu ADD. **d** Frequency based on SMDI in Kasungu ADD. **e** Frequency based on SWSI in Kasungu ADD

as shown in Fig. 8, highlighted high severities in Kasungu, Ntchisi, and Dowaboma, and lowest severity in Mchinji. In 1994, the maximum severity was 7.92, with a minimum of 0.63. In 1999, the ultimate value was 5.36, with a minimum value of 0.48, and in 2015, the maximum value was 5.33, with a minimum value of 0.03. These severities revealed an increasing trend

in the severity of droughts in the ADD. The drought severity was also correlated to the elevation configuration in the ADD.

It was observed from Fig. 8d that Kasungu is at a lower elevation than most areas. This suggested that the area receives less rainfall as there is reduced moisture into the atmosphere responsible

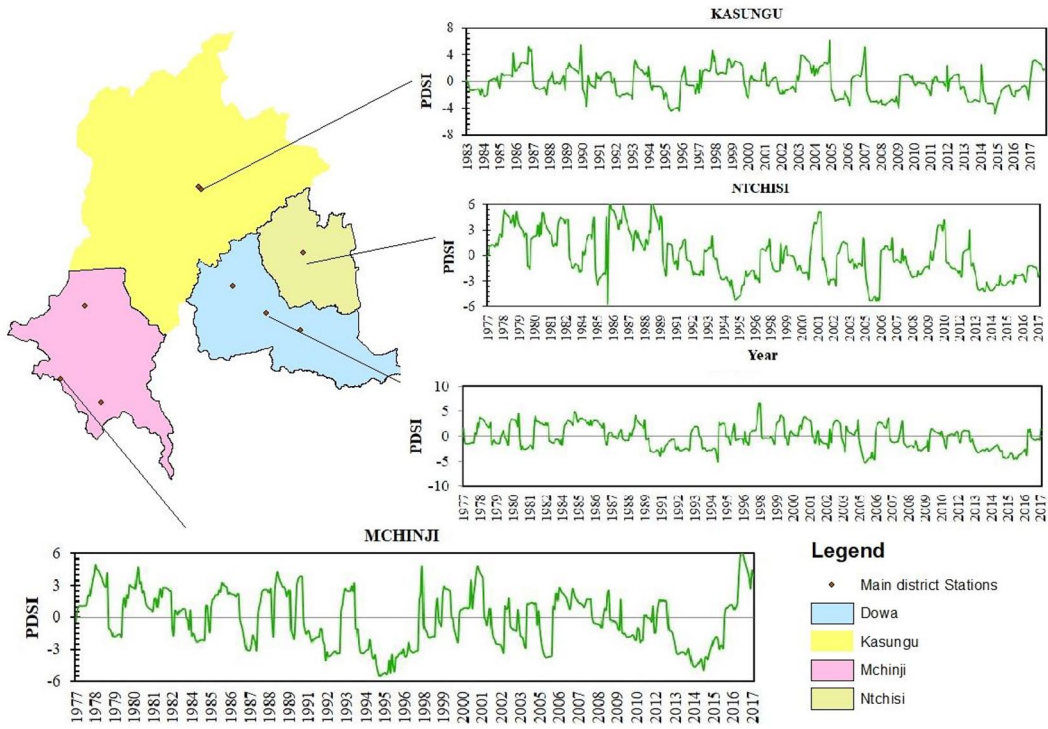


Fig. 4 PDSI severity regimes in Kasungu ADD

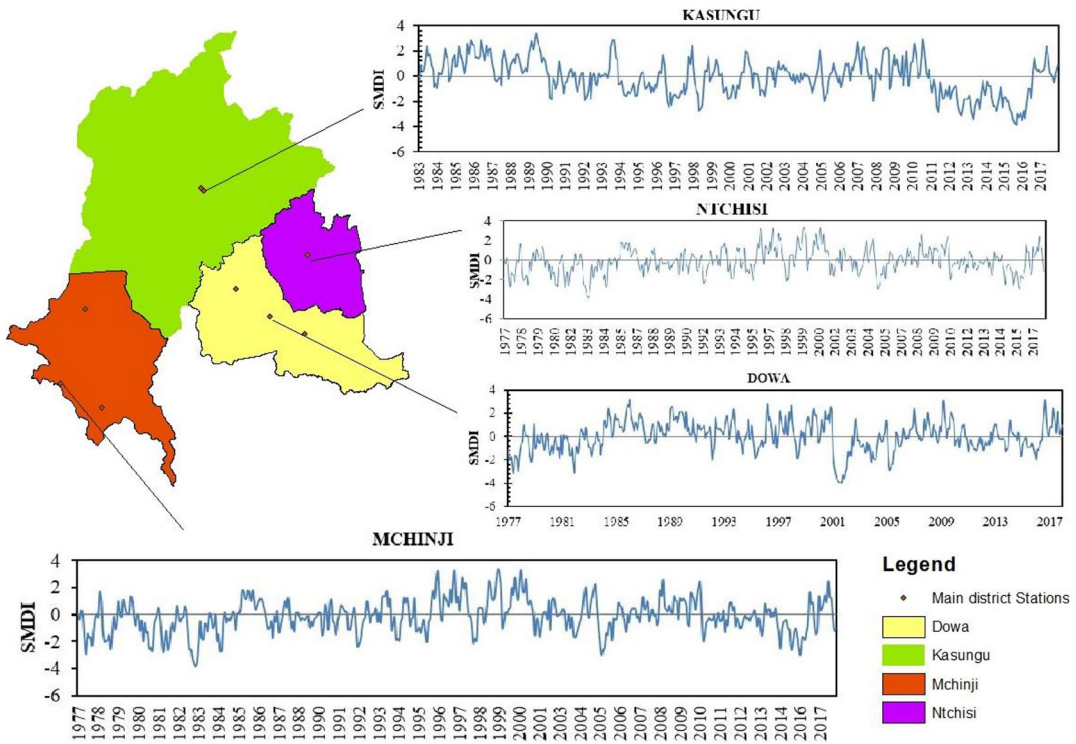


Fig. 5 SMDI severity regimes in Kasungu ADD

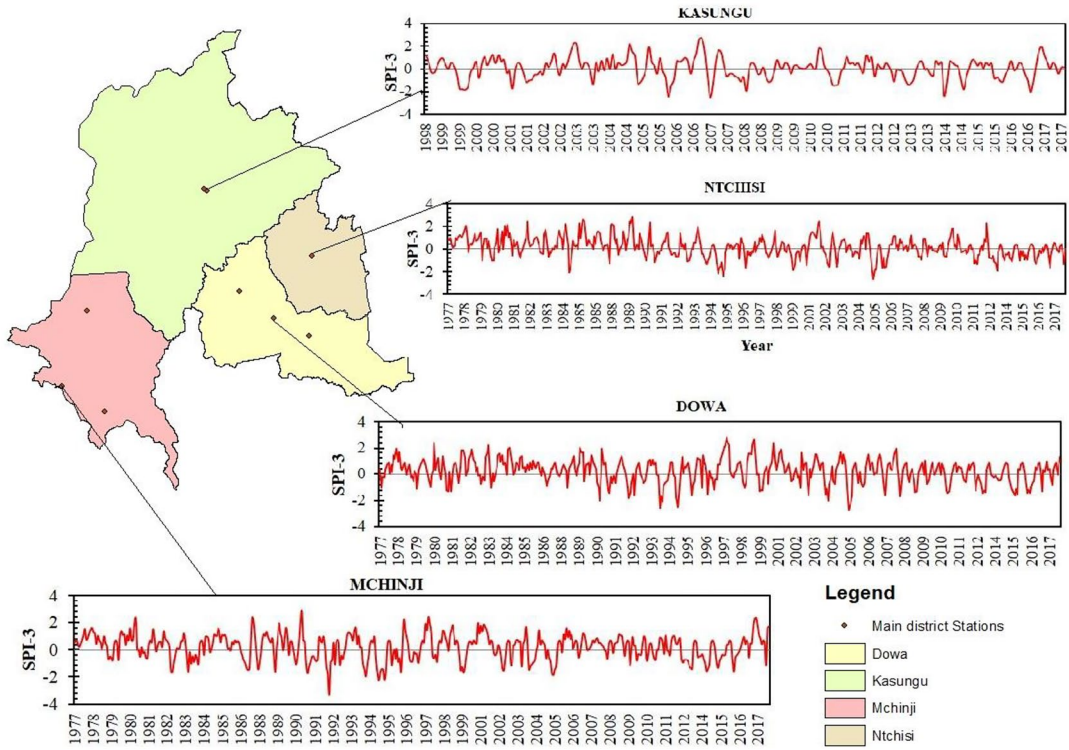


Fig. 6 SPI-3 severity regimes in Kasungu ADD

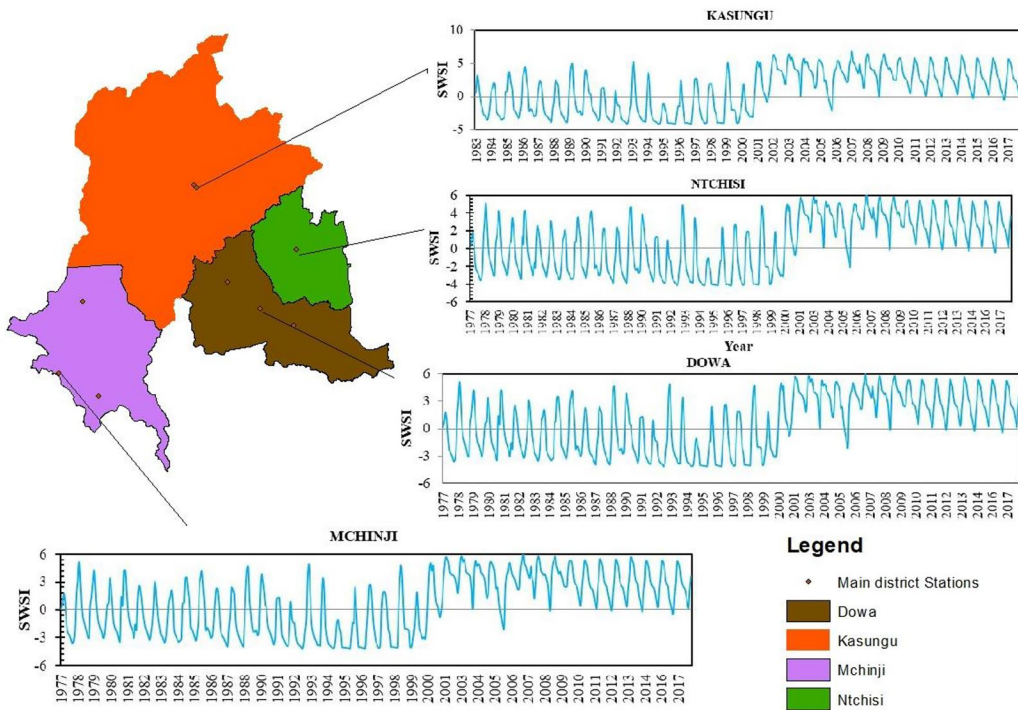
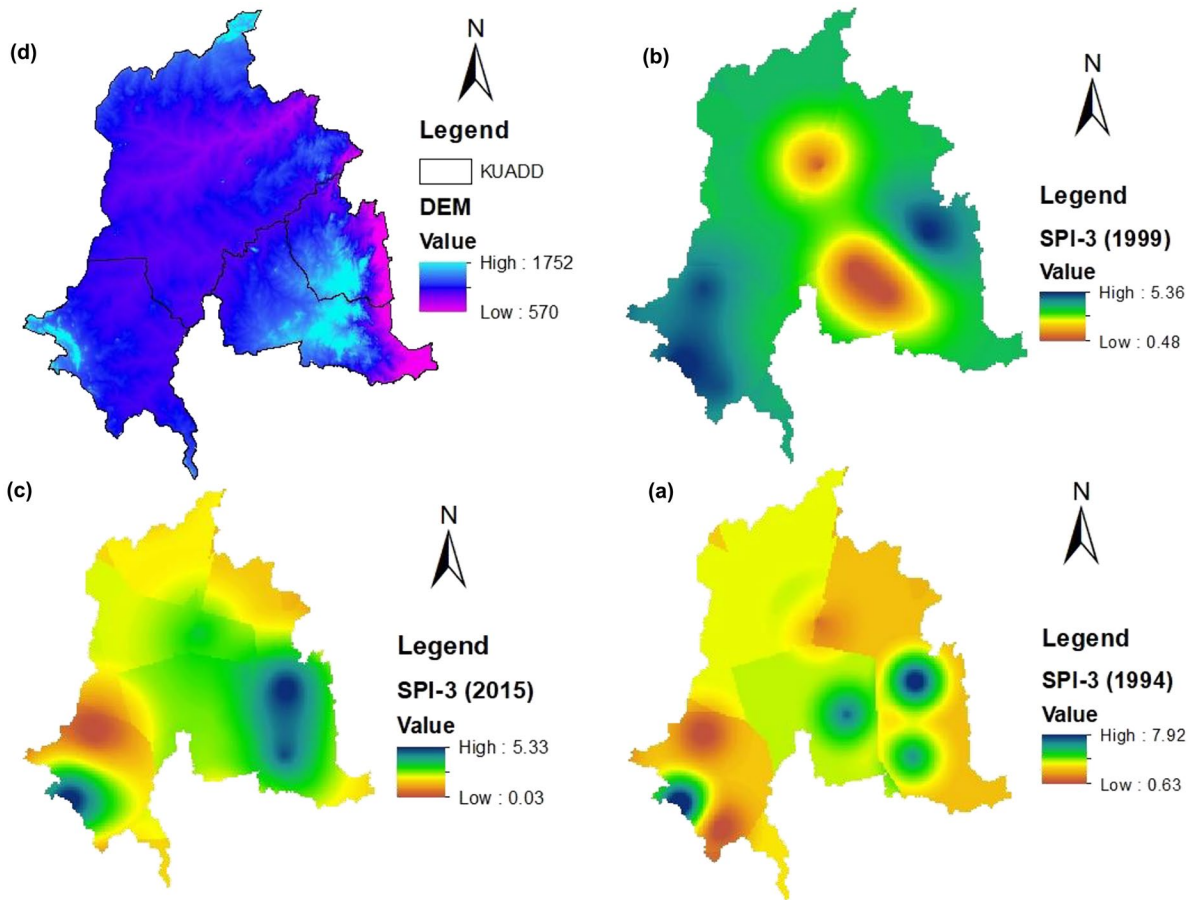


Fig. 7 SWSI severity regimes in Kasungu ADD





**Fig. 8** Spatial distribution of SPI-3 severity regimes in Kasungu ADD. DEM shows the digital elevation map of the study area (Fig. 8d)

for rainfall formation. On the contrary, some parts of Mchinji, Dowa, and Ntchisi are at higher elevations such that they receive a better amount of rainfall enough for crop production. Notably, these areas are less vulnerable to drought risks. This observation concurs with Wambua et al. (2015), who stated that regions at lower elevations are more prone to drought risks. The results have demonstrated that drought characteristics are frequent and intense in the ADD. Crop yields have also reduced significantly due to the effects of the drought conditions. As shown by this study, the knowledge of these characteristics will help address the challenges of droughts in the region through the planning of sustainable water resource usages and conservation.

**Conclusion**

This study characterized the spatial and temporal drought regimes and their impacts on dominant crop yield change over Central Malawi using SPI-3, PDSI, SMDI, and SWSI drought indices. The results showed that SPI-3 detected monthly drought severities in the ADD. The prevalence of short-timescale meteorological droughts in the ADD suggested their progression into agricultural droughts, affecting crop development, hence reduction in crop yields. It was also found out that Kasungu ADD experiences moderate and mild droughts frequently, with high severities in Kasungu and some parts of Dowa and the lowest severity in Mchinji district. In the face of climate change, this study showed that short-term drought indices are

essential tools in revealing drought severity levels and determine drought risk-prone areas. This study presents a basis for developing drought mitigation plans based on best agricultural practices by NGOs, Government Departments, and Ministries of Agriculture and Disaster Preparedness in the ADD. Based on the results, the study recommends that the ADD should promote climate-smart irrigation systems such as drip irrigation, adopt water harvesting and conservation technologies that are effective and sustainable, and promote crop diversification and the growing of drought-resistant crops such as cassava to mitigate the highly variable rainfall in the region. For drought mitigation programs, Kasungu and Ntchisi districts should be given a priority since they are highly susceptible to drought. This study recommends that future research should focus on integrated drought management and drought forecasting to crop schedules for effective water resources management in times of droughts.

**Acknowledgements** The authors would like to thank the Ministry of Irrigation and Water Development, Ministry of Agriculture and Food Security, Meteorological Department, and Kasungu ADD in Malawi for providing hydrological, crop yield, meteorological, and socioeconomic profile data, respectively.

**Author contribution** All authors contributed to the study's conception and design. Sylvester Richard Chikabvumbwa and Nasrin Salehnia performed material preparation, data collection/analysis, conceptualization, methodology, formal analysis, and investigation. Sylvester Richard Chikabvumbwa and Nasrin Salehnia wrote the first draft of the manuscript and all authors commented on previous versions of the manuscript. Nasrin Salehnia supervised this research. Final review and editing were performed by Rodrigo Manzanas. All authors read and approved the final manuscript.

**Funding** This work would not be possible without funds awarded by PAUWES (Pan African University of Water and Energy Sciences).

**Availability of data and materials** We confirm that we will present all the used data. Moreover, we confirmed that all data generated or analyzed during this study are included in this article will attached in the supplementary data.

## Declarations

**Ethics approval** We confirmed that we did not present this paper in any other journals, and we confirmed to respect all the mentioned "Ethical Responsibilities of Authors" rules that are mentioned in the website of ESPR.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Conflict of interest** The authors declare no competing interests.

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