

Spatiotemporal dynamics and drivers of agricultural droughts in the agroecological zones of Cameroon

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ABSTRACT

Droughts are some of the most devastating natural extreme events in sub-Saharan with enormous economic impacts on agrarian economies such as Cameroon. However, knowledge and information on their dynamics and drivers in the five agroecological zones (AEZs) of Cameroon is very scanty leading to poor planning and management. Therefore, this study aimed to characterize agricultural droughts based on soil moisture, explored trends and drivers of scale 3 standardized soil moisture index in the five AEZs of Cameroon at high spatial and temporal resolutions for the period 1990–2022. Results show a predominance of moderate to severe droughts in most parts of the MF AEZ, a general increase in the percent of drought area (PDA) in the last four years averaging at 48% and, a significant increase in droughts for over 65% of the country at 5% level of significance. The observed droughts were found to be significantly internally associated with precipitation, evapotranspiration, vapor pressure deficit and minimum temperature but majorly driven by evapotranspiration, precipitation and vapor pressure deficit with a 52% coefficient of determination. This relationship was well aligned with the first Empirical Orthogonal Function (EOF) mode that for 34.1% explained variance. Externally, the second EOF mode (21% explained variance) was associated with atmosphere-oceanic teleconnections including Atlantic Meridional Mode, Tropical North Atlantic Index, El-Niño Standardized Precipitation Index and Atlantic Multi-decadal Oscillation Index. While as, the third EOF (9.7% explained variance) corresponded to both precipitation and ENSOs. The results of this study not only inform effective drought planning and management but also help in boosting the forecasting capacity of the Cameroonian climate and water management agencies for agricultural droughts with a good lead time.

1. Introduction

Drought is a climatic hazard that may cause many negative impacts to food security and economic and social stability. According to Yang et al., (2017), agricultural droughts impact the agrarian societies. Thus, the agricultural droughts cause poor harvest and pecuniary damages (Bucheli et al., 2021). More than 55 million humans are directly affected by drought annually from 1970 to 2019 leading to great loss of lives subsequently causing several hundred billion dollars in economic losses worldwide. The numbers are increasing (WHO, 2023) due to climatic variability and change globally observed historically and simulated from

Global Climate Models (GCMs) (Dai, 2011). An increased risk of drought due to climate change is anticipated to affect unprotected countries, especially those with fast overpopulation and hunger problems (UNDRR, 2020). Not long ago, the Sub-Saharan countries have suffered the substantial consequences of increasingly frequent and intense climatic disasters (Taylor, 2017; WHO, 2023). Around 120,000 square km vanished every year because of water shortage and soil degradation (FAO, 2017).

In Cameroon, agriculture is the leading employer of the population at 60 % contributing up-to 23 % to GDP. Yet, the country is already facing an anormal recurrence of extreme climatic phenomena observed over

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the last 50 years (PNACC, 2015). For some years now, rainfall has been unstable resulting in adverse consequences for farming activities, particularly the disruption of the agricultural calendar and a fall in productivity in the long-run. These climatic changes are strongly felt in the Sahelian zone resulting in rivers and lakes such as Lake Chad gradually drying up forcing people to migrate. These unplanned migrations are at the root of tensions and conflicts between herders and farmers. In the mountainous areas of the west, surface water is drying up which is likely to have an impact on agricultural production. The agroecological zones (AEZs) most affected by rising temperatures are the bimodal rainfall forest zone and the Guinean high Savannah zone (Aoutacksa, 2014).

However, the magnitude, dynamics and drivers of these drought events are not well documented especially in AEZs other than the SS(SS) zone limiting planning and policy. Furthermore, despite the sheerness of existing studies on droughts in Cameroon, it's worth also noting that most of the studies such as Guenang and Mkankam Kamga, (2014), Aoutacksa, (2014), Njounwet et al. (2021), Ntali and Lyimo, (2022) and recently Ntali et al., (2023) generally adopted the standard precipitation index (SPI) for drought characterization whose application is mostly limited to meteorological drought characterizations other than agricultural. For example, studies by Sepulcre-Canto et al., (2014), Vyas et al., (2015), Black et al., (2016) and Asfaw et al., (2018) stressed its weakness in determining an agricultural drought as soil humidity is also influenced by air temperature variations, wind intensity and vegetation presence (Watson et al., 2022). Furthermore, precipitation-based indices detect agricultural droughts with a long time-lag limiting prompt response and planning.

As such, in order to better analyze the case of agricultural droughts in Cameroon, it is important to explore agricultural droughts based on a more direct indicator such as soil moisture. Therefore, this study purposed to; (i) characterize the spatial and temporal distribution of soil moisture droughts in five AEZs of Cameroon, (ii) examine trends in both Soil moisture and soil moisture droughts, (iii) explore the relationship between Soil moisture droughts and lagged meteorological droughts indices and, (iv) determine and attribute the spatiotemporal variability of soil moisture extremes with a view to proposing viable mitigation or adaptation measures to populations in order to limit their impact on agricultural production. Our study therefore analyzed the dynamics of agricultural droughts and their drivers over the five AEZs of Cameroon.

2. Study area description

Cameroon is situated in the Central Africa, bounded by Nigeria in the West, northeast by Chad, with Gabon, Congo and Equatorial Guinea in the South and Central African Republic in the East. The country boasts a total surface area of 475 650 km² (MINOF, 2018).

2.1. Ecology of Cameroon

Cameroon's diverse ecology can be condensed into five agro-ecological zones (Fig. 1) that include (1) Monomodal woodland with high trees density and rainfalls, (2) Bimodal tropical forest with substantial water bodies, (3) Sudano-Sahelian (SS) grassland with less rain and water, (4) High savannah (HS) zone and (5) High Plateau (HP) zone. Fig. 2.

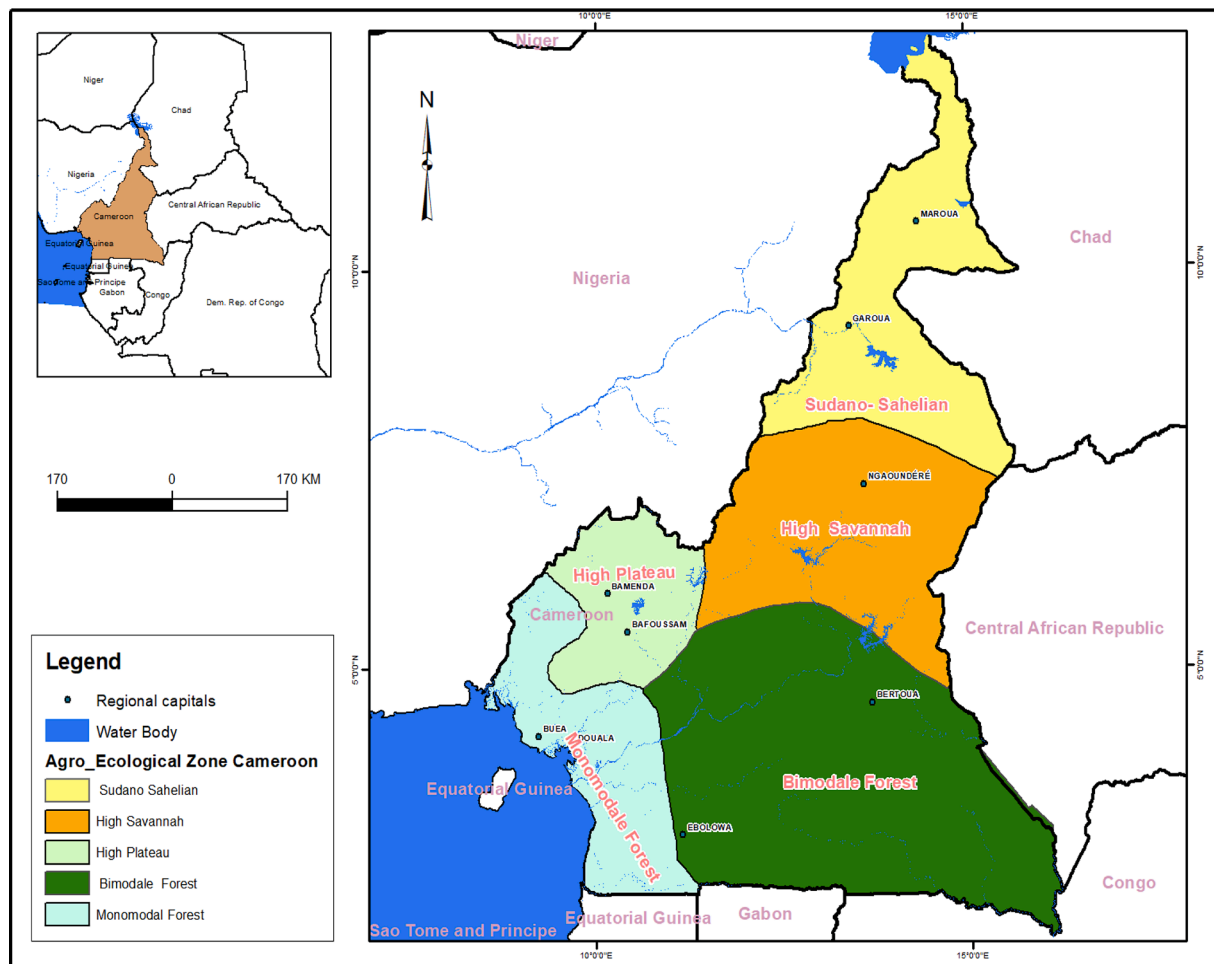


Fig. 1. Agroecological Zones of Cameroon.

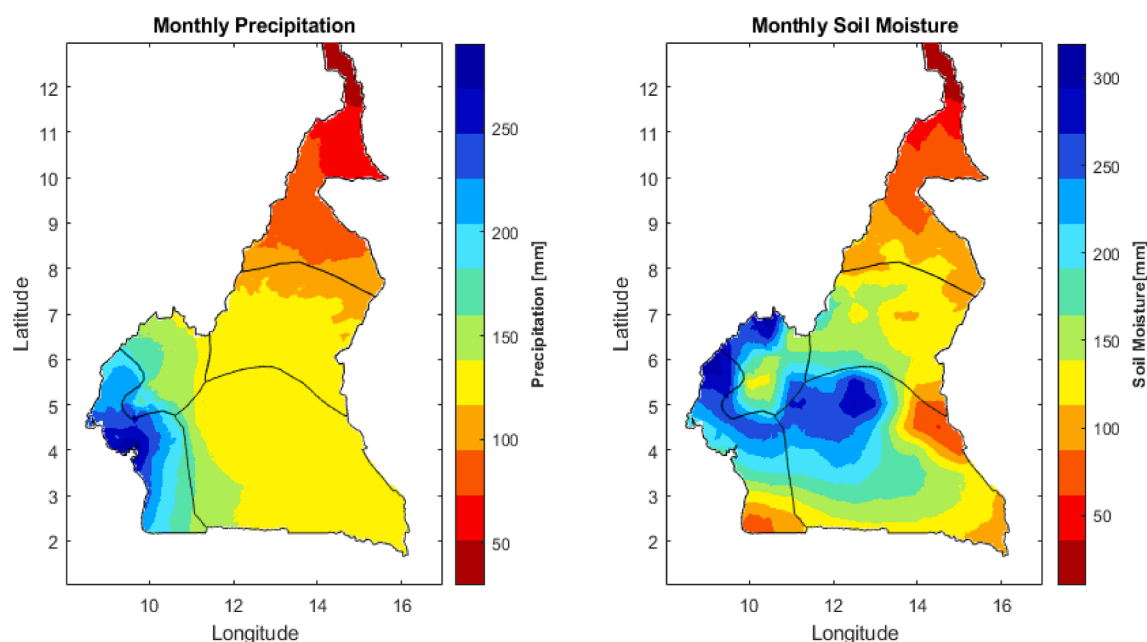


Fig. 2. Precipitation and Soil moisture climatology over Cameroon based on Terraclimate data (Abatzoglou et al., 2018) used in this study.

2.2. Climate and relief of the different AEZs

Cameroon's topography is highly varied with five major geomorphological complexes notably in the coastal zone, ancient plateau of the South, Central Highlands and in the mountainous regions of the West. This diversity influences the climatic characteristics of the country in the 5 AEZs, as shown in Table 1.

Meters above sea level (M.A.S.L.).

3. Data and methods

In this study, high spatial resolution agroclimatic data sets were sourced from Climatology Lab (Climatology Lab, 2015) for Root zone Soil Moisture (SM) at 1 m depth, Precipitation (P), Minimum Temperature (TMIN) at 2 m height above ground, Vapor Pressure Deficit (VPD) at 2 m height above ground and Potential Evapotranspiration (PET), and Atmosphere-oceanic teleconnections timeseries from Physical Science Laboratory (Climate Indices, 2024) for Quasi-biennial Oscillation (QBO), Atlantic Meridional Mode (AMM), Tropical North Atlantic Index (TNA), North Atlantic Oscillation index (NOA), El Nino Standardized Precipitation Index (ESPI), Atlantic Multi-decadal Oscillation index (AMO) at a monthly resolution for a period 1990 to 2022. The agroclimatic variables spatial resolution was $1/24^\circ$ (~4-km) (Abatzoglou et al., 2018). This data was subjected to preprocessing and then used to compute drought indices at a 3-month scale. Soil Moisture droughts were characterized and later compared with internal agroclimatic

variables using correlation and multiple regression analysis. Furthermore, Soil moisture anomalies were subjected to dimensionality reduction analysis using EOF. The associated Principal components (PCs) were extracted and compared with both internal climatic drivers and teleconnections using both linear correlation and frequency analysis.

3.1. Data Sources and Pre-Processing

Agroclimatic datasets were obtained in Network Common Data Form (NetCDF) format within the Cameroon country bounding box of Latitude 2° N to 13° N; Longitude $8^\circ 25'$ E and $16^\circ 20'$ E, read into MATLAB programming language and masked using the Cameroon country boundary vector file before formal analysis. The data was also explored for completeness using MATLAB scripts. The Atmospheric-oceanic teleconnections timeseries data was on the other hand received in ASCII format from the National Oceanic and Atmospheric Administration (NOAA) website as shown in Table 2. The adopted agroclimatic data from TerraClimate (Abatzoglou et al., 2018) which uses satellite and climatic data has received recognition from researchers globally for its high spatial resolution, accuracy and low Root Mean Square Error (RMSE) (Lemenkova, 2022) compared to other gridded and satellite data sets.

3.2. Data analysis

3.2.1. Computation of Standardized climate indices and drought indices

A variety of indices using meteorological, hydrological, agricultural data or a combination of both have been used to quantify droughts (Gebrehiwot et al., 2011). The widely used technique is the z-scores method to standardize a given Agro or hydrometeorological variable X (Gebrehiwot et al., 2011; WMO, 2012; Wu et al., 2022) whose probability has been transformed to a parametric distribution such as gamma (WMO, 2012; Vreugdenhil et al., 2022) and beta or Weibull distribution (Hao and Aghakouchak, 2014) distributions for precipitation and moisture data respectively. However, studies such as Farahmand and Aghakouchak, (2015) have noted weaknesses of parametric probability distribution functions such as gamma at fitting hydrometeorological data in spatiotemporal domains. We therefore adopted the empirical probability distribution (Farahmand and Aghakouchak, 2015) to derive

Table 1

A summary of climate and relief of the agro-ecological zones.

AEZ	Annual Precipitation (mm)	Elevation (M. A.S.L.)	Annual temperature (range)
I. Sudano-Sahelian Zone	500–900	250–500	28 °C (7.7)
II. High Savannah	1500–1800	500–1500	23 °C (6.4)
III. High Plateau	1800–2400	1500–2500	21 °C (2.2)
IV. Monomodal Forest	2000–11000	0.2–500	26 °C (2.8)
V. Bimodal Forest	1500–2000	400–1000	25 °C (2.4)

Table 2

Data and Sources.

Variable	Temporal	Spatial	Period	Depth/Height	Reference
Soil Moisture	Monthly	~4km	1990–2022	1 Meter	(Abatzoglou et al., 2018)
Precipitation	Monthly	~4km	1990–2022	—	(Abatzoglou et al., 2018)
Vapor Pressure Deficit	Monthly	~4km	1990–2022	2 Meters	(Abatzoglou et al., 2018)
Minimum Temperature	Monthly	~4km	1990–2022	2 Meters	(Abatzoglou et al., 2018)
Potential Evapotranspiration	Monthly	~4km	1990–2022	—	(Abatzoglou et al., 2018)
QBO	Monthly	—	1990–2022	—	(Anstey et al., 2022)
AMM	Monthly	—	1990–2022	—	(Deng et al., 2018)
TNA	Monthly	—	1990–2022	—	(Jiang & Li, 2019)
NOA	Monthly	—	1990–2022	—	(Deng et al., 2018)
ESPI	Monthly	—	1990–2022	—	(García-García & Ummenhofer, 2015)
AMO	Monthly	—	1990–2022	—	(García-García & Ummenhofer, 2015)

a non-parametric standardized index. The Empirical Gringorten plotting position (Gringorten, 1963) used in the transformation is given as;

$$p(x_i) = \frac{l - 0.44}{N + 0.12} \quad (1)$$

where N is the sample size, l denotes the rank of non-zero hydrometeorological data from the smallest, and $p(x_i)$ is the corresponding empirical probability. The output is then transformed into a Standardized Index (SXI) as;

$$SXI_{m,y} = \frac{X_{m,y} - \bar{X}_m}{\sigma_m} \quad (2)$$

where, X is the empirical probability ($p(x_i)$) of SM/PET/TMIN/VPD/Precipitation, y is the percentile year from 1990 to 2022, m is the percentile month from January to December, and $\bar{X}_m$ and σ_m are the average and standard deviation of X in month m respectively.

For this study, a 3-months SXI [03] for soil moisture (SSI [03]) was adopted as recommended by Carrão et al. (2016). The SSI [03] provides a comparison of the Soil moisture over a specific 3-month period with the Soil moisture totals from the same 3-month period for all the years included in the historical record. That's, a 3-month SSI [03] at the end of February compares the December–January– February Soil moisture total in that particular year with the December–February Soil moisture totals of all the years on record for that location. Alternatively, a 6-months scale (SXI [06]) was considered for the remaining meteorological drought indices to account for the time lag associated with processes of the hydrological cycle. The drought indices were implemented in MATLAB using the Standardized Drought Analysis Toolbox (SDAT) (Farahmand and Aghakouchak, 2015).

3.2.2. Computation of drought Classes, area and characteristics.

In this study, the drought classification was based on three classes, including moderate (−1.49 to −1), severe (−1.99 to −1.5), and extreme droughts (≤ -2) as recommended by Bhuiyan et al. (2006). If the SSI [03] value is lower than −2 in a certain month from 1990 to 2022, it represents an extreme drought event.

SSI [03] is dimensionless and is used to detect drought (Carrão et al. 2016). When SSI [03] is greater than 0, it can be considered that it is wetter than that in the same period of many years; otherwise, it is drier (Wu et al., 2022).

The overall temporal evolution of the area in drought in each AEZ was determined using Non-contiguous drought areas (NCDA) method (Perez et al., 2011). The Percentage of area in drought (PDA) at time t and relative to A_{tot} (total land area considered: a given AEZ) is given by;

$$PDA(t) = \frac{100}{A_{tot}} \sum_{c=1}^{\eta} (D_s(t) \cdot A) \quad (3)$$

where, A is the area at each cell, η is number of cells and discrete Drought state per cell D_s is;

$$D_{s(t)} = \begin{cases} 1 & \text{if } SSI_t < T_t \\ 0 & \text{if } SSI_t \geq T_t \end{cases} \quad (4)$$

where, T_t is the threshold per time step equivalent to −1.

Three commonly used drought metrics such as Duration, Severity and Intensity (Tuyisenge, 2018) are considered in this study.

The Drought duration (DD) is determined by the period of time the SSI is under the drought threshold (−1). Average drought duration (ADD) (Perez et al., 2011) is therefore given as;

$$ADD = \frac{\sum_{i=1}^N D_s}{N} \quad (5)$$

where ADD is the average drought duration at cell c . N is the number of drought months per cell.

Drought Severity (DS) (Perez et al., 2011) is computed by summing the deficit depth (Dd) which is computed by accumulating the monthly deficit.

$$Dd_i = \sum_{t=t_b}^{t_e} (SM_t - \Psi_t) \quad (6)$$

where, Dd_i is the deficit depth of the event i . Ψ_t is the absolute SM (drought) value corresponding to the drought threshold (−1) for a given cell. The initial and final time steps of the drought event are represented by t_b and t_e respectively.

The Average Drought Severity (ADS) at cell c is given as;

$$ADS = \frac{\sum_{i=1}^N Dd_i}{N} \quad (7)$$

Finally, Average Drought Intensity (ADI) (Perez et al., 2011) per cell is given as;

$$ADI = \frac{ADS}{ADD} \quad (8)$$

A detailed methodological description of the three adopted drought characteristics can be found in Cavus and Aksoy, (2020).

3.2.3. Trend test and Sen's slope estimator

In order to examine long-term temporal and spatial tendency, the modified Mann Kendall Trend test and Sen's slope estimator (MKSSE) was utilized. Mann Kendall is internationally used in climatology, and in thermal and hydrometeorological analysis (Yue and Wang, 2004) such as temperature, rainfall, evaporation, evapotranspiration, streamflow and water quality (Alashan, 2020). The test is preferred for two main reasons; 1) Non-parametric and hence no data normality requirement and, 2) a low sensibility to short interruptions due to heterogenous time series (Tabari et al., 2011). The null hypothesis H_0 presumes that there is no tendency, and this is tested against the substitute hypothesis H_1 , which accepts a trend. The Z statistic is used to evaluate a trend; a positive (negative) value of Z means an increasing (decreasing) trend

(He et al., 2022). The hypothesis that there is no trend is rejected when the Z value is greater in absolute value than the critical value, at a chosen level of significance (α) for example in this study $\alpha = 0.95$. In the Mann-Kendall test, the null hypotheses were tested at 95 % confidence level for SM and SSI [03] droughts and their respective magnitudes using the non-parametric Sen's slope. The test was implemented in MATLAB using the trend function with Kendall type option (Greene et al., 2019).

3.2.4. Correlation analysis

We computed the Pearson correlation coefficient between the SSI [03] droughts and a given SXI drought per pixel (Mohapatra and Weisshaar, 2018) using the Corr function in MATLAB. The significance of the association was tested at $\alpha = 0.05$ level of significance.

3.2.5. Multiple linear regression (MLR) model

MLR represents the connections between different variables with a unique practical procedure (Baik et al., 2019). In order to assess the performance and ability of the selected internal variables such Precipitation, Vapor pressure deficit, Minimum Temperature and Potential Evapotranspiration at simulating soil moisture extremes over the five agroecological zones of Cameroon, an iterative stepwise process was considered. Initially, all the four SXI [06] were feed into the model and the strength of each predictor was evaluated using the computed p-value of the F-statistic with or without the potential predictor. For our case, the pEnter and pRemove were set to 0.06 and 0.1 respectively.

The Stepwise-based MLR, with one dependent (SSI [03]) and more independent variables (SXI_n [06]) utilize the following formula:

$$SSI[03] = C + \beta_1 SPI[06] * SPETI[06] + \beta_2 SVPI[06] * SPETI[06] + \beta_3 STMINI[06] \quad (9)$$

where $\beta_{i(i=1,2,3)}$ is a regression coefficient for the free variable, SSI [03] represents the controlled variable and C is an intercept of the regression formula. The ordinary least squares method, which regression coefficients estimation (Anshuka et al., 2019), was used.

3.2.6. Empirical Orthogonal function (EOF) for spatiotemporal covariance analysis

The EOF procedure was used to examine of the datasets spatially and temporally variation with a devoted use in meteorological (Lorenz, 1956) and agrometeorological studies (Wu et al., 2022). Its applications range from identification to separation of dominant and underlying processes as well as essential parameters of a given use case for example major drivers of potential evapotranspiration patterns and its corresponding signals. Its EOFs work by decomposing parameters of the local climate region into fewer patterns for each variable. According to Yosef et al., (2017), in atmospheric research, the source data common layout is mentioned as a S-mode examination illustrating the sample's position (EOF) and the principal component (PC). Matrix is composed of $M \times N$, where M refer to spatial and N the common sampler feature. Computation of EOFs involves removal of the mean first; the matrix F will be

$$F = \frac{1}{N} SSI^T SSI \quad (10)$$

where SSI represent the raw data, SSI^T is the transpose matrix, and N is the sample total.

The next step is to find eigenvalues and eigenvectors (EOFs) of F by solving the eigenvalue problem;

$$FC = \Lambda C \quad (11)$$

where, Λ is a diagonal matrix containing the eigenvalues λ of F . The eigenvectors of F are then defined as the column vectors of C corresponding to the eigenvalue λ_i denoted by C_i . These patterns represent empirical models (EOFs) (Mestas-Nuñez and Enfield, 1999; Yosef et al.,

2017).

The principal component corresponding to the eigenvalue i is given as;

$$PC_i = SSI * C_i \quad (12)$$

where, C_i denotes the empirical mode i .

The PC amplitudes were standardized to unit variance as well as the eigenvectors which were reweighted by the square root of their corresponding eigenvalues to give higher weight to the leading spatial modes. The EOF function under the CDT toolbox (Greene et al., 2019) in MATLAB was used to implement the EOF analysis.

3.2.7. Transformation and correlation.

To further attribute the causes of soil moisture extremes in the five AEZs of Cameroon, we further analyzed the correlation between the main principal components (PCs 1–6) that together account for over 80 % explained variance and both internal and external drivers using Pearson's correlation coefficients described in 3.2.4. However, given the fixed [-1,1] range of PCs, it was prudent to transform the corresponding SXIs and Teleconnections to a similar range to facilitate a smooth comparison. The normalization to a [-1,1] range was done using the min-max scaling method (Claverie et al., 2016).

3.2.8. Spectral analysis

Spectral analysis techniques represent a wide range of statistical approaches for decomposing and identifying periodicities subjacent in data series (Ghil et al., 2002). The approaches have been widely applied in the Earth and planetary sciences especially in solar periodicity related research (Jos et al., 2022). We adopted the periodogram method to identify hidden cyclic patterns in principal components of SSI which would help strengthen the evidence of the identified SSI-Climatic relationships (Fig. 3). Similarly for spectral analysis, the 6 main PCs that together account for 80 % explained variance in SSI were considered. The non-parametric periodogram was computed using the periodogram function in MATLAB.

4. Results

4.1. Spatial distribution and characteristics of soil moisture droughts for the period 1990–2022

4.1.1. Climatology of Standardized soil moisture Index (SSI [03]) droughts

Fig. 4 shows the configuration of the soil moisture droughts over the five AEZs of Cameroon between 1990 and 2022. Based on the drought classification scheme, Cameroon was majorly associated with droughts of moderate to severe category in the range of -1.4 to -1.6 . A uniform distribution of severe droughts was observed in the Bimodal Forest (BF) zone at an average magnitude of -1.51 with an exception of the north eastern part that experienced moderate droughts. The MF zone on the other hand was associated with values ranging from -1.5 to -1.6 , indicating severe droughts on its western parts. The western highland was associated with severe droughts with a mean magnitude of -1.52 . The HS and SS zones were associated with a mix severe and scattered moderate drought magnitudes.

On a seasonal scale (Fig. 5), the planting seasons of March–April–May (MAM) and September to December (SOND) were associated with severe droughts especially in the BF, MF and HP zones. While, the HS and SS zones were associated with a fusion of moderate severe droughts. The harvesting seasons of January to February (JF) and June to August (JJA) were associated with both moderate and severe droughts. Notably, a uniform distribution of droughts can be observed in during the JJA season over the SS, HS, BF and major parts of the High Plateau and MF zones. However, distinct spike centered in the western flank is observed in the Monomodal zone.

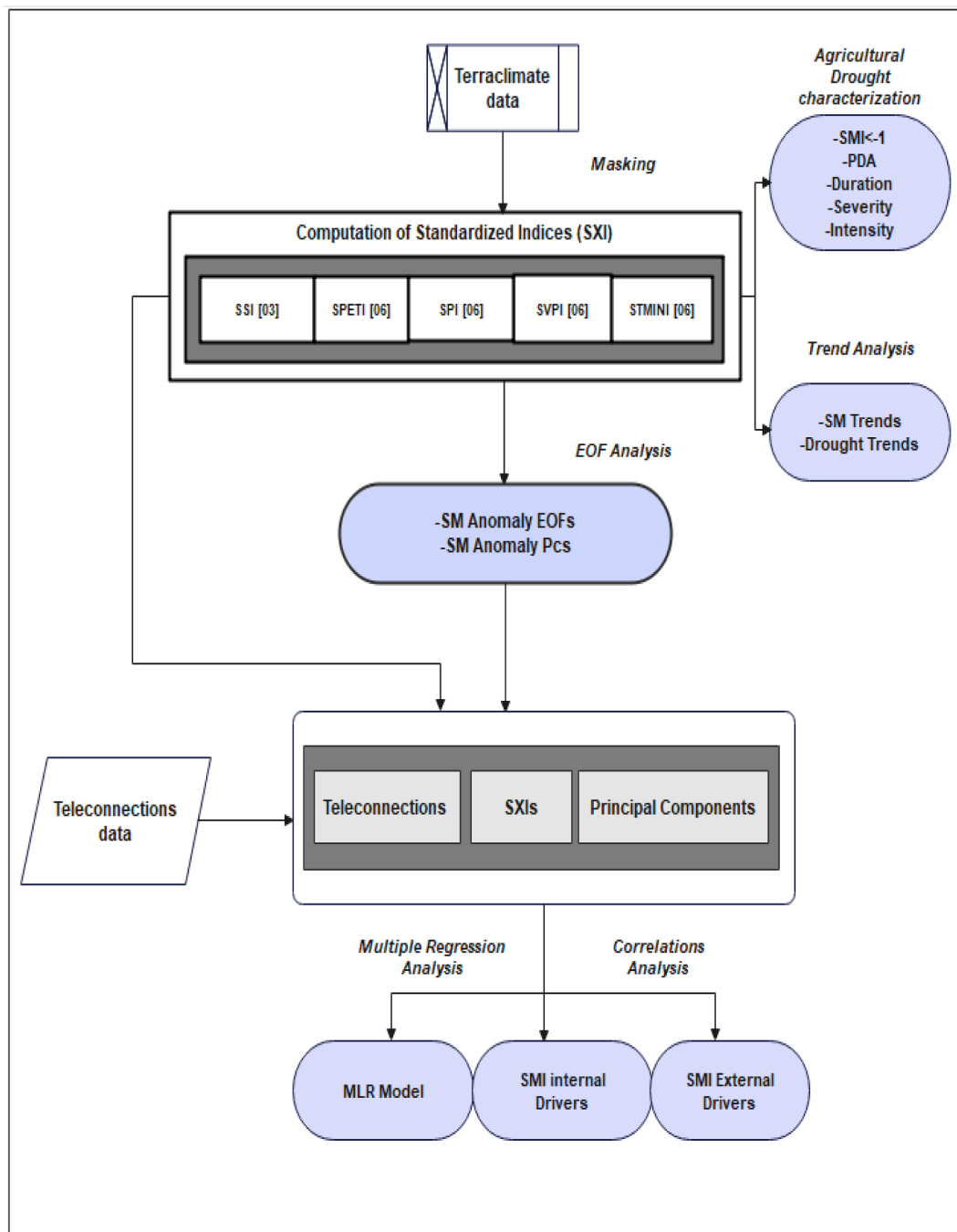


Fig. 3. Research Framework of the study.

4.1.2. Percent of drought area based on SSI [03] for the period 1990–2022

Figs. 6 and 7 show the Percent of drought area (PDA) based on soil moisture drought index (SSI [03]) for the period 1990–2022 in the five AEZs. The heterogeneity of drought distribution across the AEZs in space and time can evidently be seen.

In the SS zone, over 20 % of the total area was dominated by drought of the moderate category in early 1990 s to the 1995. The zone experienced a period of recess up to early 2000's characterized by marginal moderate droughts covering less than 10 % of the total land area. The coverage spiked again in mid-2001 with a PDA of 80 % associated with both moderate, severe and extreme droughts. This pattern continued repeatedly through the OND and JFMA months of 2004, 2005 and 2006 with an average PDA of 50 %. From September 2009, a resumption in drought intensification and distribution was observed and continued to

prevail until July 2015. This witnessed the most severe and extreme categories of droughts with an average PDA of 15 % per drought category. A final spike was observed again in June 2020 lasting up to June 2022.

The HS zone displayed a slightly different pattern to that of the SS zone with marginal to no droughts until the early 2000's. The zone witnessed a general start of continuous drought episodes in May 2001 that continued through the mid 2000's and early 2010's characterised with more pronounced extremes and a PDA averaging at 30 %. This pattern was more pronounced in the OND and JFM months. A general recess characterized by marginal PDA was observed through the mid until the late 2010's. A final spike was observed again in November 2020 lasting up to June 2022.

The HP experienced a period recess up to early 1998 characterized

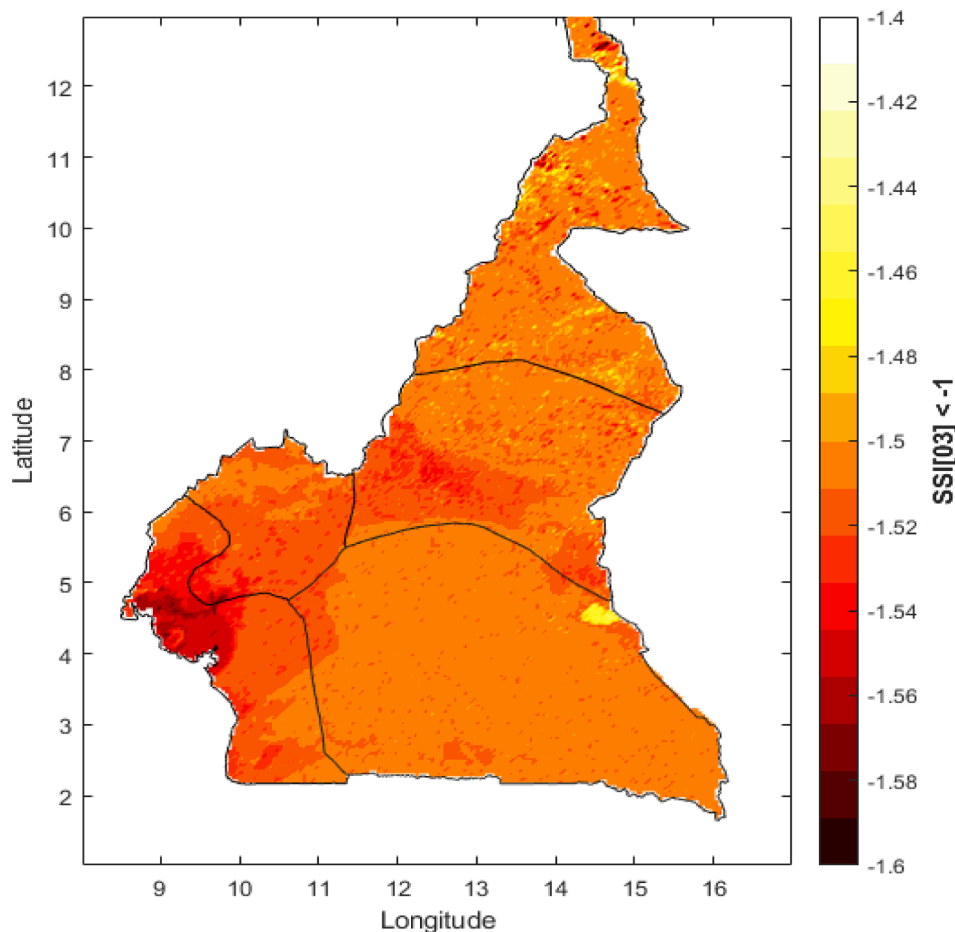


Fig. 4. Average distribution of soil moisture droughts over the five agroecological zones of Cameroon (1990–2022).

by marginal moderate droughts covering less than 15 % of the total land area. Over 30 % of the total area was dominated by drought of the moderate category in early 1998 to the 2000. The coverage spiked again in mid-2000's with a PDA of 60 % associated with majorly moderate and extreme droughts. This pattern continued repeatedly through the ND and JFM months of 2000, 2005 and 2006 with an average PDA of 30 %. From April 2008, a resumption in drought intensification and distribution was observed and continued to prevail until July 2014. The most established period of drought was observed between March 2020 lasting up to December 2022.

The MF zone showed a mix of moderate and severe deviations, indicating a more complex response to changing environmental conditions. Over 20 % of the total area was dominated by drought of the moderate category in early 1990's to the 2000. The zone experienced a period recess up to early 1998 characterized by marginal moderate droughts covering less than 15 % of the total land area. The coverage spiked again in 2006 with a PDA of 65 % associated with both moderate, and extreme droughts. This pattern continued repeatedly through the ND and MAM months of 2000, 2005 and 2008 with an average PDA of 40 %. From July 2010, a resumption in drought intensification and distribution was observed and continued to prevail until February 2015. This witnessed the most severe and extreme categories of droughts with an average PDA of 25 % per drought category. A final spike was observed again in March 2020 lasting up to November 2022.

The BF zone also exhibits a mix of moderate and severe deviations, similar to the MF zone. Over 20 % of the total area was dominated by drought of the moderate category in early 1990's to the 1998. The zone experienced a period recess up to early 2004 characterized by marginal moderate droughts covering less than 15 % of the total land area. The

coverage spiked again in 2006 with a PDA of 80 % associated with both moderate, and extreme droughts. This pattern continued repeatedly through the AMJ and JF months of 2000, 2010 and 2015 with an average PDA of 40 %. From January 2018, a resumption in drought intensification and distribution was observed and continued to prevail until February 2018. This witnessed the most severe and extreme categories of droughts with an average PDA of 20 % per drought category. A final spike was observed again in March 2020 lasting up to November 2022.

The risk of soil moisture droughts in these zones may be variable depending on the specific climatic drivers and the resilience of the local agricultural systems and other water-reliant sectors.

4.1.3. Average drought Duration, severity and intensity for the period 1990–2022 based on SSI [03]

Fig. 8 presents the spatial distribution of the parameters characterizing droughts according to the SSI [03] in the five AEZs of Cameroon. As far as drought duration is concerned (Fig. 8a), the length of soil moisture deficit varies between values of 5 and 25 months with a general mean of duration of 6 months. These values represent the number of months of the drier than normal event between 1990 and 2022. The northern part of the SS zone has the highest deficit duration of up to 25 months implying drought persists longer in this part of the country. The Maroua subzone of the SS zone had a significantly lower drought duration that centers at below 7 months.

As for severity (Fig. 8b), the results show that drought severity varies between values of -40 and -10 . These values represent the sum of the deficits in relation to a drought threshold set between 1990 and 2022. The SS zone (particularly Lake Chad area), drought severity was very

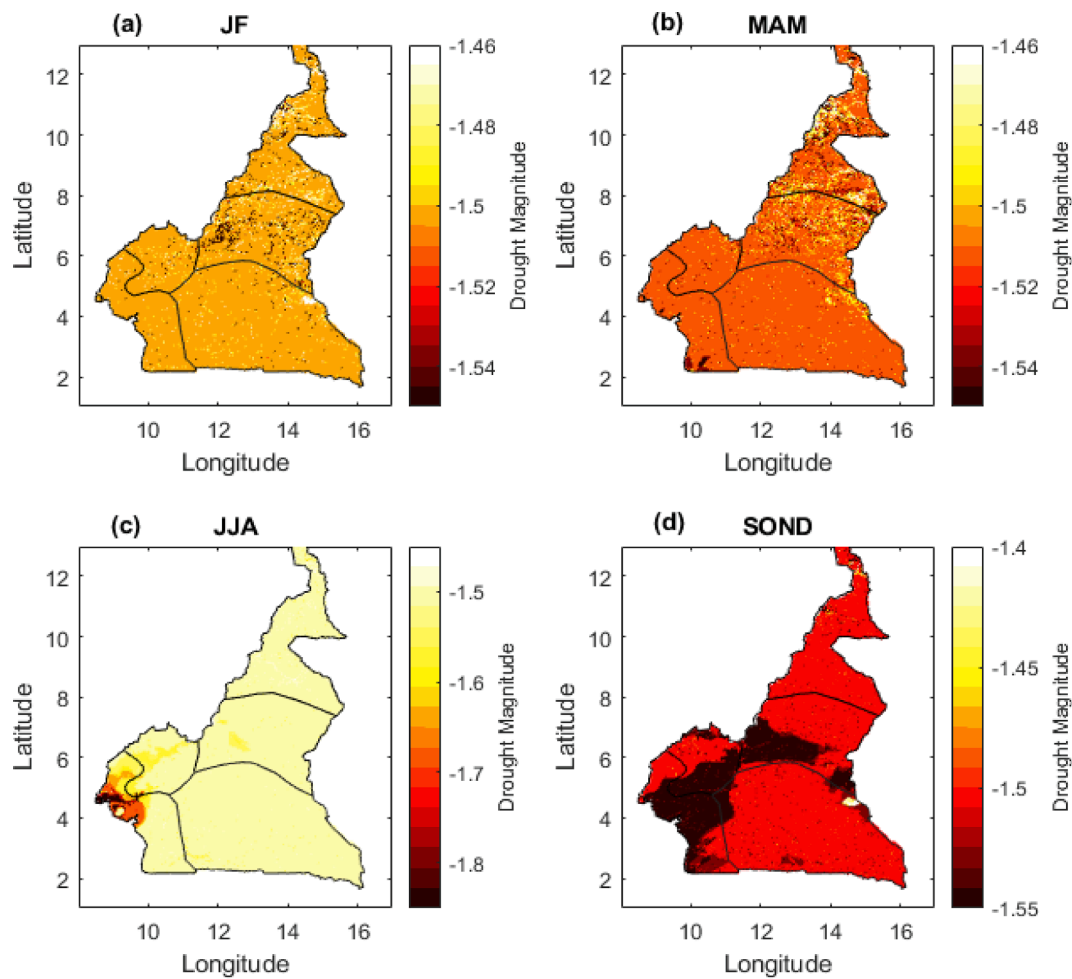


Fig. 5. Average distribution of soil moisture droughts during the major planting (Fig. 5 b and d) and harvesting (Fig. 5(a) and 5(c) seasons.

high clocking -40 mm which makes it the region with highest drought severity in Cameroon. Similarly, the severity of the drought was also remarkable in the northern part of the BF zone, particularly in the forest-savannah transition zone. However, in the rest of the country's three AEZs, drought severity remains relatively low, with values above -10 .

Regarding intensity (Fig. 8c), the results show that drought intensity varies between -1.6 and -1.2 . Drought intensity is moderately pronounced in the south, particularly in the MF and HP zones. However, in the rest of the country's AEZ, such as the HS zone, the BF and the SS zone, drought intensity remains below -1.4 but significant.

4.2. Spatiotemporal trends in soil moisture and soil moisture droughts

Fig. 9a, the 1990–2022 period was dominated by decreasing soil moisture especially in the BF, HP, HS and MF zones. The SS zone was characterized with both decreasing and increasing soil moisture trends in the Garoua and Maroua subregions respectively. However, significant trends were only observed in the MF (North and south eastern parts) and extreme north of the SS zone at an average magnitude of 0.08 mm month $^{-1}$ and 0.02 mm month $^{-1}$ respectively.

Fig. 9b shows that the SS zone was associated with positive trends in its extreme north and in the southern parts of the Garoua and Maroua subzones. Scattered negative trends were observed in the south eastern extreme of the Maroua and western stretch of the Garoua subzones of the SS zone. These trends had a mean trend magnitude of 0.0018 drought units/month and -0.0015 drought units/month respectively. Only the increasing trends were found to be significant at 5 % level of significance with a mean magnitude of 0.0015 drought units/month. From the HP

zone, significantly increasing trends in drought were dominated in the mid to northern stretch. While, a considerable portion of the south was associated with decreasing drought trends. The mean magnitude of change of droughts in the HP zone was 0.0015 drought units/month and -0.0013 drought units/month. The MF zone was both negative and positive trends in the mid and north/south extremes respectively. The positive trends were significant with a mean magnitude of change of 0.0012 drought units/month. Finally, the BF zone was dominated by positive significant trends. The mean trend magnitude in the BF zone was 0.0015 drought units/month.

4.3. Relationship between SSI [03] droughts and internal lagged climate drought indices

4.3.1. Spatiotemporal association between SSI [03] and internal climatic indices

Fig. 10 shows the correlation between SSI [03] droughts and lagged meteorological drought indices based on precipitation (Fig. 10a), Tmin (Fig. 10b), VPD (Fig. 10c), and potential evapotranspiration (Fig. 10d). Precipitation-based droughts were dominantly inclined to a strong positive correlation across the AEZs with only a marginal exception of the extreme north SS zone and areas in the lower boarder of the HP and MF zone that had weak negative correlations, weak to no correlation in the south HP, mid Monomodal, south and western strides of the Bimodal zone as well as the eastern parts of the Maroua subzones of the SS zone.

Minimum temperature-based drought extremes were associated with a balance between positive and negative weak to strong correlations across the AEZs. For example, the SS zone was associated with negative

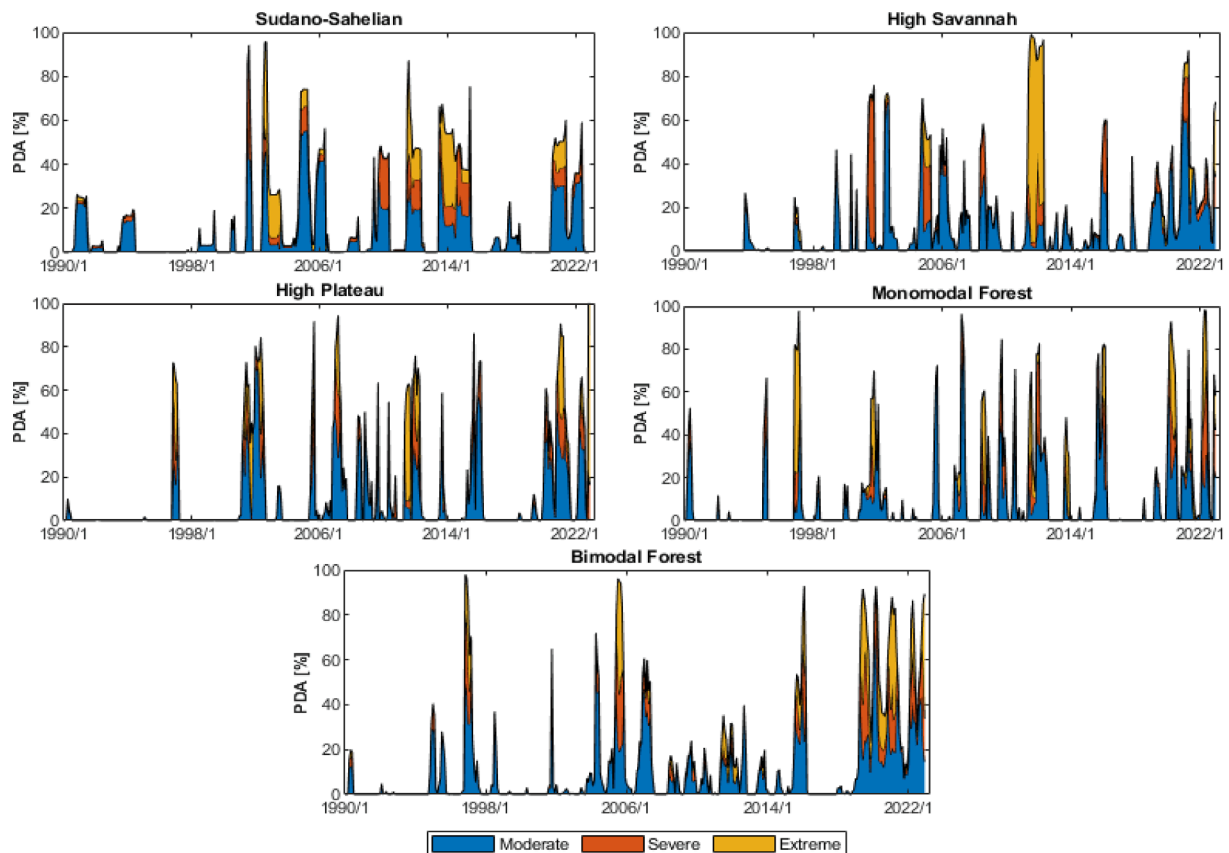


Fig. 6. Area charts showing observed soil moisture droughts classes by percent of drought area in the five AEZs for the period (1990–2022).

and positive correlations in the Garoua and Maroua subzones respectively. This balance was equally observed in the HP zone where negative and positive correlations were observed in the north and south respectively. The MF zone was on the other hand associated with a dominance of negative correlations. In the BF zone, negative correlations were observed to dominate. Finally, the HS zone was dominated by strong positive correlations.

Vapor pressure deficit-based droughts were similarly observed to exhibit alternating associations with SSI drought across the AEZs. For example, in the BF zone, strong negative correlations dominated the north, west and mid-south while, strong positive correlations were observed in the south west and north eastern parts. Monomodal Forest (MF) was dominated by strong negative correlations except the extreme south and extreme north western parts. HP zone had a balance between negative and positive correlations in the west and east respectively. The HS zone was dominated by positive correlations. Finally, negative and positive associations were observed in Maroua and Garoua subzones of the SS zone respectively.

Potential Evapotranspiration-based drought extremes were dominated by positive correlations with SSI [03] droughts across the AEZs. For example, in the MF zone positive correlations dominated with only the exception of eastern central portion. HP zone was dominated by positive correlations in the mid and northern parts. The HS zone was associated with strong positive correlations in south west, south east and eastern parts with strong negative correlations in the north. The SS zone was associated with an interplay of positive and negative correlations. Only the only the south eastern flank of the Garoua subzone of the SS zone had significant (positive) correlation. Finally, the BF zone had a fair balance of negative and positive correlation patterns spanning the central, north-west, south-eastern parts and north, south west, mid-eastern parts respectively.

4.3.2. MLR of SSI [03] and internal lagged climate drought indices

Out of the four considered internal climate variables, 3 climate indices including potential evapotranspiration, precipitation and vapor pressure deficit emerged the major drivers of Soil moisture droughts in Cameroon at a significance level of 5 % based on step-wise MLR model.

The model coefficients, t-stats and associated p-values are presented in Table 3.

The relationship could thus be presented as a multiple linear function of SSI [03] and the 3 lagged climatic indices. Equation (13) shows SSI [03] in Cameroon as a function of lagged internal climate drought indices with an explained variance of 52 %.

$$SSI[03] = 0.17(SPI[06]*SPETI[06]) + 0.17(SVPDI[06]*SPETI[06]) + 0.15 \quad (13)$$

The strength of the internal climate drivers can be explained by their paired coefficients, number of presences in pairs and overall coefficient of determination.

Furthermore, timeseries plots (Fig. 11) and scatterplots (Fig. 12) were used to visually present the performance and model error diagnostics respectively.

The error diagnostic plot indicates that there are no dependencies between the residuals and predicted SSI [03] values which implies that there are no violations to errors normality.

4.4. Spatial covariance and drivers of soil moisture anomalies in the AEZs of Cameroon

4.4.1. Eofs for soil moisture anomalies (leading 9 EOF modes)

From the EOF analysis, the nine main PCs that together account for 87 % of Soil moisture variance are shown in Fig. 13 expressed as correlations. 34.1 % and 21 % of observed covariance of soil moisture in the five agroecological zones be explained by the leading PCs PC1 and PC2

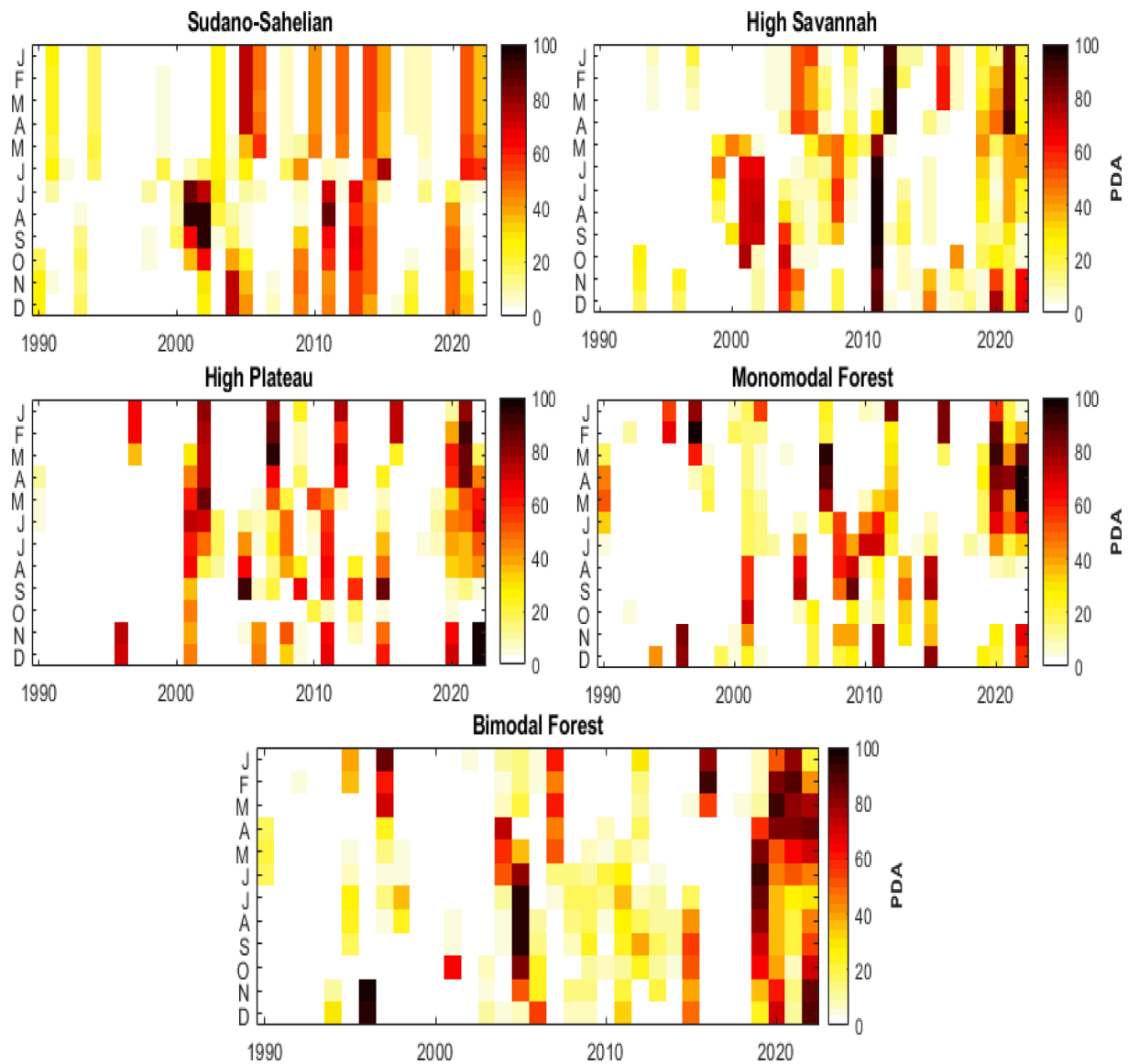


Fig. 7. Heat maps showing temporal distribution of the area under drought in the five AEZs for the period (1990–2022).

respectively. While 9.7 %, 7.1 %, 4.8 %, 3.6 %, 2.8 %, 2.4 % and 1.5 % covariance can be explained by PC3, PC4, PC5, PC6, PC7, PC8 and PC9 respectively. We observe that the 1st EOF mode that accounts for 34.1 % variance in soil moisture in both space and time for the period 1990–2022 reveals a uniform spatial covariance mainly in the HS and HP zones but with a less significant impact over the Northern part of the SS Zone. While, the second EOF (21 %) divided the country into two distinct halves. The Northern half spanning the SS, HS and northern flank of the HP zones was associated with a positive covariance while the southern half spanning the HP, MF and BF zones were associated with a negative covariance separated by a central unassociated belt. The third EOF (9.7 %) on the other hand revealed strong negative covariance in the SS zone and moderate covariance with the zones that fall below 0.5°N while the central belt had a strong positive covariance especially in the HP and Savannah zones.

Additionally, the corresponding amplitude (PC) timeseries are given in Fig. 14. All PC timeseries reveal episodes of high modulations in soil moisture over time.

4.4.2. Relationship between leading SM anomaly PCs and both teleconnections (External drivers) and lagged climatic extremes (Internal drivers)

Table 4 shows a summary of correlation coefficients between lagged climate indices and the 6 leading soil moisture anomaly amplitudes that have a combined explained variance of 80.3 %. The first EOF was associated with internal climate drivers such as PET extremes ($r = -0.35$) and Precipitation extremes ($r = 0.56$) at 5 % level of significance. This further affirms the results from the MLR model obtained earlier. The second EOF was on the other hand associated with external drivers (teleconnections) such as the AMO ($r = 0.23$), TNA ($r = -0.17$), ESPI ($r = 0.14$) and AMM ($r = -0.16$). The third EOF was associated with both internal and external drivers such as precipitation extremes ($r = 0.21$) and the ESPI ($r = 0.15$). The fourth EOF mode (7.1 explained variance) corresponded to internal drivers such as Tmin extremes ($r = -0.17$) and VPD extremes ($r = -0.17$). While the fifth (4.8 %) and sixth (3.6 %) modes corresponded to VPD extremes ($r = -0.12$) and QBO ($r = -0.16$) respectively.

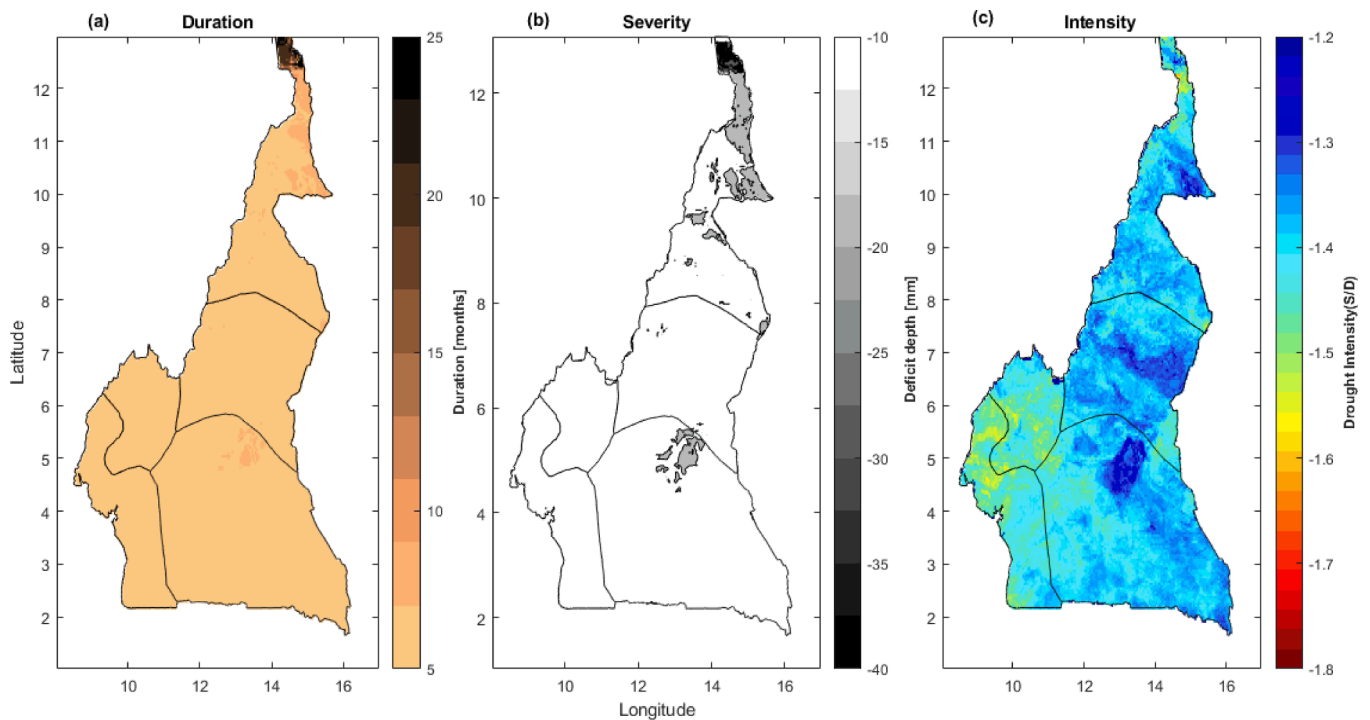


Fig. 8. Drought Duration, Severity and Intensity in Cameroon (1990–2022).

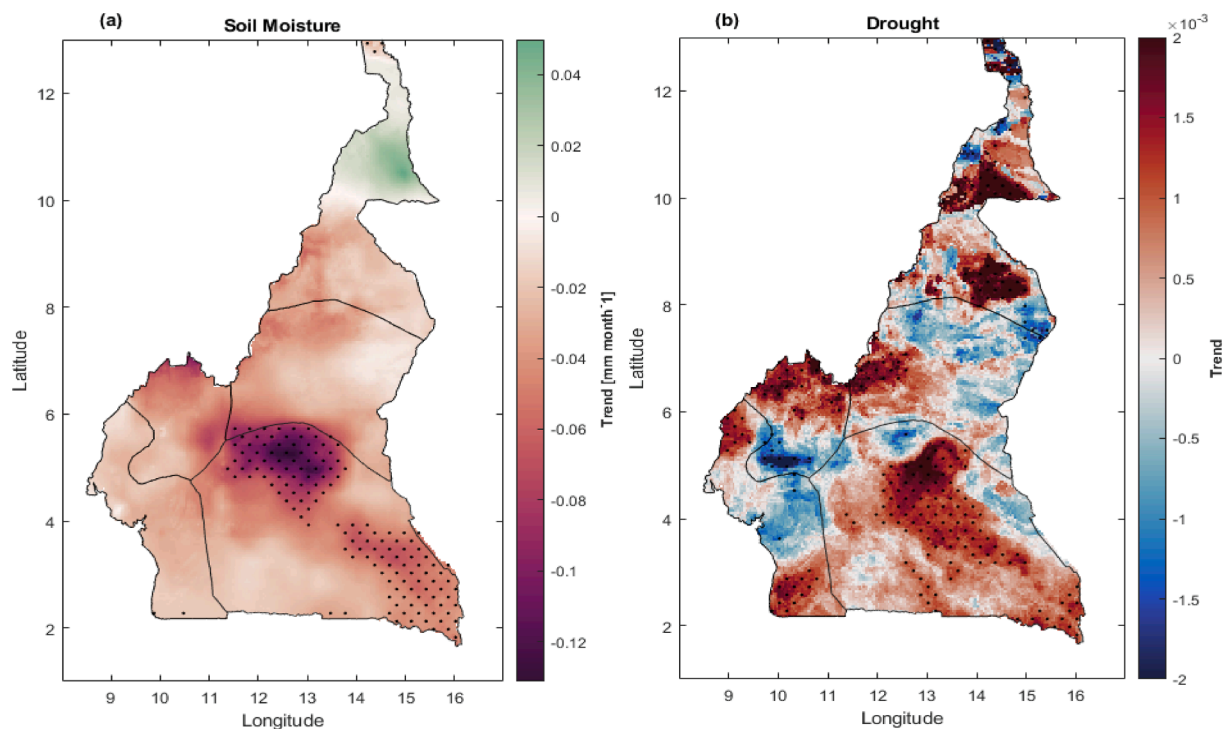


Fig. 9. Soil moisture trends 9(a) and drought trends 9(b) over AEZs of Cameroon (1990–2022). Stipples indicate areas where the trend was significant at a 95% confidence level.

Finally, spectral analysis of the 6 leading PCs (Fig. 15 Appendix) revealed an El-Nino like frequency characteristic in PC3 with periodicities of 5–7 years or 2–7 years further affirming the observed ESPI relationship.

5. Discussions

5.1. Variations in soil moisture drought distribution, Duration, severity and intensity in the AEZs

Drought during the study period exhibited high spatial and temporal patterns of variability cross the AEZs. This variability can be attributed

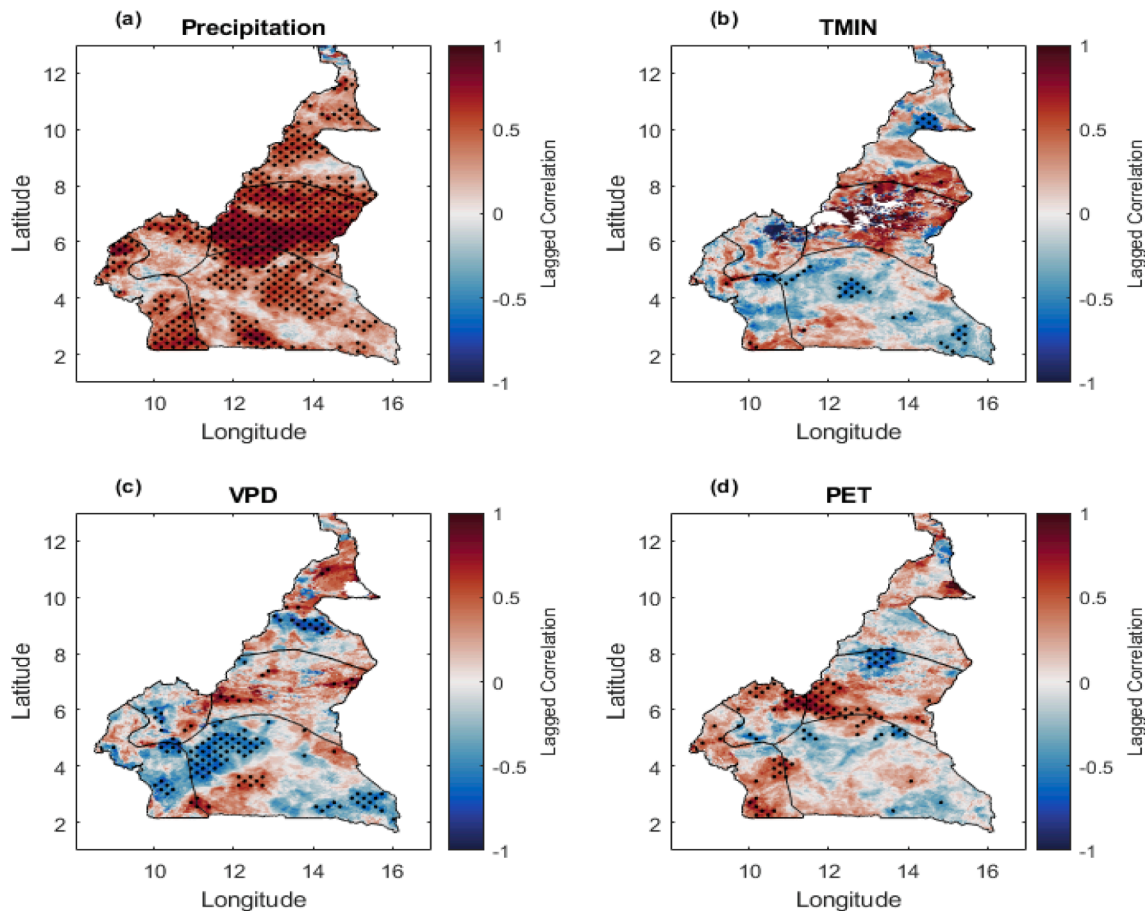


Fig. 10. Correlations between SSI [03] droughts and lagged scale 6 Climatic droughts. Stipples indicate areas where the correlation was significant at a 95% confidence level.

Table 3
Final SSI [03] MLR model coefficient and their significance.

	Estimate	SE	t-stat	pValue
Intercept	0.14557	0.022292	6.5302	2.0795e-10
SPI [06]	0.53823	0.041241	13.051	1.7333e-32
SVPDI [06]	0.046405	0.038612	1.2018	0.23017
SPETI [06]	−0.31518	0.032424	−9.7203	4.0678e-20
SPI [06]:SPETI [06]	0.17039	0.053173	3.2044	0.0014663
SVPDI [06]:SPETI [06]	0.16628	0.056913	2.9216	0.0036874

to a combination of anthropogenic and natural factors, such as soil properties, topography (Vondou et al., 2021), land-use landcover change and local climatic conditions (Brice, 2022). While the greatest percent of soil moisture droughts experienced over the five AEZs of Cameroon are of moderate magnitude ($-1 > -1.5$) at an average coverage of 10 %, the spike in severe and extreme droughts during mid 2000's, early and late 2010's present a huge concern to both agricultural and pastoral sectors that dominate the country's economy especially the Sahelian zone. For example, there's evidence on the migration of herders, modification of the agricultural calendar, loss of biodiversity and reduction in crop yield which is the main source of sustainability to the rural population in the northern part of the country (Ntali et al., 2023). Furthermore, the observed longer drought duration and high severity especially in the BF and SS zones may disrupt crop growth cycles and hinder agricultural productivity due to the low soil moisture levels necessary for crop growth consequently contributing to food insecurity. These findings are consistent with Njounwet et al., (2021) that found high risks of agricultural drought in the SS region during the cropping season. In summary and contrary to current beliefs and

perceptions, the MF and HP regions experienced stronger drought magnitudes than the HS and SS zones. This is an eye opener for disaster managers and policy planners as these zones have previously neglected in disaster preparedness terms. Additionally, the largest areas of farmland are in the Bimodal and MF zones necessitating the modification of the agricultural calendar in these zones to abate drought impacts.

5.2. Variations in observed changes in soil moisture and soil moisture droughts

The evolution of soil moisture droughts in five AEZs of Cameroon presented relatively complex behaviors that did not conform to regular perfect linear relationships between soil moisture and its extremes. For example, the dominant decrease in soil moisture over 65 % of Cameroon was not fully reflected in the observed increasing drought patterns across the AEZs. Specifically, the observed increase in soil moisture in the Garoua subzone of the SS zone could not conform to the corresponding increase in droughts over the central and flank of the Garoua subzone. Nevertheless, the observed decrease in soil moisture could be attributed partly to subsequent decreases in precipitation in the AEZs of Cameroon (Brice, 2022) and, increases in evaporative demand (Vicente-serrano & Beguería, 2014) especially in the south eastern region of the HS, and the bordering regions of Bimodal, Monomodal and HP zones. The observed decrease in droughts in western parts, northern and south eastern edges of the SS zone, north-east, central and western parts of the HS, north and eastern parts of the Bimodal, mid Monomodal and southern flank of the HP zones presents hope to the pastoral and agricultural communities in these regions for the increased availability of water for both animals, pasture and crop growth (Maroti, 2022). The

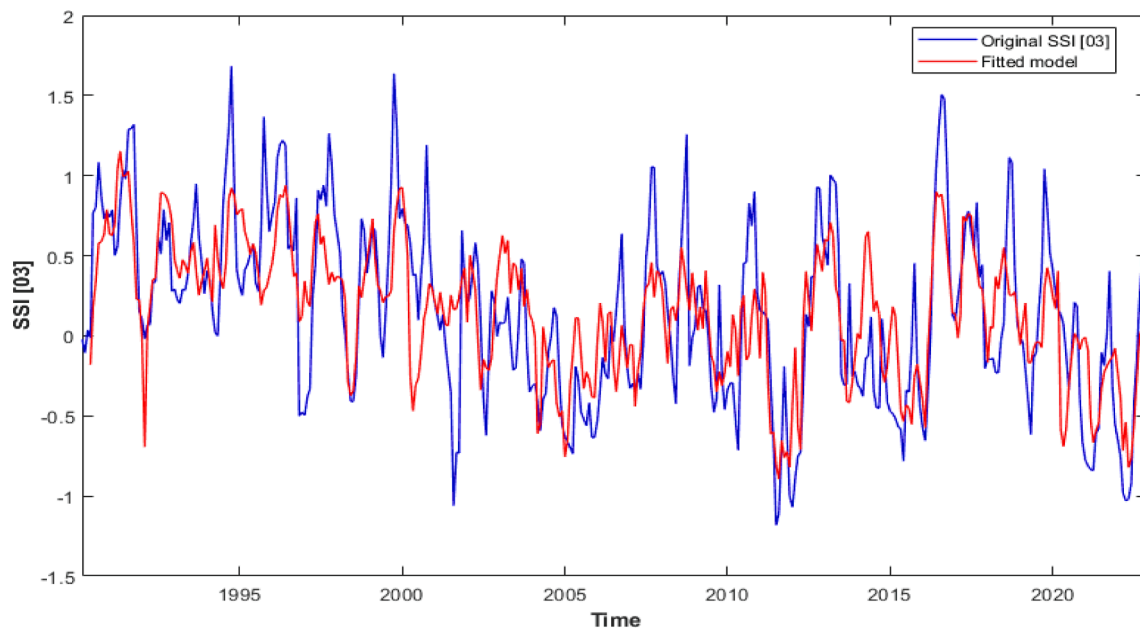


Fig. 11. Comparison of SSI[03] (blue line) and Simulated SSI[03] (red line) based on internal drivers. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

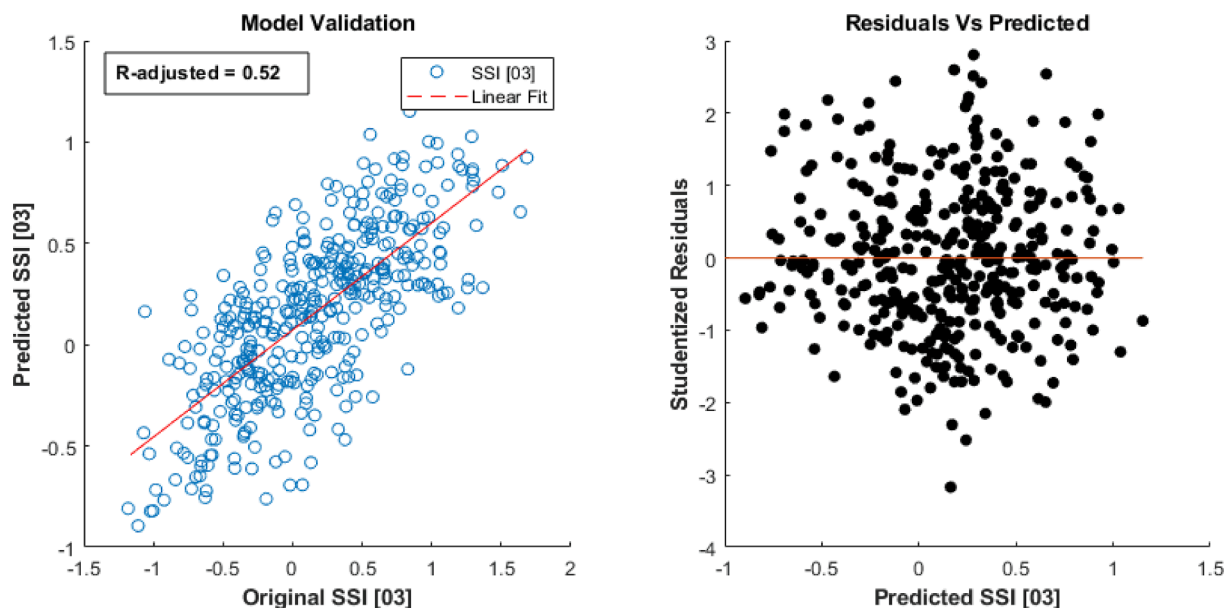


Fig. 12. Model Validation (L) and Model error diagnostics (R).

increasing drought manifestation over the remaining 65 % of the country driven by soil moisture reductions may threaten food security (Tingem et al., 2008; Ntali and Lyimo, 2022) and livelihoods (Bomdzele and Molua, 2023) of over 27 million inhabitants (UNICEF, 2024) of Cameroon. The observed changes are also expected to worsen bushfires, as well as the current internal displacement and regional crises especially in the far Sahelian-Sudano, Bimodal and MF Zones (UNICEF, 2024).

5.3. Internal climatic drivers of soil moisture droughts

One of the major achievements of this study was the demonstration of the empirical relationship of climatic extremes and soil moisture droughts over the five AEZs of Cameroon. Our findings partly

corroborate similar researches in Cameroon (PNACC, 2015), in the region (Masih et al., 2014) and over several semi-arid areas. However, it can be deduced in this study that precipitation negative extremes are not the sole drivers of drought in Cameroon as PET equally contributed. Precisely, PET plays a double role both in intensifying precipitation deficits and elevating the evaporative demand of the atmosphere hence contributing to soil moisture deficits. This role has equally been underscored by Vicente-Serrano & Beguería, (2014), Voda et al. (2018) and Omondi & Lin, (2023). These results imply that soil moisture extremes with emphasis on negative deficits in the five agroecological zones of Cameroon are majorly driven by elevated evaporative demand represented by positive VPD and PET anomalies, and precipitation. As such, adoption of farming practices and water conservation methods that reduce the evapotranspiration rates is recommended as an effective

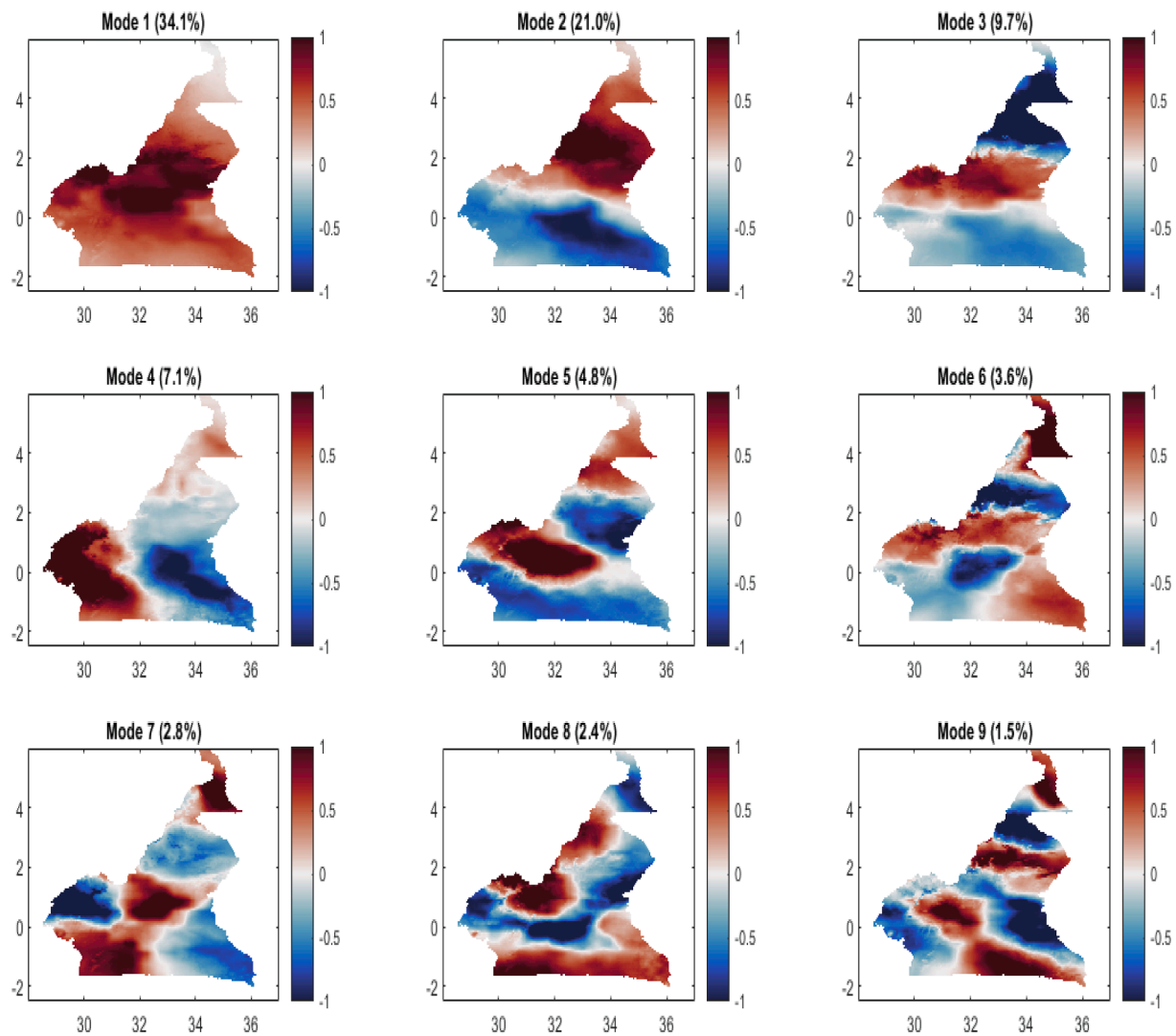


Fig. 13. The Leading 9 EOF modes expressed as Pearson's correlation coefficients and their associated explained variance.

measure of the increasing agricultural droughts in mainly the previously neglected Agroecological zones 2, 3, 4 and 5.

5.4. Spatiotemporal variation and the role of teleconnections in soil moisture extremes

Soil moisture over Cameroon's AEZs exhibited complex pattern of variance in both space and time. Its fluctuations were largely internally driven. However, several external teleconnections such as AMO, TNA, AMM and ESPI were similarly influential in variability. Previous studies by [García-García and Ummenhofer, \(2015\)](#) and [Tao et al., \(2021\)](#) although at a continental level, linked the AMO to climate extremes such as precipitation extremes over the sub-Saharan belt between 20° N and 2° N. [Masih et al., \(2014\)](#) found links between hydrological droughts and ENSO phenomena in the sub-Saharan region. Similarly, [Omondi & Lin, \(2023\)](#) successfully connected SPEI-based droughts to ENSO events. These results not only inform effective drought planning and management interventions but also help boosting the forecasting capacity of the Cameroonian climate and water management agencies for agricultural droughts with a good lead time.

This study boosts self-validatory characteristics given the compound adopted approach. Nevertheless, further studies on other drivers using higher resolution data, varying time-scales and non-meteorological variables such as land-use land-cover are highly recommended.

6. Conclusions

In conclusion, this study revealed a general increase in the percent of drought area (PDA) over Cameroon in the last four years averaging at 48 % especially in the months of August, December and January and, a significant increase in droughts for over 65 % of the country at 5 % level of significance with a strong internal association with lagged precipitation, evapotranspiration, vapor pressure deficit and minimum temperature. A predominance of moderate to severe droughts in most parts of the MF AEZ was also demonstrated. Potential evapotranspiration, precipitation and vapor pressure deficit were the major drivers with a 52 % coefficient of determination which together corresponded to the first Empirical Orthogonal Function (EOF) mode accounting for 34.1 % explained variance. Externally, the second EOF mode (21 % explained variance) was associated with atmosphere-oceanic teleconnections including Atlantic Meridional Mode, Tropical North Atlantic Index, EL-NINO Standardized Precipitation Index and Atlantic Multi-decadal Oscillation Index. While as, the third EOF (9.7 % explained variance) corresponded to both precipitation and ENSOs.

The results of this study would not only effectively contribute to drought planning and management but also help in boosting the forecasting capacity of the Cameroonian climate and water management agencies for agricultural droughts with a good lead time hence increasing resilience. We further recommend investment in climate

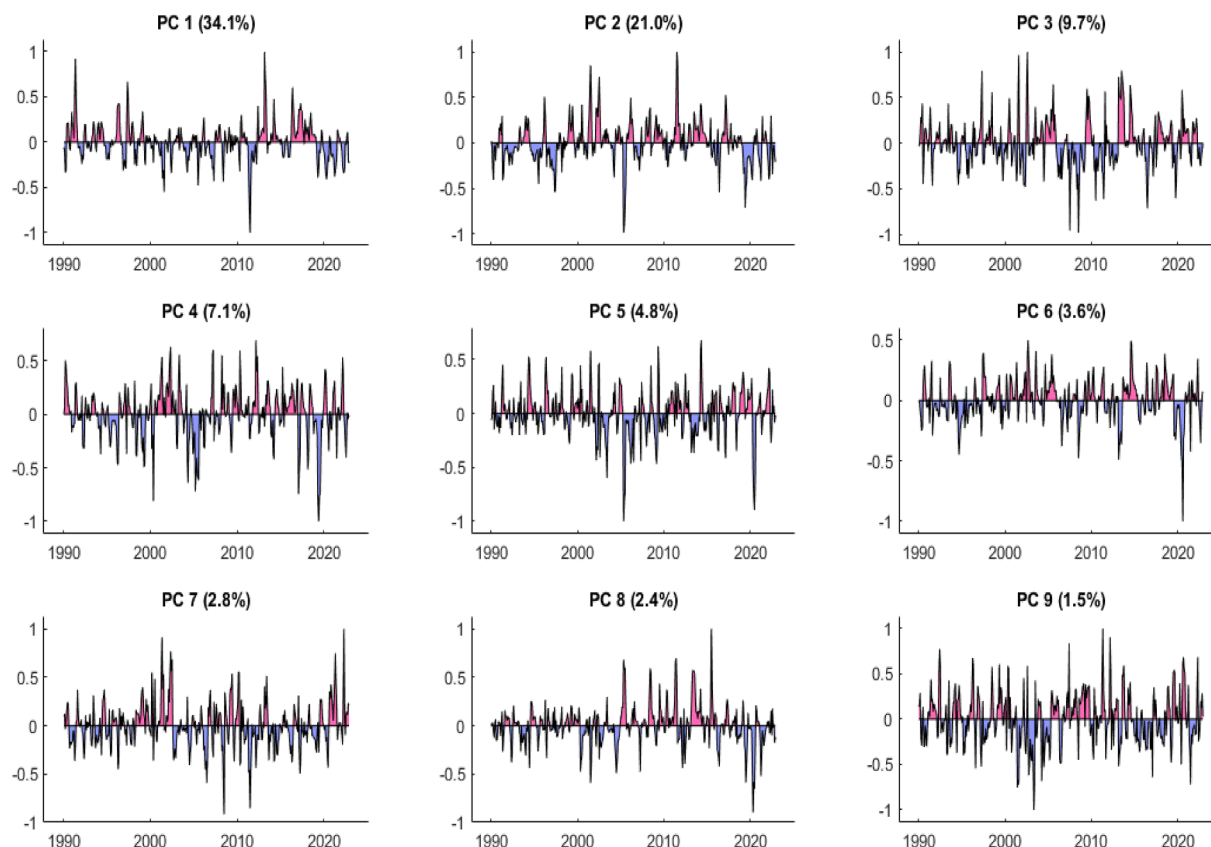


Fig. 14. Timeseries of the 9 leading PCs.

Table 4

Pearson's correlation coefficients(*r*) between Soil moisture anomaly Principal components and both lagged internal and external drivers.

Principal component/Drivers	QBO	AMM	TNA	NOA	ESPI	AMO	STMINI > 1	SPI < -1	SPETI > 1	VPDI > 1
PC1	0.0296	-0.0306	-0.0991	-0.0315	0.0518	-0.0704	0.1218*	0.5559***	-0.3520***	-0.0551
PC2	-0.0342	-0.1604**	-0.1700**	-0.0138	0.1422**	0.2290***	0.0070	0.0690	0.0111	-0.0003
PC3	0.0729	-0.0430	-0.0696	-0.0424	0.1456**	0.0358	-0.1158*	0.2140***	-0.0347	-0.1125*
PC4	0.0996	0.0160	0.0075	-0.0345	-0.0038	-0.0655	-0.1780**	-0.0767	-0.0241	-0.1670**
PC5	0.0129	0.1191	0.1239	-0.0622	-0.0618	0.1277	0.0590	-0.0775	0.1244	-0.1234*
PC6	-0.1610**	0.0141	0.0055	-0.0344	-0.0474	-0.1339	-0.0483	0.0099	-0.0109	-0.0331

Significance codes $P < 0.0001$ (***), 0.001 (**), 0.01 (*).

smart practices and precision agricultural technologies to abate drought consequences using the little available moisture.

CRedit authorship contribution statement

Ronald Ssembajwe: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jovis Nguetack:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Karol Lavoine Mezafack:** Writing – review & editing, Writing – original draft, Validation, Conceptualization. **Godfrey H. Kagezi:** Writing – review & editing, Supervision, Resources. **Anthony Gidudu:** Writing – review & editing, Resources. **Geoffrey Arinaitwe:** Writing – review & editing, Resources. **Mihai Voda:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

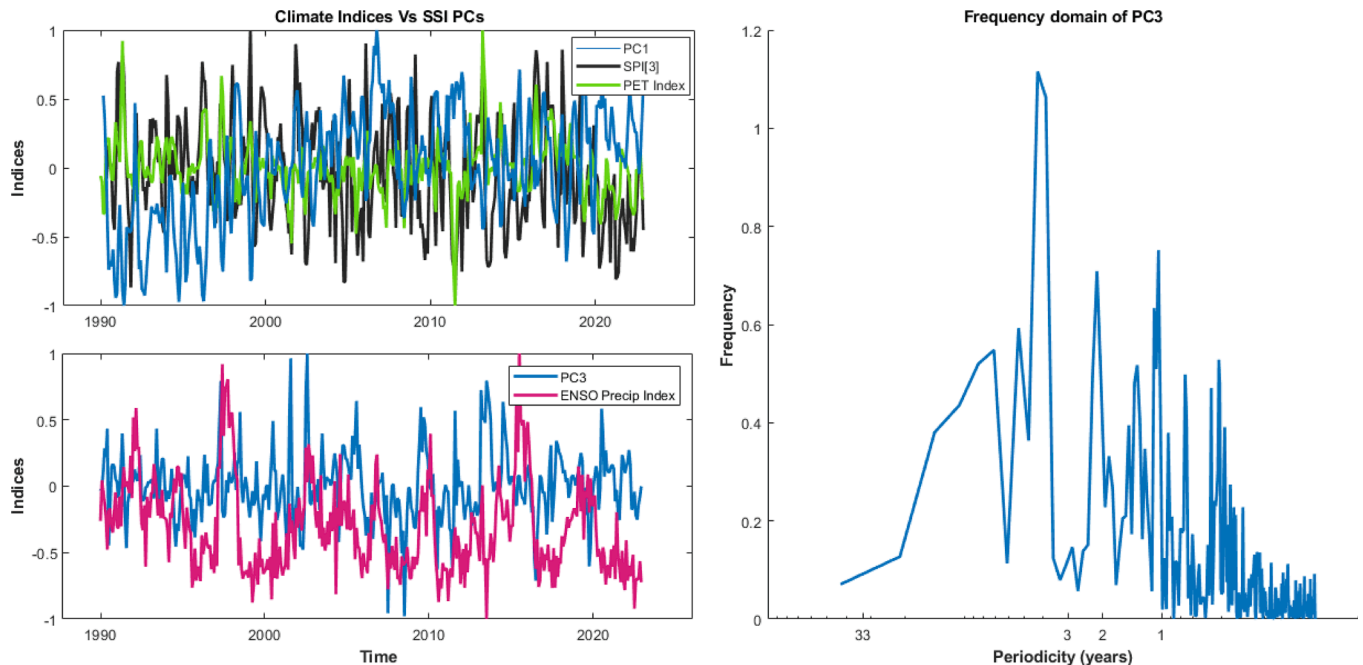


Fig. 15. Comparison of Principal Components and climatic drivers (L), and Frequency analysis of the third PC.

Data availability

Data will be made available on request.

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