CLIMATIC PATTERN ANALYSIS OF RAINFALL AND DRY SPELLS DURING THE AGRICULTURAL SEASON IN MALAWI

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Abstract. The study identified the basic structural characteristics of dry spells, seasonal, and extreme rainfall events to offer localized information which in data-scarce regions is typically extrapolated from syntheses of regional or satellite climate data. Utilizing observed daily station rainfall datasets from the rainy season (November to April) spanning the years 1961 to 2007, a set of indices including percentile, absolute, threshold, and duration measures, resulting in 16 indices, was derived for locations at low (Balaka), medium (Bunda, Chitedze, KIA), and high (Dedza) altitudes in Malawi. For each site, a separate analysis was conducted in which the indices were subjected to principal component analysis, followed by composite analysis and K-means clustering of the extracted principal components. Climatic patterns at Bunda and KIA were predominantly characterised by wet events, whereas Dedza, Chitedze, and Balaka exhibited patterns defined by the characteristics of the growing season coupled with dry events, and wet events were of secondary importance. Notably, in Balaka, wet events had a significant influence on the rainfall regime, indicating a location prone to compound events. Key indices that defined climatic patterns included the number of wet days, wet pentads, maximum one-day rainfall, extreme intensity, extreme percentage, 6 to 10 and ≥ 15 days dy spells, length, and end date of the growing seasons. The results highlight that climatic frameworks for analysing rainfall and dry events must consider multi-index analyses and cannot be uniformly applied across geographically diverse areas or assumed to be homogeneous within regions.

Keywords: Climate, dry spells, K-means clustering, Malawi, principal component analysis, rainfall

INTRODUCTION

Malawi's climate is classified as semi-arid, characterised by spatio-temporal variations in rainfall that result from altitude, relief, and lake effects (Tadeyo et al., 2020). The country's dependence on rain-fed agriculture renders it particularly vulnerable, as it experiences only one rainy season annually, leading to a single major harvest. This situation becomes precarious in the event of rainfall extremes (Libanda et al., 2017). To enhance resilience against the uncertainties of weather, sustainable land management practices, such as climate-smart agriculture, have been promoted among small-scale farmers (Dougill et al., 2017). However, these advancements have not been accompanied by thorough evaluations of their appropriateness across different agroecological zones, each with its unique spatial and temporal rainfall patterns. Previous research has identified a significant knowledge gap in understanding rainfall characteristics, especially in many developing countries (Hubertus et al., 2023). At the field level, an understanding of rainfall variability is essential for the formulation of policy choices, as well as the implementation of adaptation and mitigation strategies, and making location-specific management decisions (Moore et al., 2016).

The failure to effectively establish and interpret signals for climatological features, such as rainfall and dry spells, represents a significant initial barrier to effective adaptation. This has implications for whether an adaptation response is initiated and the type of response selected (Moser and Ekstrom, 2010; Eriksen et al. 2021). Even in regions considered climatically homogeneous, seasons with similar rainfall totals can exhibit markedly different rainfall patterns (Nicholson et al., 2014). This variability is attributed to the complex interplay of atmospheric, terrestrial, and marine factors, including sea-surface temperatures, wind patterns, geomorphic features, and teleconnections, particularly the El Niño Southern Oscillation (ENSO) (Jury, 2013; Hoell et al., 2014). Thus, a detailed examination of the variable characteristics of rainfall and dry spells in historical records is essential. Such analysis is needed to enhance the availability of seasonal prediction products and to increase the specificity of predictions that are both temporally and geographically precise (Chimimba et al., 2023; Libanda et al., 2017). Additionally, this would support agricultural and natural resource management interventions that currently depend on near real-time observations, measurements, and responses.

There is a significant body of recommendations advocating for an integrated assessment approach to address climate extremes and vulnerability at both the national and local levels in the Southern Africa region (Ericksen et al., 2021). From the perspective of rural households, such analyses are crucial at a scale that targets specific geographic locations, enabling rural dwellers and their representatives to learn effective strategies for tackling climate extremes (Vogel et al., 2007; Godsmark et al., 2019). Our work is in response to such local-level analytics that is aimed at rural agents who need to address practical questions concerning seasonal rainfall and dry spells, and to provide information and field services for climate and weather adaptation strategies. Moreover, the results address the concerns of climate science experts who consistently criticize the lack of spatial instrumentation coverage. It emphasizes the need to invest in and enhance climate data harnessing capabilities, thereby generating higher quality and innovative products and services at local levels.

Characterising climatological features for rainfall and dry spells is possible by identifying and measuring a variety of indices of various types, as well as computing subsidiary indices, which are specific properties and processes defined by local, regional, and global atmospheric and geomorphological systems. The issue is often to completely analyze huge datasets to avoid information loss, while also individuating the estimation of a large number of indices capable of best characterizing rainfall quality (Stellacci et al., 2012). Among feature selection approaches, principal component analysis (PCA) has been used to select representative minimum datasets that frequently account for about the same amount of information as a much larger collection of original data often encountered in climatic observations. This statistical technique has a long history in precipitation studies, where it is used to pre-filter data sets for subsequent applications (Widmann and Schar, 1997), identify temporal or spatial precipitation patterns (Ngongondo et al., 2011a; Libanda et al., 2017), or climatic regionalization (Almazroui et al., 2013, Nicholson et al., 2014).

However, there is no consensus on the optimal strategy for selecting interpretable results in PCA, a gap highlighted by Peres-Neto et al. (2005). This challenge is frequently addressed through the cross-validation of PCA with other supervised methods in multivariate group designs to ascertain the structure and relative importance of outcome indices (Sajobi, 2020; Stellacci et al., 2012; Jombart et al., 2010). In this paper, we propose an integrated approach that combines PCA, composite analysis, and sequential K-means clustering. This methodology characterizes and valorises climatological features of rainfall and dry events. It supports site-specific, station-based analyses, which often record a limited subset of indices in countries with limited weather instrumentation. It analyzes five precipitation time series from stations in three representative agroecological zones in Malawi, continuously operating at a daily resolution from 1961 to 2007. To capture various properties of precipitation, we utilize a suite of seasonal and extreme indices expressed in percentiles, absolute values, thresholds, and durations. The percentile indices—extreme intensity, extreme frequency, and extreme percentile—as discussed by Haylock and Nicholls (2000), have not been extensively examined in Malawi. The study focuses on the rainy season to improve the availability of data for rain-dependent agricultural and hydrological applications. The organization of our paper is as follows: Section 2 introduces the research region, data and analyses; Section 3 presents the results; and Sections 4 and 5 offer the discussion and conclusions, respectively.

MATERIALS AND METHODS

Geographic profiles of study locations

The meteorological stations utilized represent three broad agroecological zones. Kamuzu International Airport (KIA), Chitedze Agricultural Research Station (Chitedze), and Bunda College (Bunda) in the north, central, and south of Lilongwe, respectively, represented the mid-altitude zone. Dedza and Balaka correspondingly represented the high and low altitude zones. Table 1 provides a summary of the features of these stations, while Figure 1 illustrates the locations of the five meteorological stations.

Table 1

List of meteorological stations and their geographical features

S/N	Station name/type	WMO ID	Latitude (S)	Longitude (E)	Altitude (m. a. s. l.)	Annual rainfall (mm)	Annual temperature (°C)
1	Balaka, gauge	-	14° 98'	34° 97'	625	801	25
2	Dedza, reference	67689	14° 32'	34° 25'	1,590	970	16
3	Bunda, gauge	-	14° 18'	33° 77'	1,118	1030	21
4	Chitedze, reference	67585	13° 97'	33° 63'	1,149	868	20
5	KIA, synoptic	67586	13° 78'	33° 78'	1,229	944	21

The stations at Bunda, Chitedze, and KIA are located on the extensive, undulating Lilongwe plain in Central Malawi, which ranges in elevation from 1,000 to 1,400 meters above sea level (m.a.s.l.) and comprises 6.5% of Malawi's total land area (Lorkeers and Venema, 1991). This zone is known as the 'breadbasket' of the country, where maize, the staple cereal, is the principal crop grown in the deep, fertile latosols characteristic of the plain. It is characterized by a longer growing season and cooler temperatures and the rainfall is generally considered good.

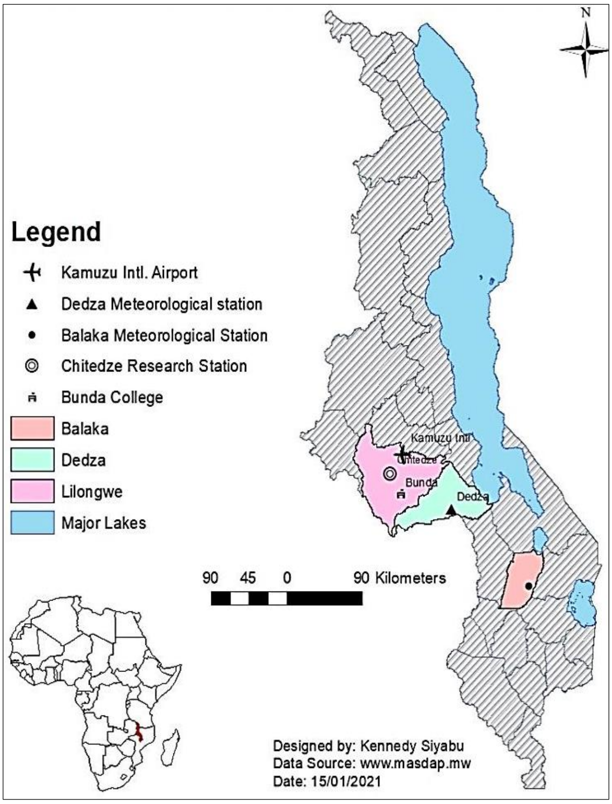

Fig. 1. Map of Malawi showing location of the five meteorological stations used in the study

Dedza is situated at the foot-slopes of the Dedza Highlands (2,200 m.a.s.l.) and represents the highest point in Central Malawi, rising proximally to the western arm of the Lake Malawi basin. Both the relief and the lake significantly influence the climate over Dedza, typically resulting in elevated rainfall (McSweeney et al., 2010). Balaka, located in Southern Malawi, lies on an extensive low-land plateau with isolated hills, ranging in elevation from about 350 to 800 m.a.s.l., covering 2.5% of the country's total land area (Venema, 1991). Balaka is considered highly vulnerable to climate hazards, including both drought and flooding (Mloza-Banda et al., 2016).

Datasets

Daily rainfall datasets, prescreened for November to April over 47 years from 1960/61 to 2006/07, were obtained for recording stations at KIA, Chitedze, Bunda, Dedza, and Balaka under the auspices of Malawi's Meteorological Services Department and the Famine Early Warning Systems (FEWS) Malawi program. These datasets underwent several basic quality-control procedures by the agencies, adhering to World Meteorological Organization (WMO) standards. Datasets spanning 30 years and above are considered optimal for climatological studies, with the period from 1961 to 1990 designated as the reference epoch for studies related to climate change (WMO 1988, 2009). The data period also falls within the 1948-1988 interval, which is consistent with the most rapid apparent global warming of the 20th century (Lattenmeir et al., 1994). Several studies have conducted climate analyses using data from the same period (Ngongondo et al., 2011; Fiwa et al., 2014; Warnatzsch and Reay; 2019)

Rainfall indices

The indices listed in Table 2, which were used in the study have previously been applied in regional climate studies in Southern Africa (Usman and Reason, 2004; New et al., 2006; Stern and Cooper, 2011). The Expert Team on Climate Change Detection and Indices (ETCCDI) advocate for employing indices that capture diverse facets of global climate change, such as variations in event intensity, frequency, and duration (Alexander, 2016). They recommend including indices representing recurrent seasonal or annual events for their robust statistical attributes, alongside measures of extreme events that might not occur annually.

Table 2

Description of selected seasonal and extreme rainfall indices (DP = daily precipitation amount)

Index name	Description	Units
Threshold indices		
Wet days	Seasonal total number of wet days (DP > 0.85 mm)	Days
Dry days	Seasonal total number of dry days (DP < 0.85 mm)	Days
Onset of growing season	First occasion from 1 November with 20 mm or more of rain within 3 days and no dry spell exceeding 10 days in the following 30 days	Date
End of growing season	Last day before May 30 that accumulated 10 mm or more rainfall	Date
Duration indices		
Wet spell/pentad	Five consecutive days with more than 4.25 mm of rainfall	Number
Dry spell	Five consecutive days with less than 4.25 mm of rainfall	Number
Growing season length	Date of the beginning from the date of the ending of the growing season	Days
Absolute indices		
Maximum 1-day rainfall	Seasonal maximum precipitation in 1 day	mm
Maximum 5-day rainfall	Seasonal maximum precipitation in five consecutive days	mm
Percentile-based indices		
Extreme intensity	The average intensity of events greater than or equal to the 1961-2007 mean 95th percentile of the wet days	mm
Extreme frequency	The number of days in the season with rainfall exceeding the 1961-2007 mean 95th percentile of the wet days	days
Extreme percent	The proportion of total seasonal rainfall from all events above the average long-term 1961-2007 mean 95th percentile of the wet days	%
Other indices		
Seasonal rainfall	Seasonal total precipitation from wet days (DP≥0.85 mm)	mm

The frequency of wet and dry days was determined based on counts for each season, not by the difference method used by Kimaro and Sibande (2008), to avoid the confounding effect of zero cases. Secondly, a day with zero precipitation was not counted as a dry day; instead, a day with less than 0.85 mm of rain was considered dry. A wet spell/pentad was defined as five days with more than 4.25 mm of rainfall, based on the minimum value for a wet day of 0.85 mm of rain, and the opposite was defined for a dry day/spell (Usman and Reason, 2004). Dry spells of different durations were consistently determined based on the definition of the 5 days mentioned above. The total number and/or duration of days for 5-day, 6-to-10-day, 11-to-15-day, and more than 15-day dry spell occurrences were calculated. These thresholds were adopted following (Malvern et al., 2012), who found that dry spell lengths of 7 days can cause stress to shallow-rooted crops, 10 days to medium-rooted crops, 15 days to deep-rooted crops, and 20 days to almost all crop root categories. The length of the growing season was calculated by subtracting the start date from the end date of the growing season.

The start date of the season was defined as the first instance after November 1st when 20 mm or more of rain fell within 3 days, with no subsequent dry spell exceeding 10 days in the following 30 days. This definition is a modification from Stern and Cooper (2011), who used November 15th as the starting point. The end date of the season was identified as the last day before May 30th on which there was an accumulation of 10 mm or more of rainfall.

Principal Component Analysis

Principal component analysis in spatial mode (S-mode) using Statistica software (StatSoft Inc., 2020, Tulsa, OK, USA) was performed to identify principal directions in which data varied and to reduce the dataset to interpretable size by identifying factors that contain most of the variance of the associated with the original 16 rainfall indices (Starkweather, 2011). The PCA approach was motivated by arguments that the eigenmodel PCA is a scientific tool that decomposes indices into invariant modes of variation, which are considered to be fundamental elements in explaining the relationships among the indices and to some extent PCA represent the true modes of variation (Demsar et al., 2013). Often analyses are reported with 60-70% as an acceptable level of variance explained by the PCA model. Principal components (PCs) with eigenvalues > 1 were retained and those with eigenvalues < 1 were not considered further as they could explain less variance than that for a measured climate attribute. In each PC, a rainfall/dry spell attribute with a high factor loading of ≥ 0.5 was considered the best representative of each series. The procedure resulted in a reduction in the number of indices from 15 to 11 at both Balaka and Dedza. A reduction from 16 to 14, 13 and 12 indices was obtained for Bunda, Chitedze and KIA, respectively.

Composite analysis

The study employed a composite analysis method and sequential K-means analysis of principal components, which necessitated data transformation using PCA as a preliminary step, thereby ensuring that the indices analyzed were perfectly uncorrelated (Jombart et al., 2010). The composite analysis procedure first converted data on rainfall and dry event indices normalized using PCA, into a numeric value that transcended a mere static descriptor (Sharma et al., 2008). The process generated coefficients facilitating the ranking of variable sets according to their contribution to the principal components (PCs) or the delineation of groups or clusters. Additionally, this method allowed for the meaningful combination of these elements into a single index, enhancing the precision of assessing the PCs and series. Each PC accounted for a certain percentage of the variation in the total dataset for each series. This percentage, when divided by the total percentage of variation explained by all PCs for the series, provided the weighted factors for a given PC. The weighted factor values were then multiplied by the variable weights or loadings for the corresponding PC to yield scores. After completing these steps, to calculate a composite score for each PC, the scores for each index constituting each PC were aggregated.

Sequential K-means clustering

Sequential K-means clustering, utilizing scores obtained from composite analysis, was conducted to achieve statistical differentiation and grouping of indices for each PC which enabled identification of those that significantly contributed to each selected PC. The procedure uses a statistical framework similar to Discriminant Analysis or Discriminant Analysis of Principal Components, based on a classical ANOVA model (Jombart et al (2010). In our work, we run the approach with varied numbers of clusters, each producing a unique statistical model and related likelihood. To prevent the creation of incorrect groups based on scores from indices that inherently share little common variance, we employed an iterative method. This approach concentrated on choosing the most reliable model and grouping indices that initially had loadings of at least ≥0.5. As a result, the statistical findings from the cluster analysis are based solely on indices identified through PCA with communalities above the predetermined threshold loading. According to SPSS (2020), the F-tests in the K-means clustering procedure serve descriptive purposes, aimed at maximizing differences among clusters. The observed significance levels are not adjusted for this usage and should not be interpreted as hypothesis tests.

RESULTS

Long-term mean and variation in seasonal rainfall and dry spell events

The mean and coefficient of variation for seasonal (November – April) rainfall and dry spell events from 1961 to 2007 are summarized in Table 3. Among the wet indices, the maximum 5-day rainfall (Rx5day) displayed the highest (CV = > 0.30 - 0.50) to extreme variability (CV > 0.50), while the extreme proportion (RXP) showed the lowest (CV < 0.20) to moderate variability (CV = 0.20 - 0.30) across locations. For dry indices, the number of 5-day dry spells exhibited the highest variability with 11 to 15 dry spells showing the lowest. The average length of dry spells across different classes was largely consistent across locations. The median onset dates of the season were within one pentad, i.e., 22-27 November, whereas the median end dates of the season fell within the pentad of 7-17 April. The length of the growing season varied between 129 to 137 days and showed low variability across the study locations. Dedza recorded the highest number of indices with low variability (CV < 0.20).

Table 3

Mean and variation of seasonal rainfall and dry spell events for (November – April) 1961-2007

Seasonal climatological features for rainfall	Balaka		Dedza		Bunda		Chitedze		KIA	
	Mean	CV	Mean	CV	Mean	CV	Mean	CV	Mean	CV
Wet indices										
Seasonal rainfall (mm)	795.3	0.29	878.0	0.18	872.0	0.24	835.1	0.22	793.6	0.21
Max 5-day rainfall (mm)	104.0	0.62	118.5	0.42	91.0	0.53	106.4	0.35	108.8	0.45
Max 1-day rainfall (mm)	72.1	0.32	69.9	0.31	64.2	0.30	71.5	0.28	66.0	0.35
Number of wet pentads	2.2	0.23	4.7	0.24	2.7	0.24	3.3	0.54	3.0	0.22
Number of wet days	49.0	0.29	68.0	0.17	59.0	0.23	62.0	0.19	60.0	0.15
Extreme intensity (mm)	48.2	0.29	43.4	0.19	44.2	0.20	47.7	0.19	43.3	0.21
Extreme frequency (days)	2.8	0.32	2.7	0.33	2.9	0.36	2.6	0.30	2.9	0.30
Extreme proportion (%)	43.1	0.19	34.4	0.14	35.8	0.25	35.4	0.20	38.2	0.13

Dry indices										
Number of dry days	82.0	0.23	59.0	0.26	75.0	0.24	63.0	0.29	61.0	0.32
5-day dry spells	1.6	0.53	1.8	0.48	2.0	0.47	1.5	0.39	1.8	0.48
6 to10 days dry spells	7.4	0.17	7.4	0.18	7.6	0.18	7.7	0.19	7.6	0.17
11 to 15 days dry spells	12.6	0.10	12.4	0.10	12.7	0.13	12.8	0.11	12.6	0.10
>15 days dry spells	20.1	0.23	18.2	0.17	20.2	0.18	17.8	0.13	19.4	0.20
Timing of season										
Median onset date	23/11	15.0	27/11	14.0	22/11	15.0	25/11	15.0	24/11	15.0
Median end date	14/04	19.0	15/04	21.0	09/04	21.0	10/04	20.0	07/04	20.0
Length of growing season (days)	134	0.17	136	0.17	137	0.16	134	0.17	129	0.17

[a]Data for mean 5-day dry spells per season is based on the number of dry spell events not the mean length of spells

Groupings of rainfall and dry spells indices

Eigenvalues, cumulative total variance, and component loadings for rainfall indices for Balaka and Dedza are presented in Table 8. The first three principal components (PCs) retained for Balaka accounted for 63.1% of the total variability in the measured data. The scores and associations in Equations (1) to (5) were derived from composite analysis and sequential K-means clustering analyses. Scores with the same superscript are not significantly different. Coefficients in square brackets indicate sub-groups or clusters, while the initial number of sub-groups or clusters is denoted in subscripts alongside each PC header.

In Equation (1), PC2 was the most dominant for the series, though marginally more so than PC1. PC2 was associated with dry events and seasonal length features. Three subgroups emerged, with the most dominant consisting of the combined indices GSL and DD. The first PC was associated with wet events, where the leading subgroup consisted of WD and WP. The paired indices RXI and Rx1day were most influential in PC3, which was associated with rainfall intensity attributes. Seasonal rainfall emerged as a complex index for Balaka, having loaded onto both PC1 and PC3.

$$Y_1 = 1.32\ (PC1) + 1.33\ (PC2) + 0.67\ (PC3) \quad (1)$$

Where:

$PC1_{(6)} = [0.38^a\ (WD),\ 0.33^a\ (WP)],\ 0.25^b\ (PRCPTOT),\ -0.36^c\ (RXP)$

$PC2_{(6)} = [0.33^a\ (GSL),\ 0.33^a\ (DD)],\ 0.28^b\ (EGS),\ [0.20^c\ (6\text{-}10DS),\ 0.19^c\ (>15DS)]$

$PC3_{(5)} = [0.25^a\ (RXI),\ 0.24^a\ (Rx1day)],\ 0.18^b\ (PRCPTOT)$

Table 4

Performance of rainfall indices in terms of factor loading/eigenvector values in principal component analysis for Balaka (low altitude) and Dedza (high altitude)

Extraction Sums of Squared Loadings/ Indices	Balaka PC1	Balaka PC2	Balaka PC3	Dedza PC1	Dedza PC2	Dedza PC3
Eigenvalue	3.8	3.3	2.4	4.1	3.2	2.02

% of Variance	25.0	21.9	16.2	27.3	21.1	13.4
Cumulative %	25.0	46.9	63.1	27.3	48.4	61.8
Attribute	Factor loading/eigenvector					
Seasonal rainfall (PRCPTOT)	**.62**	.02	**.69**	.11	**.79**	.37
Wet pentads	**.83**	-.09	.21	-.09	.21	**.79**
Wet days	**.94**	.05	.05	.34	.23	**.76**
Dry days	-.28	**.94**	-.01	**.91**	-.13	-.23
Maximum 1-day rainfall (Rx1day)	-.20	-.02	**.94**	.03	**.82**	-.38
Maximum 5-day rainfall (Rx5day)	.43	-.13	.49	-.32	**.64**	.18
Extreme intensity (RXI)	.01	.00	**.95**	.06	**.96**	-.21
Extreme frequency (RXF)	.07	-.19	-.09	.08	-.27	-.03
Extreme per cent (RXP)	**-.89**	.03	.11	.00	.46	**-.87**
6 to 10-day dry spells (6-DS)	-.16	**.58**	-.09	.41	-.06	.09
11 to 15-day dry spells (11-DS)	-.35	.20	.22	.11	-.38	-.01
>15-day dry spells (>15-DS)	-.12	**.54**	-.17	**.66**	-.14	-.32
Growing season length (GSL)	.29	**.95**	.02	**.93**	.00	.19
Onset of growing season (OGS)	-.33	-.47	.17	-	-	-
End of growing season (EGS)	.09	**.79**	.15	**.86**	.04	.22

Absolute loadings > ± 0.5 are highlighted; loadings represent zero-order correlations of a particular factor with each item

In Table 4, three PCs explained 61.8% of the total variance for Dedza. Equation (2) provides the composite indices and scores associated with each of these PCs.

$$Y_2 = 1.48\ (PC1) + 1.1\ (PC2) + 0.53\ (PC3) \quad (2)$$

Where:

$PC1_{(5)} = [0.41^{a}$ (GSL), 0.40^{a} (DD), 0.38^{a} (EGS)], 0.29^{b} (>15DS)

$PC2_{(6)} = 0.33^{a}$ (RXI), [0.28^{b} (Rx1day), 0.27^{b} (PRCPTOT)], 0.22^{c} (Rx5day)

$PC3_{(4)} = -0.19^{a}$ (RXP), [0.17^{b} (WP), 0.17^{b} (WD)]

In Equation (2), PC1 emerged as marginally the most dominant in the series compared to PC2 and was linked with characteristics of the length of the season and dry events. PC1 resulted in two subgroups, with GSL, DD, and EGS being the predominant indices. The indices of PC2 were primarily associated with rainfall intensity, leading to the establishment of a three-cluster solution with RXI as the most influential index. The indices for PC3 related to the proportion of high rainfall events and the cumulative epochs of such events, with RXP being the leading index in PC3 with WP and WD forming a subgroup.

Table 5 presents the eigenvalue, proportion of variance, and cumulative variance for PCs, as well as the proportion of variance for rainfall and dry spell attributes explained by PCA for the three mid-altitude locations on the Lilongwe Plain in Central Malawi, namely Bunda, Chitedze, and KIA.

Table 5

Eigenvector values and variable loadings explained by the principal components (PCs) of the analysis for Bunda, Chitedze, and KIA in the mid-altitude Lilongwe Plain

Extraction Sums of Squared Loadings/ Indices	Bunda				Chitedze				KIA		
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4	PC1	PC2	PC3
Eigenvalue	4.2	3.1	1.9	1.4	4.1	3.2	2.1	1.3	3.7	3.1	2.5
% of Variance	28.1	20.7	12.4	9.0	25.6	20.0	13.0	8.0	24.7	20.6	16.5
Cumulative %	28.1	48.8	61.2	70.2	25.6	45.6	58.6	66.6	24.7	45.3	61.8
Attribute	Factor loading/eigenvector										
Seasonal rainfall (PRCPTOT)	**.70**	.49	.41	.12	.14	**.73**	.48	.03	**.89**	.08	-.21
Wet pentad (WP)	**.86**	.01	-.06	-.17	-.09	**.81**	-.18	.07	.33	-.32	**-.60**
Wet days (WD)	**.85**	.38	-.10	-.07	.27	**.92**	-.01	.10	**.54**	.49	-.45
Dry days (DD)	-.37	**.75**	.19	.42	**.67**	-.26	-.12	.26	-.18	**.75**	.29
Maximum 1-day rainfall (Rx1day)	-.08	.06	**.88**	.12	.09	-.15	**.88**	-.01	**.88**	-.00	.39
Maximum 5-day rainfall (Rx5day)	**.75**	-.08	-.10	.06	-.02	.42	.44	.07	.44	-.34	-.18
Extreme intensity (RXI)	.14	.18	**.86**	.28	-.22	.02	**.92**	-.04	**.92**	-.06	.33
Extreme frequency (RXF)	.15	.02	**-.61**	.25	**.60**	.13	-.01	.17	-	-	-
Extreme per cent (RXP)	**-.70**	-.44	.35	.14	.38	**-.55**	.33	.32	.05	-.26	**-.84**
5-day dry spells (5DS)	.12	.09	.11	**.65**	.29	-.23	.10	-.47	.18	.30	**.62**
6 to 10-day dry spells (6-10DS)	-.14	.04	.01	**.67**	**.79**	-.16	-.05	-.40	-.31	**.59**	-.36
11 to 15-day dry spells (11-15DS)	-.47	.21	-.07	-.15	.09	-.36	-.09	.48	.19	.12	.48
>15-day dry spells (>15DS)	-.06	**.62**	.16	-.45	-.27	-.02	.13	**.83**	-.27	.22	.38
Growing season length (GSL)	.16	**.92**	-.05	.21	**.74**	.32	-.05	.30	.09	**.96**	.03
Onset of growing season (OGS)	-	-	-	-	**-.97**	-.14	-.02	.40	.16	**-.54**	-.11
End of growing season (EGS)	.16	**.87**	.10	.02	.19	.20	-.13	**.71**	.24	**.75**	.18

Absolute loadings > ± 0.5 are bolded; loadings represent zero-order correlations of a particular factor with each item.

Four PCs cumulatively accounted for 70.18% of the total variance of data at Bunda (Table 9). The composite indices and scores connected to each of these PCs are described in Equation (3).

$$Y_3 = 1.54\ (PC_1) + 0.95\ (PC_2) + 0.42\ (PC_3) + 0.17\ (PC_4) \quad (3)$$

Where:

$PC1_{(6)}$ = [0.34^a (WD), 0.34^a (WP)], [0.30^b (Rx5day), 0.28^b (PRCPTOT)], -0.28^c (RXP)

$PC2_{(6)}$ = [0.27^a (GSL), 0.26^a (EGS)], [0.23^b (DD), 0.19^b (>15DS)]

$PC3_{(3)}$ = [0.16^a (Rx1day), 0.15^a (RXI)], 0.11^b (RXF)

$PC4_{(4)}$ = [0.08^a (5DS), 0.09^a (6-10DS)]

In Equation (3), PC1 was identified as the most influential in the series, primarily concerning seasonal rainfall events, their intensity, and the proportion of high rainfall events. Within PC1, three subgroups were distinguished, with the pairing of WP and WD leading. PC2 focused on the characteristics of the season's length and dry events, comprising two subgroups with GSL and EGS as the leading combined indices. PC3 was concerned with rainfall intensity and the frequency of extreme indices, where Rx1day and RXI formed the most significant paired indices. The fourth PC was characterized by a pair of dry spell indices that were validated for belonging to the same class.

The analysis at Chitedze produced four PCs, which accounted for 66.6% of the total variance, as detailed in Table 9. The significant associations and scores derived from composite and cluster analyses are presented in Equation (4):

$$Y_4 = 1.43\ (PC_1) + 0.9\ (PC_2) + 0.38\ (PC_3) + 0.19\ (PC_4) \quad (4)$$

Where:

$PC1_{(7)}$ = – 0.37^a (OGS), [0.30^b (6DS), 0.28^b (GSL)], [0.25^c (DD), 0.23^c (RXF)]

$PC2_{(5)}$ = [0.28^a (WD), 0.24^a (WP), 0.22^a (PRCPTOT)], – 0.16^b (RXP)

$PC3_{(3)}$ = [0.18^a (RXI), 0.18^a (Rx1day)]

$PC4_{(4)}$ = [0.10^a (>15-DS), 0.09^a (EGS)]

The scores in Equation (4) indicate that PC1 was the foremost component for the series, primarily associated with the length of season characteristics and dry events. Within PC1, three clusters were identified, with OGS emerging as the most significant index, and the rest of the indices were categorized into two subgroups. PC2 was distinguished by two subgroups, focusing on seasonal rainfall and the proportion of high rainfall events. The third and fourth PCs were notable for yielding pairs of indices that stood out from the initial solutions of three and four clusters, respectively, with PC3 being linked to rainfall intensity indices.

The PCA analysis of data from KIA identified three PCs that accounted for 61.8% of the total variance, as documented in Table 9. Equation (2) outlines the composite indices and scores associated with each of these PCs.

Y_5 = 1.46 (PC1) + 1.19 (PC2) + 0.56 (PC3) (5)

Where:

$PC1_{(5)}$ = [0.37[a] (RXI), 0.35[a] (PRCPTOT), 0.35[a] (Rx1day)], [0.21[b] (WD), 0.18[b] (Rx5day)]

$PC2_{(6)}$ = 0.32[a] (GSL), [0.25[b] (DD), 0.25[b] (EGS), 0.19[b] (6-10DS)], -0.18[c] (OGS)

$PC3_{(6)}$ = -0.23[a] (RXP), [0.17[b] (5DS), 0.16b[b] (WP)]

The scores in Equation (5) indicate that PC1 was the most dominant component in the series, albeit marginally when compared to PC2 and significantly in contrast to PC3 (p = 0.073). PC1 was linked to rainfall intensity indices, leading to the emergence of two subgroups, with a cluster comprising RXI, PRCPTOT, and Rx1day at the forefront. In PC2, three subgroups were identified, with GSL standing out as the most influential index. PC2 was associated with the length of season characteristics and dry spells indices. In PC3, RXP emerged as the primary index, with the other indices coalescing into a subgroup.

The overall contribution of each index to the long-term rainfall and dry spell regimes based on their discriminant scores is depicted in Figure 2. The key long-term indicators of wet events, common across the different locations, include wet days, wet pentads, Rx1day, RXI, and RXP. For dry events, dry days, 6 to 10-day dry spells, and dry spells longer than 15 days were of significance. Characteristics of the growing season were influenced by the date of onset and the length of the growing season. It is also important to note the indices that were sensitive for specific locations. These include Rx5days for Dedza and Bunda, RXF for Chitedze and Bunda, and 5-day dry spells for KIA and Bunda.

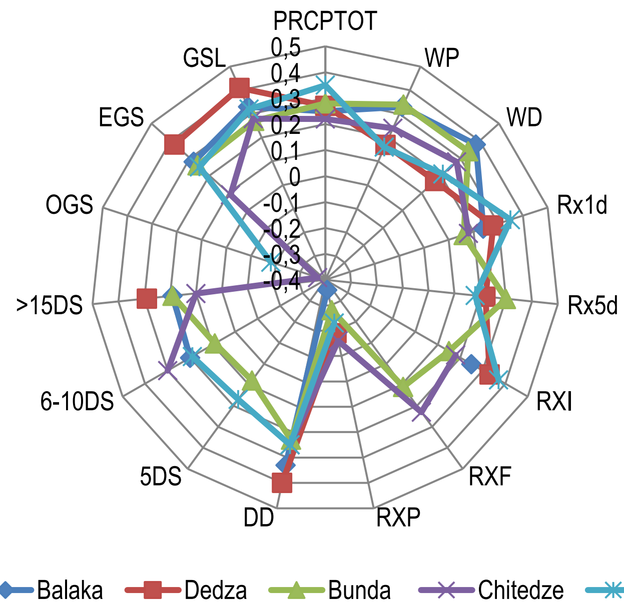

Fig. 2. Radar graph depicting the discriminant scores of rainfall and dry spells indices for each location

DISCUSSIONS

Wet indices

Wet days and wet pentads. The number of wet days and wet pentads was both lowest at Balaka and highest at Dedza. However, based on multivariate analyses, wet days significantly contributed to the long-term rainfall regime at both low-altitude (Balaka) and mid-altitude locations (Bunda and KIA), but they exerted little influence at Dedza. Conversely, wet pentads (WP) demonstrated weak discriminatory power at KIA and Dedza. Despite these indices occurring in the same clusters at all locations except KIA, wet pentads are known to reflect distinct atmospheric conditions compared to wet days, as they signify the persistence of rain-producing weather system(s) (Jury et al., 1996). They argued that wet spells, which constitute in-season oscillations of rainfall with significant amplitude over southern Africa, should be quantified for their forecast value and communicated to farmers to assist with decisions regarding irrigation demand, planting, fertilizing, and other agricultural activities.

Single-day and 5-day maximum rainfall. In various regions of Malawi, heavy convective rainfall, which can last from a few hours to several days and cover areas ranging from a few hundred square kilometres to entire regions, is common (Mwafulirwa, 1999). The indices Rx1day and Rx5day were used to measure the highest amount of precipitation received in a single day and over 5 days per season, respectively. Bunda, followed by KIA and Dedza, showed a significant contribution of Rx5day to the total rainfall variance. Meanwhile, Rx1day had a substantial influence at all sites, particularly at KIA. This index was consistently grouped with RXI at all sites except at Dedza. Libanda et al. (2017) also noted significant occurrences of Rx1day at KIA and Dedza. The persistence of rainfall at Dedza could be augmented by the Lake Malawi effect, whereas Bunda might benefit from orographic rainfall from the Dzalanyama Range to the south. The Rx5day index might not always capture the most severe rainfall extremes because it assumes heavy rain falls on each consecutive day within a 5-day period, which may not always happen. It is suggested however that the relative importance of different indices across locations should not be determined solely by their spatio-temporal rarity. Widespread increases in heavy precipitation events have been observed even in places where total amounts have decreased (Bates et al., 2008).

Extreme rainfall events. The three indices—extreme frequency (RXF), extreme intensity (RXI), and extreme per cent (RXP)—were utilized as thresholds to characterize extreme precipitation events above the long-term (1961–2007) 95th percentile. Haylock and Nicholls (2000) reported that the top three to five events generally contribute approximately 20-25% of the total rainfall. The indices RXP and RXI, consistently contributed to the total variance, correlating with rainfall amount and intensity factors, respectively, across locations. The contribution of RXF was strongly evident at Chitedze and weakly at Bunda. In scenarios of global warming, climate models commonly predict an increase in the frequency of large precipitation events (Warnatzsch and Reay (2019). Our findings are generally inconsistent with this widely accepted notion. Instead, they suggest a higher intensity or proportion of extreme values at different locations, even within what may be considered homogeneous climatic zones, such as the Lilongwe Plains. It is recognized that Malawi is situated in a transition zone between two climatic regions (Nicholson et al., 2014). Research should therefore not only consider the regional variability of rainfall patterns but also aim to understand extreme conditions within dissected geographic regions.

Building on the application of extreme rainfall indices proposed in our study, Clay et al. (2003) argued that the focus on drought and extremely low rainfall events tends to distract from the potential consequences of extremely high rainfall events and the upper tail of the rainfall distribution. Additionally, studies on climatic variability in the region typically employ linear or log-linear models to explain relationships between rainfall and crop performance or economic activity. However, such models fail to account for the negative effects of abnormal wet periods characteristic of certain seasons and locations.

Dry indices

Extreme rainfall events are situated at the tails of a time series, with excesses or deficits in amounts leading to wet and dry events. Therefore, dry events represent extremes on the lower tail of the rainfall distribution (Usman and Reason, 2004). Dry days emerged as a significant characteristic in various sites, particularly showing dominant discriminant scores at Balaka, Dedza, and KIA. Regarding dry spells, both 6 to 10-day and greater than 15-day dry spells were significant contributors to the variance in rainfall across four of the five locations, according to the results of multivariate analysis. However, discriminant scores for these two categories of dry spells were consistent with moderate to lower magnitude compared to other indices. These results validate the argument that evaluating features of a singular climatological variable can lead to oversimplification and an incomplete understanding of weather events and climate trends, as well as a distorted scientific and public understanding of weather phenomena and climate change.

Our study further features a distinctive approach where the number of dry days was not calculated by subtracting the number of rainy days from the total number of days in the season, as seen in other studies (Kimaro and Sibande, 2008). Such a method can confound the results due to days with no precipitation, leading to misleading outcomes. Instead, in our analysis, a day with zero precipitation was not classified as a dry day; a dry day was defined as one with less than 0.85 mm of rain, following Usman and Reason (2004). Furthermore, the data used to analyze dry spells of various durations was the number of dry days within each dry spell category, rather than counting each occurrence as a single event per dry spell category or threshold (Chimimba et al., 2023). This methodological distinction in determining dry days, along with the duration and frequency of dry spells, potentially affects the computation of dry events and the characteristics of the season's length, leading to varied conclusions.

Growing season indices

The long-term mean length of the growing season was found to agree with agrometeorological literature, which further identified the agronomic onset and cessation of rainfall as being stable between 1964/65 and 2008/09 (Simelton et al., 2013; Nicholson et al., 2014). The length of the growing season contributed most to the total rainfall variance between sites, followed by the end-of-season dates. These findings are consistent with those of Jury and Mwafulirwa (2002), who used multivariate regression analysis to show that early rainfall events (November, December, and January) had the lowest predictability, whereas later rainfall events (February, March, and April) were more predictable in Malawi. In recent times, local perceptions and some studies have characterized a shortening rainy season (delayed onset and earlier cessation) in Malawi (Sutcliffe et al., 2016; Zulu et al., 2017). Findings from several studies, over a longer time spectrum, show that rainfall onset and cessation tend to be delayed seasonally over Malawi, but the period of the growing season appears to be unchanged (Simelton et al., 2013; Ngongondo et al., 2014).

Location Characteristics

In the Lilongwe Plain, specifically at Bunda and KIA, climatological rainfall features' total variance was primarily influenced by wet events, which included seasonal rainfall total, RXP, and 5-day rainfall amounts. The climate regime was secondarily affected by the start and onset characteristics of seasonal rainfall and dry events. These results contrast with those from Chitedze, Dedza, and Balaka, where characteristics of the growing season, along with dry events, constituted the primary seasonal characteristics, and wet events were secondary contributors. However, in Balaka, the impact of wet events was comparable to the primary seasonal characteristics.

The first insight from our findings regarding the influence of location on the main characteristics of rainfall and dry spells is that research on mitigation and adaptation to weather and climate extremes often focuses on regions perceived as marginal rainfall areas, such as Balaka. However, our study exposes the potential for extreme variability in both dry and wet events even in areas traditionally considered to have abundant rainfall, such as Dedza and Bunda (Fiwa et al., 2014). Our findings challenge these conventional perceptions and the well-intentioned practices that follow.

The second point to acknowledge is that the differences in the variance of principal components and discriminant scores of climatological features across five locations, representing three altitudinal zones, underscore the importance of conducting isolated analyses of seasonal and extreme rainfall and dry spell events in different climatological zones. Regionalizing results in a climatologically diverse country may not accurately capture the climatic patterns of wet and dry events (Haylock and Nicholls, 2000). For instance, although RXP was a significant feature across different locations, disparate results were obtained for locations in Central Malawi, with the contribution of RXP being least at KIA and Dedza compared to Bunda and Chitedze. Yet, to identify homogeneous regions for study, Nicholson et al. (2014) grouped KIA, Chitedze, and Dedza into one homogeneous group based on a subjective evaluation from correlating 21 rainfall stations with each other. Haylock and Nicholls (2000) observed that when averaging several series, there is a possibility that series with a higher mean or variance will dominate the calculations unless each component series is normalized.

The third lesson from our study on the influence of location is the recognition that variability in rainfall and dry events may result from the relative magnitude of various sources of variability or their combined effects. For example, the variances and discriminant scores for the first (wet events) and second (dry events) principal components were equally high and indistinguishable at Balaka. This overlap in the variability of seasonal characteristics is likely due to indices that constitute the contrasting clusters of multiple events. In contrast, at Bunda or KIA, the variance in seasonal characteristics is primarily influenced by events from the first dominant component, with possible moderation from subsequent components. The WMO (2015) acknowledges that some climate characteristics and extremes may result from the accumulation of moderate weather or climate events, which in themselves constitute an extreme phenomenon. The contributing events may be similar (clustered multiple events) or of different types, aligning with observations in our study.

CONCLUSIONS

The current study underscores that accurately characterizing climatological features for rainfall necessitates identifying and measuring a diverse array of indices or subsidiary indices. These indices represent specific properties and processes defined by local, regional, and global atmospheric and geomorphological systems. For example, among the three percentile indices and the two maximum rainfall periods analyzed, the results indicated that the frequency of extreme rainfall (RXF) and five-day maximum rainfall (Rx5days) do not uniformly occur across all locations in the historical record. Likewise, dry spells lasting 6 to 10 days emerged as a significant feature of dry events, as opposed to categories of other dry spell durations. Therefore, it is crucial to measure a comprehensive set of indices that capture the entire rainfall distribution curve to draw accurate and lasting conclusions about climatic patterns.

Our findings reveal that at mid-altitude locations like Bunda and KIA, climatic patterns were predominantly characterized by wet events as the primary principal component. However, at Dedza, Chitedze, and Balaka, the primary seasonal climatic patterns were defined by growing season characteristics combined with dry events, with wet events playing a secondary role. Notably, at Balaka, wet events significantly influenced the rainfall regime, suggesting a long-term regime subject to compound events. These latter three locations, representing high, medium, and low altitude zones, illustrate that climatic constructs for rainfall and dry events should not be uniformly applied across geographically diverse areas or assumed homogeneous regions.

The combined use of statistical approaches employing Principal Component Analysis, and composite and cluster analyses successfully summarized information from multivariate datasets and enhanced the understanding of site-specific analyses of seasonal and extreme rainfall and dry spell events. Key indicator indices included wet days, wet pentads, Rx1day, RXI, and RXP, as well as dry spells lasting 6 to 10 days or 15 days or more, the length of the growing seasons, and the end-of-growing-season dates. These indices present themselves as potential candidates for identifying site-specific management strategies to optimize the efficient use of resources in production or for further study in the development of local statistical forecast models.

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