

Use of L-moments in the Regional Frequency Analysis of Meteorological Drought Duration in the Transboundary Comoé River Basin

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Received September 06, 2025; Revised October 08, 2025; Accepted October 15, 2025

Abstract This study aims to estimate the duration of meteorological droughts in the Comoé River Basin. The sparse distribution of rainfall stations motivated the use of a regional frequency analysis based on L-moments. This method was applied to drought duration series derived from the 3-month Standardised Precipitation Index (SPI-3), using a drought threshold of -0.84. Classification and homogeneity tests identified four regions characterised by different drought patterns. Region R2 (Abidjan, Adiaké, Alépé, Bassam, Adzopé) represents the transitional equatorial climate in the southern part of the basin, while Region R4 (Tafiré, Tengréla, Ferkessédougou, Bobo-Dioulasso, Niangoloko, Kampti) is typical of the Sudanian climate in the north. The other two regions, R1 (Orodara, Ouangolo, Abengourou, Ouéllé, Dabakala, Bongouanou, Daoukro) and R3 (Bouna, Bondoukou, Agnibilekrou, M'Bahiakro, Aboisso), exhibit contrasting climatic characteristics because some rainfall stations that make up these groups are not located within the same climate zone. The Wakeby distribution was found to be the most suitable for modelling drought durations. Regional quantiles, estimated using the index flood approach, demonstrated greater accuracy than site-specific quantiles. These quantiles were subsequently interpolated spatially. The results indicate a relatively homogeneous pattern of drought durations across the basin, except in the far north. High probabilities of prolonged drought were observed in this northern area, which corresponds to a transitional tropical climate zone. For return periods (T) of 2, 5, and 10 years, the average drought duration was estimated at 2, 3, and 4 months across most of the basin, compared with 4, 6, and 8 months in the northern region. For T = 20 and 50 years, drought durations are expected to reach 7–8 months in the south, and up to 11 and 16 months, respectively, in the north.

Keywords: regional frequency analysis, L-moments, drought duration, west african monsoon, Comoé river basin

Cite This Article: Ouattara Ismaïla, Bamba Adama, Coulibaly Léréyaha, Dao Amidou, and Kamagaté Bamory, "Use of L-moments in the Regional Frequency Analysis of Meteorological Drought Duration in the Transboundary Comoé River Basin." *American Journal of Water Resources*, vol. 13, no. 4 (2025): 158-169. doi: 10.12691/ajwr-13-4-5.

1. Introduction

The influence of human activity on the climate system is well established, based on evidence of increasing concentrations of greenhouse gases in the atmosphere. Climate changes induced by the rise in atmospheric greenhouse gas concentrations are occurring alongside an upsurge in hydroclimatic extremes (floods and droughts) [1]. This situation supports the conclusions of the special report on managing the risks of extreme events and disasters to advance climate change adaptation (SREX) [2]. According to this report, under scenario RCP 8.5, it is likely that, at both regional and global scales, soil moisture will decrease and agricultural droughts will

increase in currently arid areas by the end of the 21st century [1].

Drought is one of the most severe natural hazards, with far-reaching impacts on water resources, natural ecosystems, and agriculture. Frequent and intense droughts limit vegetation growth and increase soil vulnerability to erosion caused by heavy rainfall [3]. In developing countries, droughts are a major cause of famine, disease outbreaks, and land degradation, while in developed regions they result in substantial economic losses [4]. Unlike other natural hazards, drought is more difficult to detect, as it typically arises from multiple contributing factors that only become apparent after a prolonged period of deficit [5]. West Africa and Southern Africa are experiencing severe drought conditions that are disrupting agricultural and livestock production systems

across nearly 14 countries, while agriculture in the region remains approximately 95% rain-fed. As such, it is highly vulnerable to fluctuations in rainfall patterns [6].

The Comoé river basin, which is the focus of this study, is a transboundary catchment shared by Côte d'Ivoire, Burkina Faso, Ghana, and Mali. Climatic variability in this part of Africa is marked by a 20% to 30% decline in rainfall and an even greater reduction in river discharge [7]. This watershed exhibits a pronounced asymmetry between the southern coastal zone, which is directly influenced by moist Atlantic monsoon flows and receives higher rainfall (ranging from 1,200 to 2,000 mm/year), and the northern part, which is dominated by the dry Harmattan winds [8]. The severe global drought episode of 1982–1983 highlighted the need for further research into the causes and impacts of drought in order to better anticipate future events [9]. In Côte d'Ivoire, these extreme climatic events had serious consequences between 1982 and 1983, including forest and plantation fires, a significant decline in agricultural output, and widespread power outages [10].

Drought is a stochastic natural hazard triggered by an intense and persistent lack of precipitation. Following an initial meteorological event, subsequent impacts occur on agriculture and hydrology. Among natural hazards, droughts exhibit unique characteristics: in addition to delayed effects, they vary across multiple dynamic dimensions such as severity and duration. These factors, combined with their pervasive and subjective impacts, make droughts difficult to characterise. Effective drought management therefore requires a clear characterisation of drought in order to facilitate both retrospective analyses and prospective planning [11]. However, drought research faces major challenges due to the scarcity of direct observations, the limitations of the drought indices employed, and geographical inconsistencies in observed drought trends. The complexity and variability of atmospheric mechanisms such as the El Niño–Southern Oscillation (ENSO) and sea surface temperature (SST) anomalies contribute significantly to the difficulty of estimating droughts [1,4]. An efficient drought characterisation requires the identification of contiguous regions with similar drought histories. The first step in risk management is thus to establish management zones by subdividing areas into subregions based on drought criteria. Building on this principle, the regional approach has been incorporated into modelling in recent studies [12,13]. The advantage of this approach lies in its ability to characterise drought evolution in areas with sparse rain gauge networks. Furthermore, the ultimate goal of drought studies remains the prediction of future episodes in order to mitigate their impacts. To this end, more robust stochastic models have been employed by various authors [14,15]. Among the methods used are Markov chains and frequency analyses employing three, four, or even five-parameter probability distributions.

Most studies on the Comoé basin address drought from the perspective of climate variability using the Nicholson index at the annual scale, combined with trend and homogeneity analyses [16,17]. However, meteorological droughts often manifest at finer temporal scales (monthly or seasonal). Focusing solely on the annual scale tends to obscure the actual duration of drought episodes within the

year. Only the work of Ouattara et al. [18] offers a genuine characterisation of drought at the monthly scale, including a spatial analysis of the phenomenon. Nevertheless, drought duration is not modelled in terms of return periods. The study by Meledje et al. [19] on the neighbouring Bia basin provides a useful approach to describing the dynamics of drought state transitions using a Markov chain framework. Given the frequency of droughts and the magnitude of their impacts, public authorities should place greater emphasis on research related to this issue in order to build a robust information database. Identifying zones with similar drought manifestation patterns could also help policymakers design efficient response plans. The attempt to address this issue in a drought-vulnerable area specifically the Comoé River watershed, according to global climate models has motivated this study. The objective is to spatially predetermine the meteorological drought “duration” parameter across the Comoé watershed using Regional Frequency Analysis (RFA). The aim of this frequency analysis is to link the duration of drought episodes to their occurrence frequency through probability distributions.

2. Materials and Methods

2.1. Study Area

The Comoé River Basin is a transboundary watershed shared by Côte d'Ivoire, Burkina Faso, Ghana, and Mali (Figure 1). It is located between latitudes 5°02'N and 11°04'N, and longitudes 2°07'W and 5°81'W, within the WGS 84 geographic coordinate system (Zone 30N). The study area lies in the eastern part of Côte d'Ivoire. It is bordered to the north by the Niger River Basin, to the north-east by the Volta Basin, to the south-east by the Bia Basin, to the west by the Bandama Basin and the Agnèby Coastal Basin, and to the south by the Atlantic Ocean in the Gulf of Guinea (Figure 1). Administratively, the basin spans five administrative regions in Côte d'Ivoire, one region in Burkina Faso, and one region in Mali. In Côte d'Ivoire, these are the regions of Gontougo, Bounkani, Poro, Hambol, and Iffou. In Burkina Faso, it extends into the Banfora region, and in Mali, into the Sikasso region [20].

A large part of the Comoé River watershed lies within the eastern region of Côte d'Ivoire. The regional climatic phenomena prevailing in this area help to better characterise the basin's climate. The eastern part of Côte d'Ivoire encompasses two main climatic zones that correspond to the two dominant landscapes: pre-forest savannah in the northeast and dense, humid forest in the southeast. The climate of the southeast is marked by two rainy seasons: the longer and more intense rainy season peaks in June, while the shorter rainy season occurs around October. These two seasons are separated by a short dry spell during August and September. The major dry season, lasting on average three months, extends from December to February. In contrast, the northeast experiences only one rainy season, with a peak in September. The single dry season lasts between six and seven months and becomes increasingly pronounced moving northwards [8].

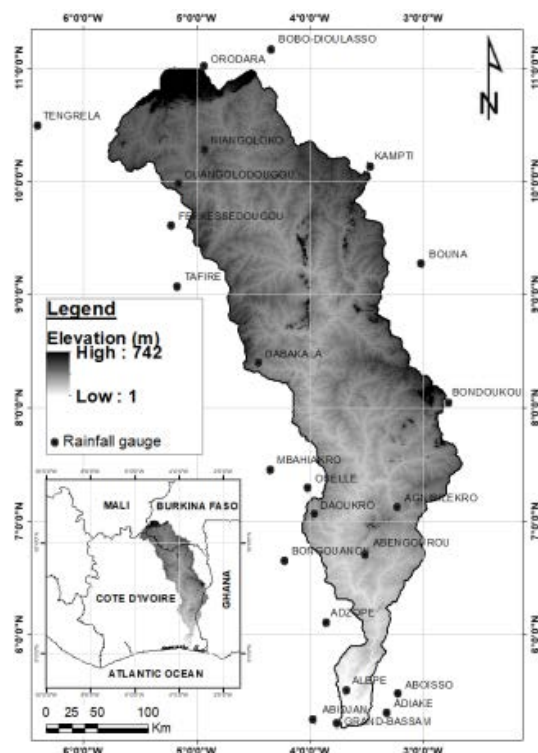


Figure 1. Location of the Comoé river basin and the rainfall stations used in the study

2.2. Data and Sources

The data used in this study primarily consist of monthly rainfall totals derived from daily observations. The rain gauge stations are irregularly distributed across the watershed, with most of them located outside the Comoé River Basin. However, only those stations influencing the basin's rainfall dynamics identified through Thiessen polygon analysis were selected and are shown in Figure 1. The dataset contains some missing values, which were imputed using a regression-based method implemented via the VIM package from the R CRAN (Comprehensive R Archive Network) repository [21]. To ensure a sufficient number of stations for spatial interpolation, the selected data cover the period from 1960 to 2000. Each rainfall time series included in the study spans at least 40 years. Rainfall data for Côte d'Ivoire were obtained from SODEXAM (*Société d'Exploitation et de Développement Aéroportuaire, Aéronautique et Météorologique*). In addition, several rain gauge stations located in Burkina Faso were incorporated into the analysis, with data sourced from the SIEREM database (*Système d'Informations Environnementales sur les Ressources en Eau et leur Modélisation*) [22].

2.3. Methods

2.3.1. Drought Index, Threshold and Duration

The Standardised Precipitation Index (SPI) was developed by McKee et al. [23] as a tool to define and monitor drought events. The SPI compares precipitation over a given timescale (typically from 1 to 24 months) to the long-term average precipitation observed at the same location. The calculation steps and associated formulas are detailed in Edwards and McKee [24]. Based on the

monthly rainfall series collected over the Comoé River Basin and using the DrinC 1.5 software [25], SPI values were calculated at a 3-month timescale (referred to as SPI-3). The 3-month SPI was chosen in this study because it better reflects short- to medium-term wet or dry conditions. It is also widely used for analysing meteorological droughts [26].

The duration of a drought event is defined as the period between its onset and termination, characterised by a sustained rainfall deficit. Technically, a month is considered dry when the SPI value falls below the threshold of -0.84 (Figure 2). The duration of a dry episode, denoted as L , corresponds to the total number of consecutive months during which SPI remains below -0.84. A drought event ends when the SPI rises above this threshold [27].

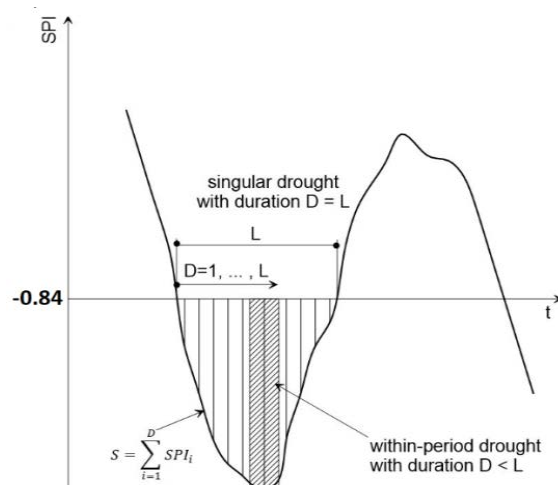


Figure 2. Schematic representation of a drought episode with a threshold value of -0.84

2.3.2. Regional Frequency Analysis

- Rainfall gauges SPI-index patterning with Self-Organising Maps

The variables selected for grouping drought manifestation patterns include both geographical and statistical characteristics. These consist of the spatial coordinates X (longitude) and Y (latitude) of the various rainfall stations, as well as descriptive statistical parameters derived from the SPI-3 time series. Specifically, kurtosis, skewness, the first quartile, the median (second quartile), the third quartile, and the interquartile range are used. The classification model is based on Kohonen's Self-Organising Maps (SOM) [28]. This type of neural network, inspired by sensory activation patterns in the human cerebral cortex, is trained in an unsupervised manner using a simple heuristic approach and is capable of identifying hidden nonlinear structures in high-dimensional data. Fundamentally, a SOM consists of a discrete two-dimensional grid of neurons (Figure 3). The hidden layer, often referred to as the Kohonen layer, is fed by an input layer [29].

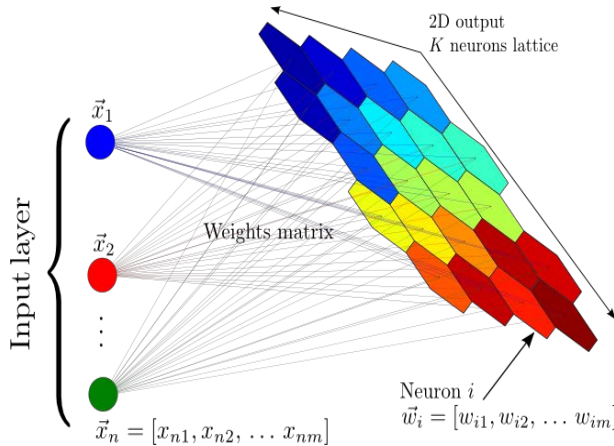


Figure 3. Overview of the Self-Organising Map (SOM) neural network

Each neuron in the hidden layer has several “neighbouring” neurons. We define the “distance” between each neuron and its neighbours as the Euclidean distance between the weights connecting the input layer to the hidden layer of each neuron. The distance defined in this way becomes important later, as it encodes low-dimensional information about the original dataset. Each hidden-layer neuron therefore has a weight vector with n

components (i.e., the input is densely connected to the hidden layer). How, then, is this network trained? The training procedure and a complete description of the algorithm are provided in Kohonen [28]. The Self-Organising Maps (SOM) functions are implemented in Matlab, enabled the entire classification procedure to be carried out. The validity of the classification (or regionalisation) was further tested using the discordance measure (D_i) and the heterogeneity index (H), as recommended by Hosking and Wallis [12].

Discordance measure (D_i)

The purpose of this measure is to identify sites (here, the sites are represented by rainfall stations) that are markedly discordant with the group (or class) as a whole in terms of drought manifestation. It is based on the L-moments of the data from the different sites. Consider a group of sites, and suppose that there are N sites in the group. Let us denote by a vector U_i (Eq. 1):

$$U_i = [t^{(i)}_1 t^{(i)}_3 t^{(i)}_4]^T \quad (1)$$

This vector contains the values, and of site, and the superscript denotes the transpose of a matrix or vector. The group mean value is denoted by $\bar{U}$ and is expressed as follows (Eq. 2):

$$\bar{U} = N^{-1} \sum_{i=1}^N U_i \quad (2)$$

The sum-of-squares-and-cross-products matrix is defined as follows (Eq. 3):

$$A = \sum_{i=1}^N (U_i - \bar{U})(U_i - \bar{U})^T \quad (3)$$

Thus, the discordance measure D_i for site i is defined as follows (Eq. 4):

$$D_i = \frac{1}{3} N (U_i - \bar{U})^T A^{-1} (U_i - \bar{U}) \quad (4)$$

A site i is declared discordant if its D_i value is large. The notion of “large” depends on the number of sites in the group. A site is considered discordant if its D_i value exceeds the critical value given in Table 1.

Table 1. Critical Values for the Discordance Statistic [12]

Number of sites	5	6	7	8	9	10	11	12	13	14	≥ 15
Critical value	1.333	1.648	1.917	2.14	2.329	2.491	2.632	2.757	2.869	2.971	3

Heterogeneity measure (H)

The heterogeneity of a proposed region is based on the magnitude of the between-site variability in L-moment ratios compared to the level of variability expected in a homogeneous region [12]. The heterogeneity measures H_1 , H_2 , and H_3 correspond, respectively, to L-Cv, L-skewness, and L-kurtosis. In practice, H_1 is the most informative measure, as it reflects whether the observed variability in L-Cv is significant. Conversely, high natural variability in L-skewness and L-kurtosis, measured by H_2 and H_3 respectively, has relatively low discriminating power. Consequently, the heterogeneity measure H_1 for the

variability in L-Cv effectively becomes the primary metric for assessing the relative heterogeneity of a given region (or group). The heterogeneity measure H_1 is calculated as follows:

- a regional weighted mean of L-Cv ($L-Cv^R$) is computed from the sample L-Cv values of the sites within a region, with weights proportional to the length of each series ;
- The standard deviation of the weighted mean for the L-Cv values across all sites is then calculated and denoted (V) ;

- a four-parameter Kappa probability distribution is fitted using the regional weighted means of the L-moment diagrams from the sites. Subsequently, 500 computer simulations are conducted using the four-parameter Kappa distribution, where each simulation has the same number of sites and series lengths as the proposed region. The mean (μ_v) and standard deviation (σ_v) are calculated from the 500 simulated samples ;
- finally, H_1 is computed as follows (Eq. 5):

$$H_1 = \frac{(V_{LC_v} - \mu_v)}{\sigma_v} \quad (5)$$

A value of H_1 equal to zero indicates that the between-site variability of the regional L-Cv values is identical to that expected for a homogeneous region, given the observed L-moment ratios fitted by a four-parameter Kappa distribution. Positive H_1 values indicate that the between-site variability of L-Cv at a site is greater than expected for a homogeneous region, with larger values suggesting potential or probable heterogeneity.

Conversely, negative H_1 values indicate that the between-site variability of L-Cv at a site is lower than expected, and the proposed region would be considered

homogeneous. Experience to date indicates that an H_1 value of 2 is a reasonable threshold for distinguishing regions that are likely heterogeneous from those that are likely homogeneous [12]. Table 2 provides guidelines for the acceptance of homogeneous regions, where external sources contribute to the variability in L-Cv beyond the statistical considerations of sampling variability [30].

Table 2. Guidelines for Accepting or Rejecting the Homogeneity of a Given Region [30]

Heterogeneity measure	Decision on regional homogeneity
$H_1 \leq 2$	Region is acceptably homogeneous
$2 < H_1 \leq 3$	Marginal heterogeneity; re-assignment of certain sites would be beneficial
$3 < H_1$	Region likely heterogeneous; re-assignment of certain sites is required

2.3.3. Selection of a Regional Probability Distribution Using L-Moments

Techniques developed from order statistics, aimed at constructing estimators that better capture the tails of distributions, led to the concept of L-moments. These combinations of order statistics account for distribution tails more effectively than conventional moments. They allow fitting to generalised families of distributions (Generalised Logistic, Generalised Extreme Value, Generalised Pareto, Pearson Type III), Generalised Log-Normal with three parameters, or even four- and five-parameter distributions (Kappa and Wakeby), which are more robust and can have heavier tails than the normal distribution [31]. To select the best-fitting distribution for drought duration series, the L-moment ratio diagram was used, together with the Z^{DIST} statistic, as recommended by Hosking and Wallis [12].

L-moment ratio diagram

L-moment ratio diagrams are increasingly used in the literature to select a probability distribution function for regional frequency analysis [12,28]. In particular, the

diagram plots the L-kurtosis against the L-skewness [33]. Two graphical methods are often employed for distribution selection: the sample mean and the best-fit line through the L-moment ratios of the sample. Homogeneous and heterogeneous regional samples have been simulated to highlight the usefulness of these two methods. For homogeneous regional data, the best distribution choice is obtained from the sample mean. For highly heterogeneous regional data, exhibiting a wide range of shape parameters, the best-fit line proves more useful for selecting the distribution. These results emphasise the importance of using heterogeneity tests, such as the Z^{DIST} statistic, alongside L-moment ratio diagrams [34].

Calculation of the Z^{DIST} statistic

According to Ben-Zvi and Azmon [35], the L-moment diagram allows the identification of acceptable distributions, but not necessarily the most appropriate one. Statistical tests should be used in conjunction with the L-moment ratio diagram [36]. To this end, Hosking and Wallis [12] developed the Z statistic test, which aims to assess whether a given theoretical frequency model can adequately represent the statistical behaviour of the parameter under study (here, drought duration) across the different sites (stations) of a homogeneous region (group).

The Z^{DIST} test measures the deviation of the L-kurtosis ratios between the theoretical value of the selected distribution and the mean value obtained from Monte Carlo simulations of the original region. The Z^{DIST} statistic was calculated using an R programme provided by Hosking [37] in the lmomRFA package (Version 3.0-1). The goodness-of-fit was evaluated for five candidate distributions: Generalised Logistic (GLO), Generalised Extreme Value (GEV), Generalised Lognormal (LN3), Pearson Type III (PE3), and Generalised Pareto (GPA). Provided that the region is acceptably homogeneous, the fit can be considered acceptable at the 10% significance level if the absolute value of Z^{DIST} is less than 1.645.

2.3.4. Regional Quantile Estimation

Regional estimation transfers information from gauged sites within a region to an ungauged or partially gauged site for which insufficient data are available. According to Ouarda et al. [38], the most widely used methods that provide adequate estimates are the Index Flood method [39] and the regression method. In this study, the flood index method was employed.

Originally proposed by Dalrymple [39], the basic assumption of the method is that data at different stations are independent and follow the same statistical distribution, up to a scale factor. The method comprises several steps, as described in [12].

2.3.5. Reliability of the Regional Quantile Estimation Method

The reliability of the regional quantile estimation method can be assessed by calculating the root mean square error (RMSE) associated with the regional estimates. This measure quantifies the overall deviation (or error) of the estimated quantiles relative to the true (empirical) quantiles. For each station within the homogeneous region, these values are computed for return periods of 2, 5, 10, 20, and 50 years [36]. Thus, it serves as an important criterion for

evaluating the superiority of one model over another. After several iterations (Monte Carlo simulation), the regional relative mean RMSE of the estimated quantile is given by the following equation (Eq. 6):

$$RMSE(\%) = 100 \sqrt{\frac{1}{N} \sum_{i=1}^N [(Q_i^R - Q_i^L)/Q_i^L]^2} \quad (6)$$

Here Q_i^R et Q_i^L represent the return-period T quantiles estimated for site i from the regional and local distribution parameters, respectively, and N is the number of stations.

2.3.6. Spatial Interpolation Technique for Estimated Quantiles

The estimated drought duration quantiles were spatially interpolated using the Inverse Distance Weighting (IDW) method. This is a simple and effective interpolation technique based on the assumption that the values of a variable at a location to be estimated are similar to those at neighbouring observation points. The method assumes that each station exerts a local influence, which decreases with distance through the use of a power parameter [40]. In this study, a power value of $p = 0.3$ was applied.

3. Results and Discussion

3.1. Formation of Rainfall Station Groups Based on Drought Manifestation

Table 3. Matrix Selection Based on Quantisation (QE) and Topology Errors (TE)

Matrix	Quantisation Error (QE)	Topology Error (TE)
[3x8]	0.37*	0.00*
[8x3]	0.38	0.00
[2x11]	0.38	0.00
[11x2]	0.39	0.00

*Lowest QE and TE values indicate the selected matrix.

The Kohonen self-organising map produced the results shown in Table 3 and Figure 4. The [3x8] matrix was found to be the most appropriate configuration, as it minimised topology and quantisation errors (Table 3).

Figure 4a shows a Kohonen self-organising map (SOM) illustrating the clustering of rainfall stations based on drought manifestation. The stations distributed across the different Kohonen cells were subsequently aggregated using an agglomerative hierarchical clustering (Figure 4b), which groups the stations on the basis of similarities in spatial coordinates and SPI-3 time series statistics. With a cut-off level of 0.7 on the Euclidean distance tree (Figure 4d), four distinct groups were obtained. However, when applying an euclidean distance of 1, three groups were identified (Figure 4c). The transition from three to four groups results from the subdivision of Group 2 in the classification of Figure 4c. For the remainder of the study, the classification yielding four groups or regions, denoted

R1 (Orodara, Ouangolo, Abengourou, Ouéllé, Dabakala, Bongouanou, Daoukro), R2 (Abidjan, Adiaké, Alépé, Bassam, Adzopé), R3 (Bouna, Bondoukou, Agnibilekrou, M'Bahiakro, Aboisso) and R4 (Tafiré, Tengréla, Ferkessédougou, Bobo-Dioulasso, Niangoloko, Kampti), was retained (Figure 4d).

The distribution of the different regions identified within the Comoé River Basin roughly corresponds to climatic zoning. Group R2 is characteristic of the transitional equatorial climate, as all stations within this group are located in this zone. The stations in Region R4 (Tafiré, Tengréla, Ferkessédougou, Bobo-Dioulasso, Niangoloko, and Kampti) are typical of drought manifestation in the tropical transitional climate. Groups R1 and R3 appear to be heterogeneous in terms of climate typology: the stations of M'Bahiakro, Aboisso, and Agnibilérou, which belong to R3, and those of Ouéllé, Daoukro, Bongouanou, and Abengourou, which belong to R1, are situated in the transitional equatorial climate zone, as is R2. The other two stations of R3, namely Bouna and Bondoukou, and the station of Dabakala in R1, are located in the attenuated equatorial climate. Furthermore, Region R1 appears more heterogeneous than R3, with stations such as Orodara and Ouangolodougou situated in the tropical transitional zone, while others are in the transitional equatorial climate.

3.2. Assessment of Cluster Validity Based on Homogeneity and Discordancy Tests

In all groups, the skewness coefficient (L-Skewness = t_3) is less than 0.23. The Hosking and Wallis type 1 (H_1) test is therefore recommended for assessing the heterogeneity of the different groups. The values of the H_1 heterogeneity index for the groups resulting from the classification indicate that they are all homogeneous (Table 4). Groups R1, R2, and R3 are homogeneous with H_1 values of 0.5, -0.27, and -0.56, respectively. They are more homogeneous compared with region R4, which is acceptably homogeneous with $H_1 = 1.71$. The values of the regional $L-C_v$ (denoted by t) for all groups range between 0.33 and 0.36 in absolute terms, indicating a large regional variability in the distribution of SPI-3 values. These high $L-C_v$ values are also associated with strong observed skewness, reflecting a marked asymmetry or dispersion of the different distributions at the regional scale. These conclusions are not sufficient to determine the homogeneity of a region within the framework of regional frequency analysis. The discordancy statistic (D_i) must also be satisfied in order to assess whether a site (station) is discordant or inappropriate within a given region (group). The computed D_i values are presented in Table 5. The sites belonging to the different regions are therefore correctly assigned. No manual reorganisation or adjustment of the clusters was carried out, as all groups resulting from the SOM procedure are homogeneous according to the recommended H_1 and D_i indices. In the subsequent analyses, these groups will be considered for further investigation of the drought duration parameter.

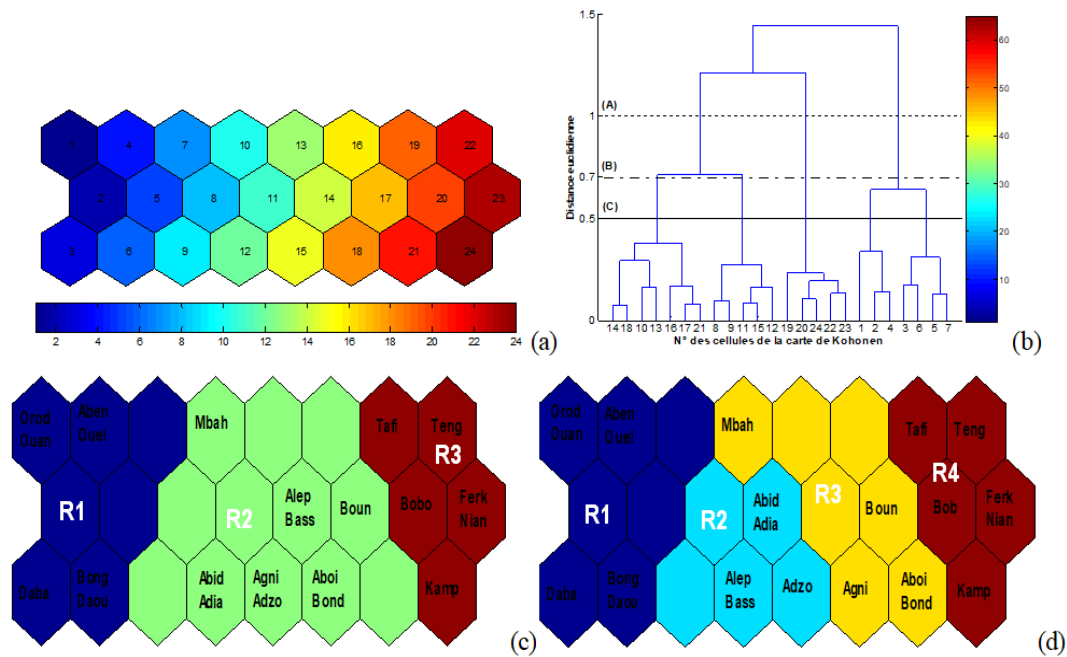


Figure 4. Group formation: (a) synoptic view of the different Kohonen cells, (b) various cutting levels of the dendrogram, (c) and (d) clusters obtained with Euclidean distances of 1 and 0.7, respectively

Table 4. Regional L-Moments for the Drought Duration Groups

Region	Number of station	Regional mean				H1
		t	t3	t4	t5	
R1	7	0.36	0.46	0.17	0.14	0.5
R2	5	0.35	0.37	0.16	0.16	-0.27
R3	5	0.33	0.37	0.11	0.09	-0.56
R4	6	0.33	0.4	0.08	0.05	1.71

Table 5. L-Moment Statistics and Discordancy Index (D_i) for the Sites (Stations) in the Previously Delineated Regions (Groups)

Region	Site	L-moments and Discordancy measure						D_i
		n	l_1	t	t_3	t_4	t_5	
R1	Orodara	37	2.0541	0.3962	0.6063	0.3317	0.2374	1.31
	Ouangolo	34	2.2059	0.3762	0.4386	0.1296	0.1312	0.46
	Abengourou	48	1.9375	0.2917	0.326	0.1038	0.162	1.72
	Ouélé	44	2.1818	0.3726	0.5016	0.2804	0.2588	0.99
	Dabakala	44	2.1364	0.3691	0.4498	0.1263	0.0787	0.22
	Bongouanou	43	2.2326	0.3844	0.4455	0.1092	0.0635	0.76
R2	Daoukro	50	1.92	0.3401	0.4711	0.1318	0.0575	1.53
	Abidjan	43	2.3721	0.3329	0.3084	0.1034	0.0958	0.72
	Adiaké	39	2.4359	0.3368	0.366	0.2243	0.1809	0.58
	Alépé	38	2.5	0.398	0.4251	0.1577	0.1534	1.29
	Bassam	17	2	0.3088	0.2571	-0.0986	-0.0165	1.3
R3	Adzopé	43	2.2791	0.3586	0.4444	0.2703	0.2873	1.11
	Bouna	40	2.15	0.3494	0.4077	0.1327	0.1046	1.1
	Bondoukou	47	2.1064	0.3219	0.3393	0.0874	0.0953	1.05
	Agnibilékrou	48	2.1667	0.3322	0.353	0.0991	0.0846	0.19
	M'Bahiakro	50	1.92	0.3525	0.5184	0.1809	0.0724	1.33
R4	Aboisso	40	2.35	0.3077	0.1999	0.018	0.1092	1.33
	Tafiré	44	2.1364	0.3563	0.4292	0.1463	0.13	0.72
	Tengréla	39	2.0513	0.3296	0.3777	0.0946	0.0887	0.7
	Ferkessédougou	46	2.0217	0.3587	0.4739	0.1379	0.0594	0.27
	Bobo-Dioulasso	47	1.7872	0.3245	0.493	0.1016	-0.0332	1.59
	Niangoloko	45	1.9333	0.2706	0.1746	-0.1072	0.015	1.61
	Kampti	47	2.0426	0.3601	0.4584	0.1113	0.0419	1.11

3.3. Regional Probability Distribution of Drought Duration

3.3.1. Z^{DIST} Statistic

The interpretation of the Z^{DIST} statistic results indicates that only the Pearson Type III and Generalised Pareto

probability distributions provide the best fit to drought duration in region R2, as the absolute value of the Z^{DIST} statistic is less than 1.645 (Table 6). For the other regions, none of the tested distributions appear suitable for the estimation of drought duration across the basin. This statistic should be combined with the L-moment ratio diagram to ensure an optimal distributional choice.

Table 6. L-Kurtosis Coefficient and Z^{DIST} Statistic of the Drought Duration Series

Probability distribution	Clusters statistics							
	$L\text{-Kurtosis}$				Z^{DIST}			
	R1	R2	R3	R4	R1	R2	R3	R4
Generalised Logistic (GLO)	0.342	0.283	0.28	0.302	5.73	3.44	6.32	7.24
Generalised Extreme Value (GEV)	0.329	0.263	0.26	0.285	5.32	2.87	5.6	6.7
Generalised Log-Normal (LN3)	0.29	0.233	0.231	0.251	4.06	2.01	4.54	5.65
Pearson Type III (PE3)	0.223	0.181	0.179	0.194	1.89	0.52*	2.71	3.83
Generalised Pareto (GPA)	0.276	0.199	0.196	0.225	3.62	1.04*	3.29	4.8

*Values of the Z^{DIST} statistic less than 1.645

3.3.2. L-Moment Ratio Diagram

L-moment diagrams (more precisely, diagrams of the L-skewness (t_3) and L-kurtosis (t_4) are similar to classical moment diagrams but have the advantage of being less sensitive to sampling fluctuations. They allow the assessment of the degree of homogeneity of a region and the selection of a theoretical distribution to construct a growth curve. Assuming that the group formed by the rainfall stations in region R1 is homogeneous, all stations would be represented by the same point in these diagrams (generally by the mean). This regional value is denoted by

the symbol '+'. Based on this diagram, none of the distributions is formally appropriate for predicting the future evolution of drought duration at the regional scale (Figure 5). However, region R2 appears close to the Pearson Type III (PE3) model. Additionally, at the individual site level, some stations resemble the Generalised Logistic distribution in terms of drought duration. In such cases, it is recommended to use the Wakeby or 5-parameter Kappa distributions, which are more robust. Table 7 summarises the probability distributions selected for the subsequent analyses.

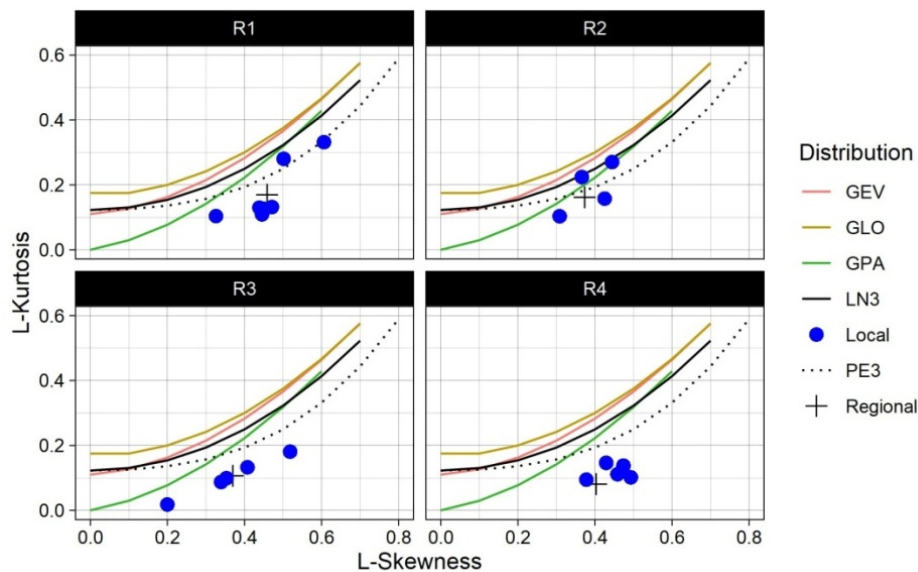


Figure 5. L-moment ratio diagrams of drought duration for the groups or regions

Table 7. Parameters of the Probability Distributions Selected for the Estimation of Drought Duration

Group	Distribution probability	Parameter				
		ξ	α	β	γ	δ
R1	Wakeby	0.3749	0.0000	0.0000	0.4641	0.2576
R2	Wakeby	0.3279	0.0000	0.0000	0.6137	0.0870
R3	Wakeby	0.3598	0.0000	0.0000	0.5896	0.0790
R4	Wakeby	0.3826	0.0000	0.0000	0.5255	0.1488

3.4. Estimation of Regional Drought Quantiles Associated with Return Periods

The quantile here represents occurrence of a drought of a given duration (in months) over a return period of T years. Longer drought durations for a given return period indicate a higher risk of drought onset. Figure 6 shows the probable drought durations for several return periods. For a return period T of 5 years, the probable drought duration would be on average 3 months for groups R1, R3, and R4, whereas it would be 4 months for group R2, characteristic of the transitional equatorial climate. For $T = 10$ years, this duration increases to 4 months for groups R1, R3, and R4, while it would be approximately 5 months for group R2. For long-term estimation ($T = 50$ years), groups R2 and R1 would have a probable duration of 8 months, and groups R3 and R4 a duration of 6 months. However, this variability in estimated duration remains relatively small. For example, for return periods between 1 and 4 years, the estimated drought durations, ranging from 2 to 3 months, are relatively homogeneous across all groups. For a 50-year return period, the drought duration would be estimated at 6–7 months for groups R1 and R2, whereas it would be 5–6 months on average for groups R3 and R4. The calculation of the relative mean square error (RMSE) indicates that the selected distributions provide the best fit to the different components of drought at the regional scale. Indeed, the computed RMSE values are below 15% for the regional growth curves.

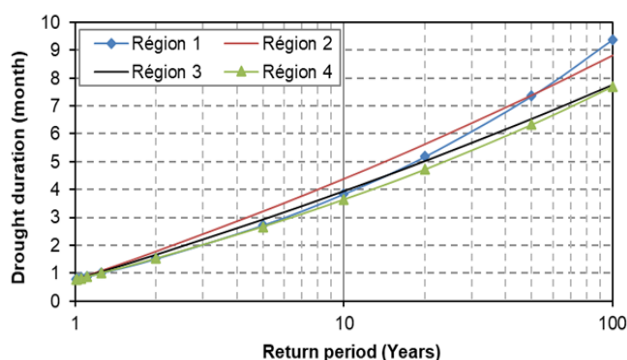


Figure 6. Regional quantiles of drought duration estimated for different return periods

Only the extreme right-hand tails exhibit errors approaching 50%, but these remain within acceptable limits. Regional estimation appears more reliable than site-specific (station-based) estimation, given the smaller RMSE values in the regional model compared with the site model. Consequently, site-specific quantiles will be estimated by normalising them using the Index Flood method. Following the estimation of station-based quantiles on the basis of the Index Flood, Section 3.5 addresses the interpolation of these estimated durations in order to provide insight into the manifestation of drought across the Comoé River basin.

3.5. Mapping of Station-Based Estimated Durations of Meteorological Drought

The catchment is predominantly characterised by short and relatively homogeneous drought durations over most

of its area (Figure 7). In contrast, in the far north of the basin (the portion located in Burkina Faso), longer drought durations are observed compared with the rest of the basin. Drought duration increases with return period, ranging from a maximum of 4 months for $T = 2$ years to 20 months for a return period of 100 years. By way of illustration, the most probable maximum drought duration is around 2, 4, and 5 months for return periods of 2, 5, and 10 years, respectively (short-term prediction), across the majority of the basin. For these same return periods, drought durations of 4, 6, and 8 months are expected in the extreme north of the basin. For long-term prediction ($T = 20$ and 50 years), the maximum expected drought persistence ranges between 6, 8, and 10 months over most of the basin. In the northern part of the basin, rainfall deficiency may extend over a full hydrological year or even two, with maximum drought durations of 11 and 16 months corresponding to return periods of 20 and 50 years, respectively.

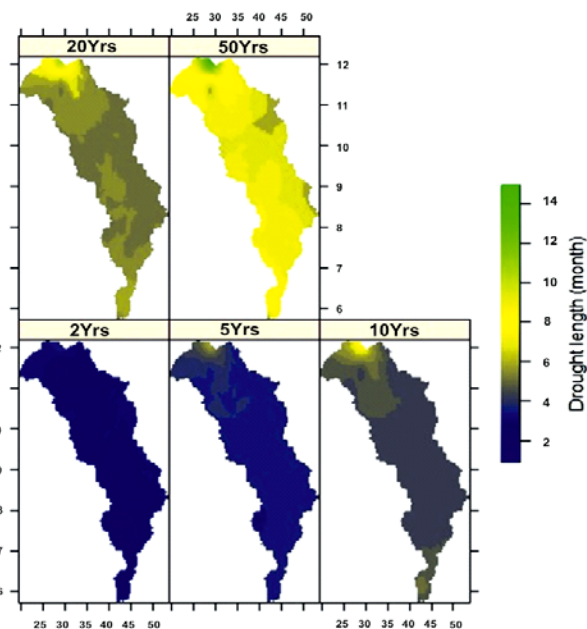


Figure 7. Spatial distribution of meteorological drought duration for return periods of 2, 5, 10, 20, and 50 years

3.6. Discussion

The classification produced four groups on the basis of the model's input parameters. These regions appear well delineated due to the variation in kurtosis from one region to another, confirming the discriminating power of the classification. Furthermore, the Hosking and Wallis [12] heterogeneity tests applied to the pre-defined regions corroborate their homogeneity. Ward's criterion remains a robust classification method, as highlighted by [41]. The correspondence between the regions and climatic zones is discussed in this section. Regions R2 and R4 are characteristic of the transitional equatorial climate and transitional tropical climate, respectively. By contrast, the remaining groups, R1 and R3, reflect a form of spatial and/or climatic heterogeneity, since stations in these regions belong to multiple climatic zones. Such heterogeneity in drought manifestation has also been highlighted in previous studies and is evident both at

national and basin scale [38,39]. According to Vicente-Serrano [13], the spatial distribution of drought is generally complex, with marked inhomogeneity even between neighbouring regions. This variability may be attributed to the complexity of atmospheric circulation and to the fact that drought cannot be linked to a single type of atmospheric condition. Moreover, pronounced inhomogeneity in drought distribution is most frequently observed in transitional climatic regions [44]. The Comoé River basin, which is the focus of this study, spans three distinct climatic zones from north to south. Additionally, this transboundary basin lies within the West African monsoon domain, one of the most complex climatic systems.

In the process of stochastic modelling, uncertainties must be minimised as much as possible, and robust methods should be employed at each stage. The use of L-moments in this study is consistent with previous research aimed at improving the robustness of estimation methods. According to Lana et al. [45], the Euclidean distance defined by L-skewness and L-kurtosis is an effective indicator for achieving a better fit between empirical distributions and statistical models, especially when sample sizes are small and the 95% Kolmogorov–Smirnov confidence interval is not restrictive. Furthermore, Hosking and Wallis [12] demonstrated that the statistical differences between return periods derived from conventional moments and those derived from L-moments are non-negligible. The adoption of more robust estimation methods (L-moments), as in the present study, is therefore recommended. The combination of the L-moment ratio diagram and the Z^{DIST} statistic proved decisive in selecting the final regional model. Based on Z^{DIST} , the GNO, PE3, and GPA distributions provided a satisfactory fit at site (station) scale. However, at the regional scale, only the Wakeby distribution was found to be the most appropriate. According to Hosking and Wallis [12], the five-parameter Wakeby distribution has the advantage of encompassing the forms of several asymmetric distributions commonly used (GEV, GNO, PE3, etc.). The technical parameterisation of the Wakeby distribution reveals a generalised form of the Generalised Pareto probability law. In drought analyses by [13] and [46], the Wakeby distribution has been widely used to simulate both drought duration and severity using the SPI and SPEI indices. Hosking and Wallis [12] suggest that two- or three-parameter distributions are adequate for site-based frequency analysis, whereas regional analyses are better suited to three- to five-parameter distributions for improved estimation.

High probabilities of long drought durations are observed in the transitional tropical climate (Region R4) rather than in areas close to the equator. The risk of drought occurrence is relatively homogeneous across the basin, except in the extreme north. In this part of the basin, drought severity is exacerbated by long durations for return periods of 20 and 50 years. This northern zone is the most arid, being close to the Sudano-Sahelian climate. According to Lebel and Vischel [47], tropical regimes exhibit two features that distinguish them from mid-latitude regimes: (i) their seasonal cycle is well marked and more stable from year to year; and (ii) rainfall is below potential evapotranspiration (PET) for most of the

year, particularly in semi-arid subtropical areas. These two features help to explain why, apart from areas close to the equator where the ITCZ influence is almost permanent, tropical regions are especially sensitive to drought, even though their annual rainfall totals are often comparable to, or greater than, those of temperate regions. In these tropical zones, water balances are controlled by rainfall amounts, whereas in temperate regions they are controlled primarily by temperature. With respect to future drought occurrence, the findings of this study are consistent with projections based on global climate models, which suggest that drought frequency and intensity will likely increase in the Mediterranean basin and West Africa, but decrease in central North America and north-western Australia since 1950 [1]. Africa is expected to be particularly vulnerable to extreme droughts affecting multiple regions simultaneously [42]. More localised studies further indicate that semi-arid and sub-humid regions in Africa are especially prone to drought [48]. The uncertainties estimated using RMSE remain within acceptable limits, lending credibility to the modelling results. However, it is important to note that considerable uncertainties and inconsistencies persist in drought projections for Africa, owing to model limitations and the complexity of multiple mechanisms influencing rainfall trends [42]. These uncertainties are further compounded by the scarcity of direct observations, the dependence of inferred trends on the choice of drought indices, and the geographic inconsistency of observed trends [1].

4. Conclusion

Current and future climatic conditions project the persistence of hydrological extremes (droughts and floods). At the same time, pressures on water resources are intensifying due to the diversification of uses and demographic growth. One of the main challenges for basin managers remains ensuring the availability of resources in both quality and quantity, while also establishing an early warning system to mitigate the adverse impacts of drought. This study was undertaken to construct a spatio-temporal perspective of the occurrence of meteorological drought at the scale of the Comoé River basin. A threshold of -0.84 in the Standardised Precipitation Index (SPI) was adopted as the limit below which drought conditions are declared. Regional analysis subsequently identified four homogeneous regions, one of which is representative of the transitional tropical climate (Region R4) in the north, another representative of the transitional equatorial climate (Region R2) in the south, and two others (Regions R1 and R3) with contrasting climatic characteristics. The reliability of the classification, assessed using the discordance (D_i) and heterogeneity (H_i) indices, led to the implementation of regional frequency analysis. Accordingly, the five-parameter Wakeby probability distribution was found to be the most appropriate for stochastically reproducing the duration of meteorological drought across the basin. The estimation results indicate prolonged drought events in the far north of the basin (transitional tropical climate), in contrast with the central and southern zones, which are characterised respectively by attenuated transitional equatorial climate and

transitional equatorial climate. This study concludes that the Comoé River basin is vulnerable to extended droughts. This vulnerability is further amplified by the basin's strong dependence on rain-fed agriculture and by the lack of water resource management and drought disaster management infrastructure. These important preliminary findings provide a foundation for more detailed research aimed at establishing an integrated system and a chain of scientific approaches for drought early warning in the transboundary Comoé basin.

ACKNOWLEDGEMENTS

All this work could not be done without material and financial support. I would like to express my special thanks to the facilitators of the PAES (Programme d'Appui à l'Enseignement Supérieur) in the ECOWAS region for agreeing to finance my research project.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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