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Meteorological Drought Detection and Forecast Using Standardized Precipitation Index and Univariate Distribution Models: Case Study of Bamako, Mali

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Abstract

As an extended period of unusually dry weather conditions without sufficient rain, drought poses enormous risk on societies. Characterized by the absence of precipitation for long periods of time, often resulting in water scarcity, droughts are increasingly posing significant environmental challenges. Drought is therefore considered an important element in the management of water resources, especially groundwater resources during drought. This study therefore sought to investigate the rainfall variability and the frequency of drought for the period 1991 to 2020 in Bamako based on monthly rainfall data from Bamako-Senou gauge station. The standardized precipitation index (SPI) for 12-month, 6-month and 3-month timescales and the SPI for annual totals were used to characterized drought in the study area (Bamako). Univariate parametric probability distributions such as Normal, Log-normal, Gumbel type I and Pearson type III (P3) distributions were fitted with drought variables (severity and duration) for future planning and management. Non-parametric test such as Mann-Kendall trend test was also used to detect trend in annual rainfall data. The results showed that based on 12-month SPI, Bamako experienced two (02) extreme droughts one in July 2002 (SPI = −2.2165) and another in June 2015 (SPI = −2.0598). Drought years represented 46.67% for the overall periods according to the SPI for annual totals. The result further indicated that based on the goodness of fit test, the P3 distribution represents the best fitted distribution to both drought severity and duration over Bamako. Bamako is expected to experience several severe severities with higher and shorter duration in the future. Severities with 1, 2, 6, and 10-month duration had return periods ranged from 2.4 to 3.8 years, while 5, 10, 20, 25, 50, and 100-year return periods had 18.51, 26.08, 33.25, 35.50, 42.38, and 49.14 severities, respectively, and durations associated to these severities were 19.8, 26.9, 33.5, 35.6, 42, and 48.2 months, respectively.

Keywords

Standardized Precipitation Index (SPI), Rainfall Variability, Univariate Probability Distribution, Drought, Bamako

1. Introduction

Atmospheric temperature rise may affect rainfall pattern and surface temperature, which could consequently affect water availability in some regions with high risk of droughts and floods. Drought is characterized by lack of precipitation for an extended period, usually resulting in water scarcity. Most African countries, more precisely sub-Saharan countries, are projected to be affected by the most devastating impacts due to their geographical position, low income, and low capability to adapt to these rapid changes among others (Boatemaa et al., 2020). However, recent trends on climate variability and change are found to strongly affect societal activities across Mali (World Bank Group, 2011), as a climate report found that the mean annual temperature across Mali has increased by 0.7˚C since 1960 with an average rate of 0.15˚C/decade. The mean annual temperature across Mali was however, projected to increase by 1.2˚C to 3.6˚C in 2060s, and by 1.8˚C to 5.9˚C in 2090s while the rate of warming was projected to be similar across all seasons (World Bank Group, 2011). Bamako is part of the Sudanian zone in Mali. Climate can be described as having a rainy season which lasts up to six (6) months with a maximum peak generally in August, and one (1) dry season occurring between February to the second week of May. Rainfall is primarily controlled by the oscillation of the Intertropical Convergence Zone (ITCZ) across the northern and southern African continent, usually bringing rainfall to South Mali from June to October each year (World Bank Group, 2011). The West African Sub-region is typically known to record significant variability in rainfall especially as was observed during the 20th century (Obuobie et al., 2013; Speth et al., 2010). The West African Monsoon (WAM) is mainly affected by increased atmospheric temperatures caused by higher greenhouse gases concentrations (Christensen et al., 2013; Nikulin et al., 2012).

Drought is considered as a climatic extreme affecting more people than any other form of natural disaster (Wilhite, 2000). It is therefore classified as a natural hazard that might have a negative effect on humans, animals and the environment. Many people have been affected by drought in Africa with famine being the most negative effect (Scrimshaw, 1987), and epidemics and land degradation (UN, 2008; Bandyopadhyay et al., 2012). Drought is considered among one of the most devastating natural disasters that caused a significant number of deaths in the past few years. It was recorded that 450,000 and 325,000 people were killed in 1984 and 1974 droughts respectively (UN, 2008). Among the regions affected were Ethiopia, Soudan, and the Sahel region (UN, 2008). Droughts and floods are the most important recurring risks in Mali, with the most severe effects happening in the southern region (World Bank, 2019). On average, 0.4 million people are affected by drought every year, this number can be substantially higher in dry years (World Bank, 2019). Flooding poses a threat to lowland, highland, and urban areas, affecting 500,000 people on average each year. A much smaller number of people are at risk from landslides (World Bank, 2019). Future population and economic developments in Mali, together with changes in climate-related hazards, are predicted to amplify the effects of droughts and floods (World Bank, 2019). In Mali, 400,000 people live in areas expected to experience water scarcity each year, predominantly in the southern regions like Bamako (World Bank, 2019). Groundwater is nearly entirely used for drinking, residential use, and livestock watering, and it is accessed via both conventional and contemporary wells (USAID, 2021). It is estimated 55 percent of the population in Bamako depend on groundwater (USAID, 2021). Several projections of Mali's drought indicated Bamako is at the medium-high risk of drought. Groundwater demand may increase in the future given the high rate of projected population growth and more frequent severe droughts (USAID, 2021). Despite expected increases in precipitation, hotter temperatures could increase evaporation and decrease surface water supply in the regions like Bamako (Sanogo et al., 2023). Increased interannual variability in precipitation and more frequent drought will impact Bamako groundwater availability and population at risk (USAID, 2021).

Drought is also one of the main natural sources of economic, agricultural, and environmental damage (Burton et al., 1978; Wilhite, 1993). For instance, the average annual cost of drought damage in agricultural sector in the United States is estimated between \$6 and \$8 billion (Mirabbasi et al., 2013). Drought is obvious after a long period without precipitation, but accurately quantify its characteristics in terms of intensity, magnitude, duration and spatial extent is extremely difficult (Vicente-Serrano et al., 2010). When a drought episode occurs, moisture shortages are noticeable in many drought variables such as streamflow, soil moisture, precipitation, groundwater levels, snow pack and reservoir storage (Mirabbasi et al., 2013). Among drought characteristics computation, drought severity is the most difficult variable to accurately quantify as it is a mixture of the duration, magnitude and spatial extend of the drought (Dracup et al., 1980).

Over the years, meteorologists and climatologists have developed and used many drought indices around the world (WMO, 2012). These ranged from simple indices such as normal precipitation's percentage and precipitation percentiles to more complex indices such as the Palmer Drought Severity Index (PDSI). The PDSI relies on the demand and supply concept of the water balance equation, considering moisture supply, precipitation, runoff and evaporation demand at the surface level (Vicente-Serrano et al., 2012). One of the disadvantages of using the PDSI is its fixed temporal scale, which obviously influences the shortcoming of drought. In fact, available evidences such as (Szalai et al., 2000; Khan et al., 2008, and Vicente-Serrano, 2007) indicated that the reaction to the conditions of drought of river discharge, soil moisture level, reservoir storage, groundwater level and other environmental and economic variables occurs at different time scales. An evaluation of the meteorological droughts is fundamental for the desertification prediction and for the management of water resources, particularly groundwater resources. One of the most used indices to assess drought is the standardized precipitation index (SPI) due to its simplicity and effectiveness to evaluate drought in various time scales (Reyes et al., 2022). The World Meteorological Organization (WMO) considers the SPI as a widespread drought index because of its effectiveness to estimate for various reference periods adapting to the difference response times of typical hydrological characteristics to precipitation (Mohammed et al., 2017). The SPI can be used as a drought severity indicator or excessive wetness as well as in the drought and flood development emergency plans (Griddings et al., 2005).

The main advantage of using the SPI is that it allows comparison of droughts at any regional scale, while its minor disadvantage is that it computes only rainfall as an input variable. However, other pertinent factors and meteorological parameters in drought evaluation used in the computation of other indices are not considered (Sobral et al., 2019). In this study, the SPI is aggregated at various timescales to determine seasonal periods that occurred in Bamako during the last thirty (30)-year from 1991 to 2020. The main objectives of this study are therefore to understand rainfall variability in Bamako that occurred during the last 30-year using the 12-month, 6-month and 3-month SPI and the SPI for annual totals. Four (4) commonly univariate probability distribution functions namely the Normal, Log-normal, Gumbel type I and Pearson type 3 distributions were fitted to drought variables (severity and duration), the best fitted distribution based on the goodness-of-fit test was used to compute the upcoming return periods of severity associated with durations.

2. Materials and Methods

2.1. Source of Data

The main source of data used in this study was from the National's Meteorological Agency of Mali, MALI-METEO which provided monthly rainfall data from Bamako-Senou climate station for a 30-year period (from January 1991 to December 2020). Though an extended rainfall data beyond the thirty (30)-year period would have been more useful for accurate and reliable results in this study, only 30-year data was made available by MALI-METEO.

Monthly rainfall data from Bamako-Senou climate station were used to compute the standardized precipitation index (SPI) at 12-month, 6-month and 3-month timescales and the SPI for annual totals, respectively. Monthly rainfall data from Bamako-Senou climate station was examined statistically to assess rainfall variability in the study area (**Table 1**) using central tendency, dispersion (standard deviation, coefficient of variation) and distribution (skewness and kurtosis). Bamako-Senou rain gauge station characteristics such as longitude, latitude and elevation are provided in **Table 2**.

2.2. Study Area

Bamako is the capital city of the Republic of Mali, and Mali's administrative center and located at both sides on the bank of Niger river at 8˚0'0''W and 12˚38'21''N (**Figure 1**). The study area has a land area of 245 Km^2, and about 1.3 million inhabitants, while the population density is 5300 people per square kilometer (Keita et al., 2020). According to the World Capital Cities accessed on 23/05/2019, the greater Bamako population is about 3.1 million of people with a density of 10,000 people per square kilometer. The climate can be described as one rainy season, which lasts almost up to six (6) months from the middle of May to October each year, peaking usually in August. The dry season however, occurs between February and the second week of May. Bamako is part of the Sudanian zone in Mali, and has sufficient rainfall, fertile soils, and abundance of trees. Rainfall is largely controlled by Intertropical Convergence Zone (ITCZ) oscillations across the North and South of the African continent, usually bringing rainfall to South Mali from June to October each year (World Bank Group, 2011).

The average monthly rainfall during the rainy season usually ranges from 54.1 mm in May to 290.2 mm in August, with a mean annual rainfall of 991.3 mm. Daily maximum and minimum temperature variations of 40˚C and 17˚C exist in April and December respectively, with an average annual figure of 29˚C in March. The warmest and coolest months of the year are respectively April and May, and December to January representing the months without rain (Keita et al., 2020). Bamako can receive more than 600 mm of rainfall during the rainy season and flooding is common. Located in a valley covered with sandstone deposits, Bamako has two types of soil: one caused by rock formation, and the

Table 1. Descriptive statistics of annual rainfall series in Bamako.

Annual Rainfalls (1991-2020)						
Minimum (mm)	Mean (mm)	Maximum (mm)	Standard deviation (mm)	Coefficient of Variation (%)	Skewness	Kurtosis
750.5	946.77	1205.1	133.374609	14.09	0.311038	−0.987421

Table 2. Bamako-Senou rain gauge station characteristics.

Station	ID	Longitude	Latitude	Elevation (m)
Bamako-Senou	61291	7.95˚W	12.53˚N	380

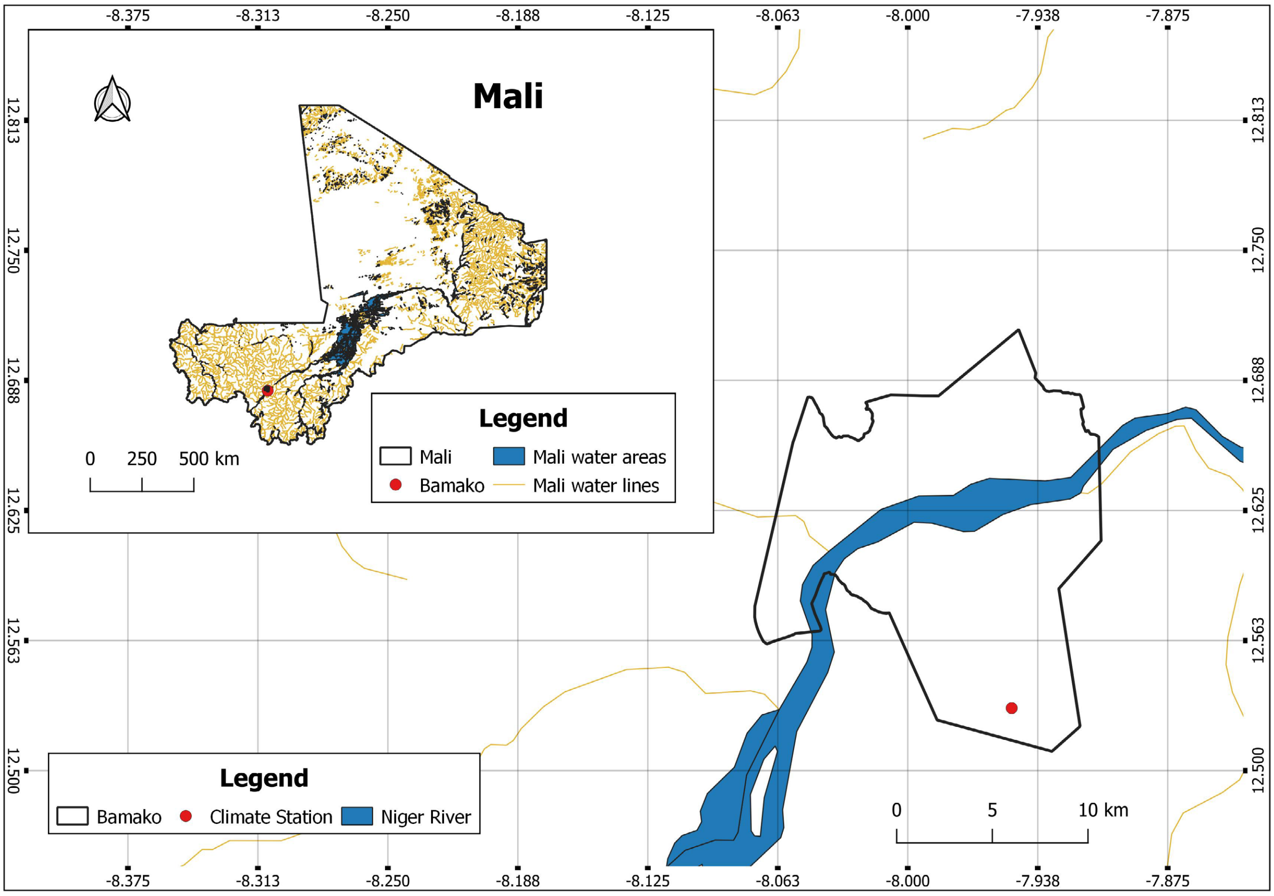


Figure 1. Study area map locating Bamako-Senou climate station.

other due to lateralization and alluvial formation occupying the primary and secondary river beds and tributaries (Keita et al., 2020). Bamako's vegetation is largely savannah forest and rivers (Keita et al., 2020). The topography of the Bamako area is given in Figure 2.

2.3. Methods

2.3.1. Coefficient of Variation (*CV*)

Variation of the mean annual rainfall for the entire study area was measured using a coefficient called coefficient of variation (CV). The CV is described as:

$$CV = \frac{\sigma}{\mu} \times 100\% \tag{1}$$

where σ and μ are the standard deviation and mean of the annual rainfall respectively.

2.3.2. Standardized Precipitation Index for Annual Totals and Annual Maximum

The standardized precipitation index (SPI) relies on the likelihood of precipitation for any timeframe based on lasting precipitation data for a given period (WMO, 2012). The lasting precipitation record is fitted to a probability distribution

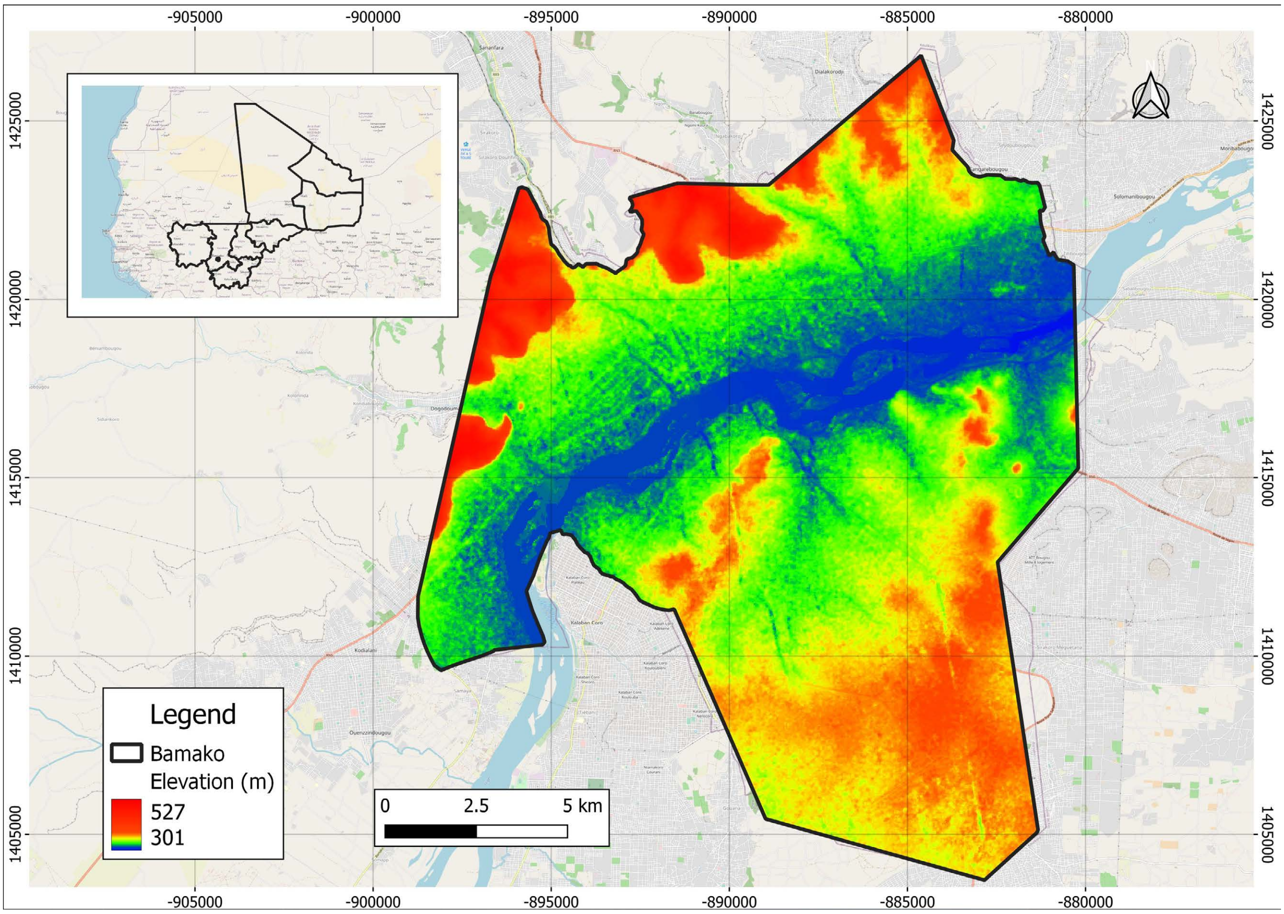


Figure 2. Topography of the study area.

and then transformed into a normal standard distribution that defines the SPI (WMO, 2012). The probability distribution that defines the SPI is the gamma distribution function which can be expressed as (Achite et al., 2021):

$$g(x)=\frac{1}{\beta^{\alpha}\Gamma(\alpha)}x^{\alpha-1}e^{-x/\beta} \tag{2}$$

where α and β are the shape and scale parameters respectively. x is consecutive precipitation and Γ(α) is the gamma function. The gamma function is defined by the following:

$$\Gamma(a)=\int_0^{\infty} y^{a-1}e^{-y}dy \tag{3}$$

The gamma distribution's parameters α and β are estimated from the precipitation time series as

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

where x is the mean precipitation value quantified; n is the number of precipitation; x_i is the precipitation's quantity in a sequence of data.

$$G(x)=\int_0^x g(x)dx=\frac{1}{\hat{\beta}^{\hat{a}}\Gamma(\hat{\alpha})}\int_0^x x^{\alpha_{pro}-1}e^{-x/\beta_{pro}}dx \tag{5}$$

To account for the chance of no precipitation, a mixture probability distribution is employed, for which the cumulative probability becomes

$$H(x) = q + (1-q)G(x) \tag{6}$$

where q is the probability that the precipitation's quantity equals zero.

The SPI computation is presented on the basis of the following equation:

$$\text{SPI} = \begin{cases} -\left(t - \dfrac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0 < H(x) \le 0.5 \\ +\left(t - \dfrac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right), & 0.5 < H(x) \le 1.0 \end{cases} \tag{7}$$

where t is determined as

$$t = \begin{cases} \sqrt{\ln\left(\dfrac{1}{(H(x))^2}\right)}, & 0 < H(x) \le 0.5 \\ \sqrt{\ln\left(\dfrac{1}{1-(H(x))^2}\right)}, & 0.5 < H(x) \le 1.0 \end{cases} \tag{8}$$

And c_0, c_1, c_2, d_1, d_2 and d_3 are coefficients whose values are:

$$c_0 = 2.515517, c_1 = 0.802853, c_2 = 0.010328,$$
$$d_1 = 1.432788, d_2 = 0.189269, d_3 = 0.001308$$

The SPI for annual totals is computed as:

$$\text{SPI}_i = \frac{x_i - \mu}{\sigma} \tag{9}$$

where SPI_i is the SPI for the year *i*.

μ and σ being the mean and standard deviation, and x_i is the areal rainfall at the year *i*. Drought classification table based on SPI is given in (**Table 3**) below.

Drought characteristics such as the duration, magnitude, and intensity were computed for the entire study area using the 12-month, 6-month and 3-month SPI timescales.

Table 3. Drought classification based on SPI value and corresponding event probabilities.

SPI value	Drought class	Probability (%)
2 or more	Extremely wet	2.3
1.5 to 1.99	Very wet	4.4
1.0 to 1.49	Moderately wet	9.2
0.99 to 0.99	Near normal	68.2
−1.0 to −1.49	Moderately dry	9.2
−1.5 to −1.99	Severely dry	4.4
−2 or less	Extremely dry	2.3

2.3.3. Drought Magnitude

Drought magnitude is the absolute SPI summation for each identified drought occurrence. It therefore represents drought severity (S) in this study. Severity for drought occurrence i, $S_i\left(i=1,2,\cdots,n\right)$ is assumed to be positive, as provided by (McKee et al., 1993).

$$S_i = -\sum_{t=1}^{D}\text{SPI}_{i,t} \tag{10}$$

2.3.4. Drought Duration

Drought duration is the time between the onset and end of a drought occurrence in the year where SPI becomes positive.

2.3.5. Drought Intensity

Drought intensity is the SPI value of less than negative unity (−1) of a drought occurrence. Peak drought intensity is described as the lowest drought episode's value. Mean intensity refers to magnitude split by drought length.

2.3.6. Drought Frequency

Drought frequency is defined as the number of times a drought event happens in a specified number of years over a given times scale (Boatemaa et al., 2020). Drought frequency was computed as:

$$F_i = \frac{N}{n}\times 100\% \tag{11}$$

2.3.7. Inter-Arrival Time (T_d) of Drought

Inter-arrival Time T_d is the period elapsed between the onset of two successive drought events, or T_d represents the sum of non-drought and drought duration (Ganguli et al., 2012). **Figure 3** illustrates drought characteristics using the SPI.

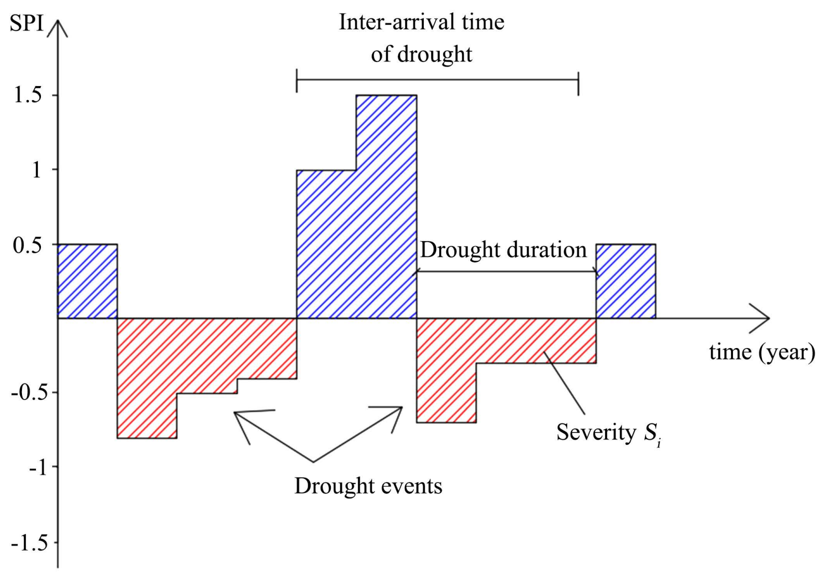


Figure 3. Drought characteristics illustration computed using the SPI.

2.3.8. Fitting Probability Distribution of Drought Variables

For fitting drought variables probability distribution among parametric distributions, Normal, Log-normal (LN), Gumbel type I, and Pearson type 3 (P3) distributions were assessed for fitting drought variables (Table 4). For the non-parametric distribution, the Mann-Kendall trend test was used to perceive statistical significance increasing or decreasing trend in annual rainfall series over the study area.

A closed form expression for the cumulative distribution function (cdf) of the P3 distribution is not available (Maidment, 1993). Tables or approximations are used to provide frequency factors $K_P(\gamma)$ which are the *pth* quantile of a standard P3 variate with skew coefficient γ, mean zero (0) and variance one (1) (Maidment, 1993). For any mean and standard deviation the *pth* quantile can be expressed as:

$$x_P = \mu + \sigma K_P(\gamma) \tag{12}$$

With,

$$K_P(\gamma) = \frac{2}{\gamma}\left(1 + \frac{\gamma z_P}{6} - \frac{\gamma^2}{36}\right)^3 - \frac{2}{\gamma} \tag{13}$$

where z_P is the *pth* quantile of the zero-mean and unit-variance.

From Equation (12),

$$K_P(\gamma) = \frac{x_P - \mu}{\sigma} \tag{14}$$

From the two (2) equations of $K_P(\gamma)$, (13) and (14) z_P is expressed as:

Table 4. Summary table of distributions used to fit drought severity and duration over Bamako.

Distribution	Pdf and cdf	Range	Moments
Normal	$f(x) = \frac{1}{\sigma_x\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{x-\mu_x}{\sigma_x}\right)^2\right]$	$-\infty < x < \infty$	μ_x and σ_x^2; $\gamma_x = 0$
Lognormal	$f(x) = \frac{1}{x\sigma_y\sqrt{2\pi}}\exp\left[-\frac{1}{2}\left(\frac{\ln x-\mu_y}{\sigma_y}\right)^2\right]$	$x > 0$	$\mu_x = \exp\left(\mu_y + \frac{\sigma_y^2}{2}\right)$, $\sigma_x^2 = \mu_x^2\left[\exp\left(\sigma_y^2\right) - 1\right]$; $\gamma_x = 3CV_x + CV_x^3$
Pearson type 3	$f(x) = \frac{\lambda^\beta (x-\epsilon)^{\beta-1} e^{-\lambda(x-\epsilon)}}{\Gamma(\beta)}$	$\beta > 0$	$\beta = \left(\frac{2}{\gamma_x}\right)^2$, $\lambda = \frac{\sqrt{\beta}}{\sigma_x}$ and $\epsilon = \mu_x - \frac{\beta}{\lambda}$
Gumbel	$f(x) = \frac{1}{\alpha}\exp\left[-\frac{x-\xi}{\alpha} - \exp\left(-\frac{x-\xi}{\alpha}\right)\right]$ $F(x) = \exp\left[-\exp\left(-\frac{x-\xi}{\alpha}\right)\right]$	$-\infty < x < \infty$	$\mu_x = \xi + 0.5772\alpha$ $\sigma_x^2 = \frac{\pi^2\alpha^2}{6} \approx 1.645\alpha^2$; $\gamma_x = 1.1396$

* μ_x, σ_x^2 and γ_x are the mean, standard deviation and skewness of *x*, respectively. $Y = \ln x$; parameters λ, β and ϵ represent the scale, shape and location respectively of the distribution, and Γ is the gamma function.

$$z_p = \frac{\gamma}{6} + \frac{6}{\gamma}\left[\frac{\gamma}{2}\left(\frac{x_P - \mu}{\sigma}\right) + 1\right]^{1/3} - \frac{6}{\gamma} \tag{15}$$

where,

$$\gamma = \frac{n}{(n-1)(n-2)s^3}\sum_{i=1}^{n}(x_i - \bar{x})^3 \tag{16}$$

Weibull plot formula was used to compute predicted values of the drought severity and duration. To test the goodness of fit between Normal, Log-normal (LN), Gumbel type I, and Pearson type 3 (P3) distributions, the test statistics such as mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), relative root mean square error (RRMSE), correlation coefficient (CC) and coefficient of determination (COD) were used to select the best fitted distribution of the drought severity and duration series as shown in Table 5.

2.3.9. Return Period of Drought Duration or Severity for Univariate Distribution

The return period is defined in water resources engineering and hydrology as the average passed time between occurrences of an event with a certain magnitude or greater (Ganguli et al., 2012). However, when applied to drought the concept of return period, it is described as the average time between occurrences with a certain magnitude or less (Ganguli et al., 2012). The return period of drought severity or duration in univariate context is defined as:

$$T_{S,D} = \frac{\mu_{T_d}}{P\left(d_{S,D} \geq D_{S,D}\right)} \tag{17}$$

where μ_{T_d} is the mean inter-arrival time of the drought which can be estimated from drought data.

Table 5. Statistical parameters for model selection.

Statistics	Formula	Best Value
Mean Square Error	$MSE = \frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2$	0
Mean Absolute Error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\lvert(O_i - P_i)\rvert$	0
Root Mean Square Error	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2}$	0
Relative Root Mean Square Error	$RRMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\frac{O_i - P_i}{O_i}\right)^2}$	0
Correlation Coefficient	$CC = \frac{\sum(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum(O_i - \bar{O})^2 \sum(P_i - \bar{P})^2}}$	−1 or 1

2.3.10. Mann-Kendall (M-K) Trend Test

Studies show that Mann-Kendall (M-K) trend test is one of the most widely used method for trends detection in climatologic and hydrologic time series (Mavromatis et al., 2011). The test was originally derived by Mann in 1945, and the test statistic called Kendall's tau statistic was later derived by Kendall in 1975. Evaluation of M-K S statistic is by the following equation:

$$S = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \operatorname{sgn}\left(x_j - x_i\right) \tag{18}$$

where,

$$\operatorname{sgn}\left(x_j - x_i\right) = \begin{cases} +1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases} \tag{19}$$

x_j and x_i —the annual values in the j^{th} and i^{th} years.

If $N < 10$, values of $|S|$ are compared directly to the theoretical distribution of S derived by Mann and Kendall. The two (2)-tailed test is used in M-K trend test to know whether trends are significant. The null hypothesis (H_0) is rejected based on the M-K test for the alternative hypothesis (H_a) if the absolute value of $S \geq S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest S, which has the probability less than $\alpha/2$ to appear in case of no trend (Karmeshu, 2012).

For $N \geq 10$, S is approximately normally distributed, where the mean and variance are as follows:

$$E\left(S\right) = 0 \tag{20}$$

Variance (σ^2) for the S-statistic is computed as follows:

$$\sigma^2 = \frac{n\left(n-1\right)\left(2n+5\right) - \sum_i^m t_i\left(i-1\right)\left(2i+5\right)}{18} \tag{21}$$

where t_i —the number of ties to extent i. The summation term is then used only if the data series contains tied values. Note that the standard test Z_s is computed as follows:

$$Z_s = \begin{cases} \dfrac{S-1}{\sigma} & \text{for } S > 0 \\ 0 & \text{for } S = 0 \\ \dfrac{S+1}{\sigma} & \text{for } S < 0 \end{cases} \tag{22}$$

The null hypothesis (H_0) indicates that there is no trend and it is rejected if the calculated value Z_s is greater than or equal to some critical value Z_{cr}, where Z_{cr} is given at some significant level α in P-value table. Kendall's τ coefficient is a statistic used to measure the association between two variables, and used to determine the existing relationship between two series of data. The Kendall rank correlation coefficient τ is computed as:

$$\tau = \frac{2S}{n\left(n-1\right)} \tag{23}$$

2.3.11. Sen's Slope Estimator

The magnitude of M-K trend test is determined by a method derived by Theil (1950) and Sen (1968). The magnitude is computed as follows:

$$Q = med\left(\frac{y_j - y_i}{x_j - x_i}\right) \text{ with } j > i \tag{24}$$

3. Results and Discussion

3.1. Rainfall Variability in Bamako

The mean annual rainfall recorded for the entire study period in Bamako was 946.77 mm characterized by a low variability (CV = 14.09%). Bamako is covered by only one climate station (the Bamako-Senou rain gauge station) and rainfall variability is therefore considered homogeneous in this case in the entire area. Bamako generally receives lower amounts of rainfall compared to other Sudanian zones in Mali because it is close to the Sahel, just located to the north where rainfall amounts and durations are largely controlled by the Intertropical Convergence Zone (ITCZ) which brings rainfall across the area once a year. The annual total rainfalls variation over Bamako is given in Figure 4 below.

3.2. Standardized Precipitation Index (SPI) for Various Timescales and Annual Totals

The SPI was used to identify the historical drought which occurred in Bamako during the last three (3) decades from 1991 to 2020 based on the 12-month, 6-month and 3-month SPI timescales. Drought is defined when the SPI reaches a negative value and continues progressively until it becomes positive. Positive values of SPI are defined as wet period, based on this definition, the computed SPI for 12-month timescale revealed that Bamako experienced a serious extreme drought once in 2002 (SPI = −2.2165) and 2015 (SPI = −2.0598). However, based on drought classification of SPI, nine (9) severe droughts occurred during the years 1993, 2002, 2003, 2013 and 2015; forty one (41) moderate droughts and in

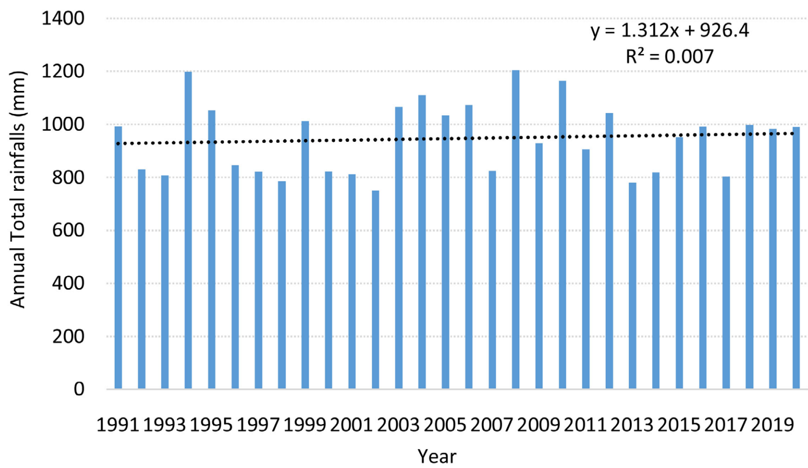
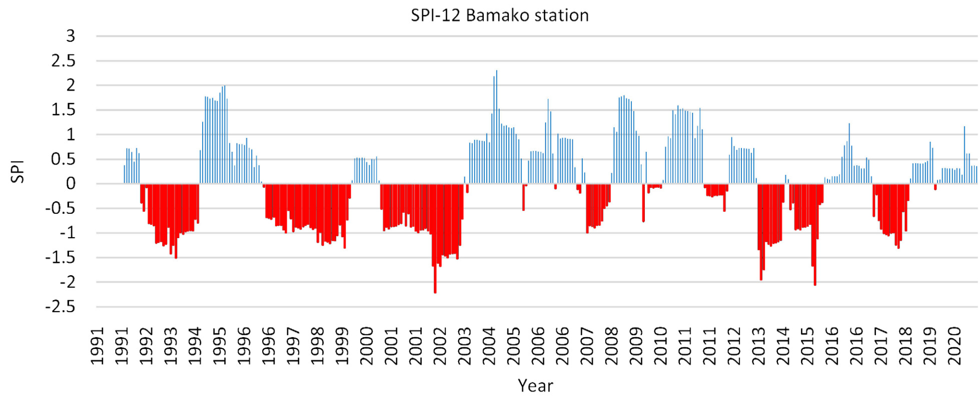
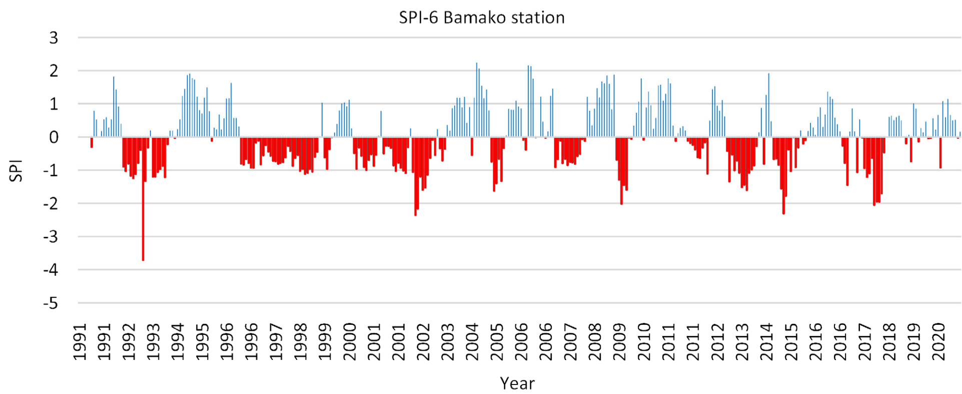


Figure 4. Annual total rainfalls variation in Bamako from 1991 to 2020.

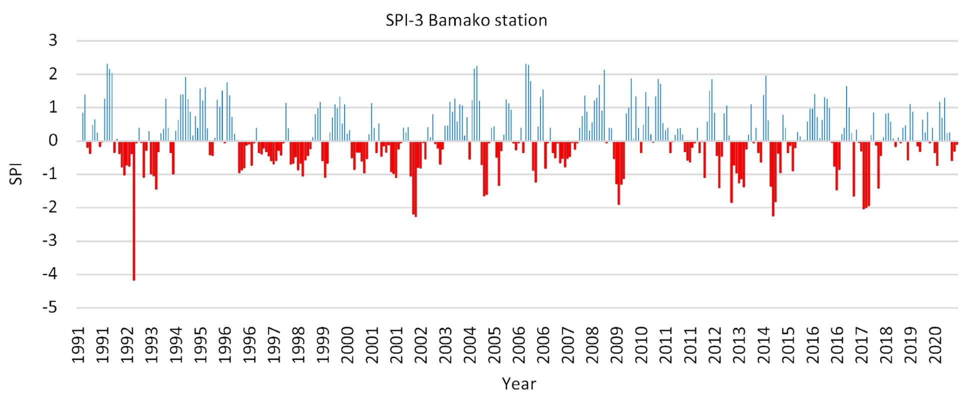
total 168 drought events occurred during 1991 to 2020 (**Figure 5(a)**). Fifteen (15) severity droughts were recorded during drought events with a severity mean value of 9.618505. The maximum severity drought occurring during drought events was $S_{\max}$ = 37.2467 and had a duration of 34 months (see **Figure 5(a)** and **Table 4**). The peak drought during the maximum drought severity was (SPI = −2.2165) and classified as extremely drought according to the drought classification based on SPI. The most prolonged drought lasted for 36 months and had a severity of 31.9951 and a peak intensity of (SPI = −1.2984).



(a)



(b)



(c)

Figure 5. Standardized precipitation index using different timescales.

Similarly, using the 6-month and 3-month SPI timescale, the number of drought events was 181 events for SPI-6 and 174 events for SPI-3 respectively. For the 6-month SPI, six (6) events extremely drought was observed in the years 1993, 2002, 2009, 2014 and 2018 with a peak intensity in 1993 (SPI = −3.715334). The most intense drought severity event was S = 22.4139 and had a duration of 32 months (from 1996 to 1999), and considered as the longest drought spell during drought events (**Figure 5(b)**). Using the 3-month SPI, the peak drought intensity was identified in 1992 with a value of (SPI = −4.158466) and fifty (50) severity droughts were observed throughout drought events. The magnitude of the most severity droughts was S = 8.16114 with 8 months duration. The longest drought duration with 3-month SPI was eleven (11) months.

The SPI for annual totals revealed the same peak intense drought that occurred in Bamako in 2002s as 12-month SPI but with lower intensity SPI = −1.486670 (**Figure 6**). Drought years represent 46.67% for the overall period whereas wet years represent 53.33%. The most intense drought severity had an intensity of S = 3.435569 with three (3) years of duration from 2000 to 2002 (**Figure 6**). The summary statistics of SPI using various timescales is shown in **Table 6**.

However, based on previous literature on Sahel drought, many studies argued that almost all the Sahel countries experienced extreme decadal variability in rainfall during the twentieth century with devastating drought over 1970s and 1980s (Taylor et al., 2017). In a recent study on recent trends in the regime of extreme rainfall in the Central Sahel Panthou et al. (2014) showed that the West African Sahel was characterized by a succession of three (3) Periods of roughly equal duration: the wet Period (P1) from 1950 to 1969; a severe drought period (P2) from 1970 to 1990 and the recent period (P3) from 1991 to 2010. The droughts of the recent period P3 observed in the Central Sahel match with almost all the droughts observed in the same period in this study (**Figure 6**). Droughts are a common hazard in Mali, as well as the broader Sahel area (Doukoro et al., 2022). They have led to some food emergencies in 1972-1974; 1983-1985; 2002-2003; 2011-2012 and 2015-2018 partly due to the 2015/2016 El Niño induced drought (Doukoro et al., 2022).

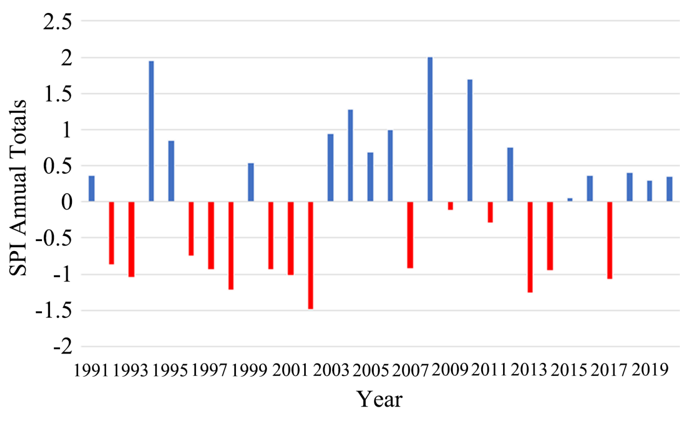


Figure 6. The SPI for annual total rainfalls in Bamako.

Table 6. Summary statistics of SPI using different timescales.

SPI timescales	Climatic Variables	Statistic (1991-2020)	Value
SPI-12	Drought	Number of drought events	168
	Drought Severity	Mean	9.618505
		Standard deviation	12.366295
		Minimum	0.0942
		Maximum	37.2467
		Skewness	1.259743
		Kurtosis	0.556482
	Drought Duration (Months)	Mean	11.2
		Standard deviation	11.760709
		Minimum	1
		Maximum	36
		Skewness	1.182199
		Kurtosis	0.446859
SPI-6	Drought	Number of drought events	181
	Drought Severity	Mean	4.138478
		Standard deviation	5.461377
		Minimum	0.00723
		Maximum	22.4139
		Skewness	1.550083
		Kurtosis	2.334523
	Drought Duration (Months)	Mean	5.323529
		Standard deviation	6.366201
		Minimum	1
		Maximum	32
		Skewness	2.427510
		Kurtosis	8.298513
SPI-3	Drought	Number of drought events	174
	Drought Severity	Mean	2.178106
		Standard deviation	2.299336
		Minimum	0.0224
		Maximum	8.16114
		Skewness	1.184149
		Kurtosis	0.373987

Continued

Drought Duration (Months)	Mean	3.48
	Standard deviation	2.727337
	Minimum	1
	Maximum	11
	Skewness	1.280124
	Kurtosis	0.927982

The Sahel climate has been extensively studied as a result of a prolonged drought's period that commenced in the late 1960s and continued into the 1990s (Hulme, 2001). This dry spell in the Sahel region followed a wet incident in the 1950s, and it was linked to severe droughts in the early 1970s and mid 1980s (Brooks, 2014). In 1990s, there was some relief from the dry conditions and pattern in annual rainfall totals persisted into the early years of the twenty first century. The year 2003 was the year with most rainfall across much of the territory, resulting in flooding and landslides in some areas of the Sahel (Brooks, 2014). The African Monsoon strength and position variation is known to be associated with the lasting climatic and environmental change in the Sahel (Brooks, 2014). Another study such as Dai et al. (2004) on the recent Sahel drought confirmed that Sahel rainfall has recovered somewhat through 2003 though drought condition was on the rise in the region.

The prevailing view of the Sahel drought in the past was that local human activity was driving local climate in a positive feedback cycle between poor land use practices land denudation among others (Charney, 1975). Studies showed that through observation or models indicate that land use changes were ever large scale to affect regional climate (Biasutti, 2019). With models progress of the general circulation of the atmosphere, it is now accepted that the primary cause of extreme decadal variability in Sahel rainfall during the twentieth century has been the variability of sea surface temperature (SST) (Zeng et al., 1999; Giannini et al., 2003 and Kucharski, 2013). The African Monsoon modulation through regional and global-scale patterns of sea-surface temperature (SST) has been considered throughout the twentieth century as the best reason for variations in Sahelian rainfall on multi-year to decadal timeframes (Brooks, 2014). However, through statistically based climatological studies, SST trends and Sahelian rainfall connections have been well established and used with some success in periodic rainfall predictions in the area (Folland et al., 1986; Ward et al., 1993). Folland et al. (1986) confirmed that during the instrumental records period, Sahel dry conditions were linked with a specific configuration of global SST patterns characterized by positive (warm) anomalies in the northern Indian Oceans and southern hemisphere, and negative (cool) anomalies in the remaining northern hemisphere oceans. Janicot et al. (1996) investigated the El Niño-Southern Oscillation (ENSO) influence on Sahelian rainfall and discovered that the correlations between Southern Oscillation and rainfall in the Sahel Index amplified during the 1970s and 1980s. However, this indicates an underlying mechanism by which ENSO influences the Sahel climate, in which changes in the atmosphere deep convection's distribution derives from the warming shifting patterns at the ocean surface, reorganizing atmospheric motion and shifting the monsoon rainfall zones positions (Brooks, 2014).

The West Africa rainfall variability is known to be influenced by the Atlantic Ocean (Hastenrath et al., 2011; Rodríguez-Fonseca et al., 2015) and the El Niño-Southern Oscillation's (ENSO) influence on the West African Climate is considered to be linked to the region's droughts. This was viewed to be an El Niño events' justification which were unexpectedly recorded in the same period as the Sahelian drought in 1972-1973, 1982-1983 and 1997-1998. The El Niño effect on weather patterns also affected rainfall across the Sahel and West Africa in 2015, this could also be an explaination of the Bamako's drought recorded in 2015.

The 12-month SPI is known to have direct effects on streamflow, groundwater and reservoir levels at longer periods; whereas a 6-month SPI indicates seasonal to medium-term precipitation trends and is still considered to be more responsive to conditions at this scale than the Palmer index. The 3-month SPI is also known to provide a seasonal estimation of precipitation (WMO, 2012). Trend analysis is used to determine whether there exists a significance increase or decrease trend over the study area Bamako. The Mann-Kendall trend test applied to the annual rainfall data showed an increasing trend in annual rainfall series but not significant at 5% and 10% significance levels ($p > 0.05$ and $p > 0.1$. The rate of increase trend according to the Sen's slope estimator was 0.475 mm/year (**Table 7**). This rate of increase could have direct effect on drought mitigation if annual rainfalls vary with this magnitude in the future. Detecting any existing trend in precipitation or in rainy season across Mali was a subject of much debate and reporting in the past years (World Bank Group, 2011), because Sahel rainfall is characterized by high variability on both annual and inter-decadal time scales, which makes trend difficult to identify, and due to the large model uncertainties in the past year (World Bank Group, 2011). Some inter-models suggested an increasing drought, while other individual models predicted humid period related to changing climate (World Bank Group, 2011).

3.3. Return Period of Drought Severity and Duration Using the Best Fitted Distribution

Weibull plot formula was used to compute predicted values of the drought severity and duration. To test the goodness of fit between Normal, Log-normal

Table 7. Summary of the Mann-Kendall trend test applied to the annual rainfall data.

Area	Mann-Kendall Statistic (S)	Tau (τ)	Sen's Slope (Q)	Z_S	Significance Level (α)	p-value (Two-tailed test)	Test Interpretation
Bamako	9	0.02069	0.475	0.14273	0.05	0.44325 > 0.05	H_0 accepted

(LN), Gumbel type I, and Pearson type 3 (P3) distributions, the test statistics such as mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), relative root mean square error (RRMSE), correlation coefficient (CC) and coefficient of determination (CoD) were used to select the best fitted distribution of drought severity and duration series. From the **Table 8** below, the P3 distribution passed the goodness of fit test for both drought severity and duration, it is therefore taken as the best fitted distribution over the study area (Bamako). Sharma and Panu (2015) on the analysis of the streamflow data from five rivers in Canadian prairies, fitted several probability distributions such as Pearson 3, the gamma (2-parameter), the exponential (1-parameter), the Weibull 3 and Weibull (2-parameter) to drought length for the computation of return periods of drought length found that the Pearson 3 distribution is the most suitable distribution for describing the characteristics of return periods for drought length at varying truncation levels. Mishra and Desai (2005) found the Gumbel type 1 distribution as the best fitted distribution to describe the frequency analysis of the drought in the Kansabati river basin in India. The 12-month SPI was used in this study to investigate drought impact on groundwater resources in Bamako, as 55 percent of the population rely directly on groundwater resources (USAID, 2021).

The return periods of the observed drought severities and corresponding durations were computed using the best fitted model over Bamako which is P3 distribution, the mean inter-arrival time for the 12-month SPI was also computed based on the description of the inter-arrival time of drought, $\mu_{T_d} = 22.5$ months was obtained as the mean inter-arrival time. From the **Figure 7(a)** below, we can observe that severities with 1-month duration have return periods from 2.4 to 2.5 years. However, severities with 2, 6 and 10-month duration have return periods ranged from 2.5 to 3.8 years, respectively. The return periods of the observed drought severity and duration data showed that highest severities are more unlikely to happen with the same duration in the future. The most prolonged severity (37.25) and duration (36 months) in the observed severity and duration data have return periods of 55.8 years and 48.7 years, respectively.

Table 8. Selection of the best fitted distribution.

	Distribution	MAE	MSE	RMSE	RRMSE	CC	CoD
Severity	Gumbel type 1	8.127651	80.18528	8.954624	34.05596	0.972632	0.946014
	Pearson 3	7.921473	76.86148	8.767068	32.34591	0.972791	0.946322
	Normal	9.979758	114.5459	10.70261	42.54298	0.95484	0.911719
	Log-normal	11.45001	512.6596	22.64199	10.57356	0.914518	0.836343
Duration	Gumbel type 1	7.862634	71.55249	8.45887	5.47349	0.978159	0.956795
	Pearson 3	7.836583	70.5177	8.397482	5.34941	0.977947	0.956381
	Normal	9.496906	101.973	10.09817	6.59509	0.966475	0.934075
	Log-normal	8.169241	107.9339	10.38912	3.301098	0.956048	0.914027

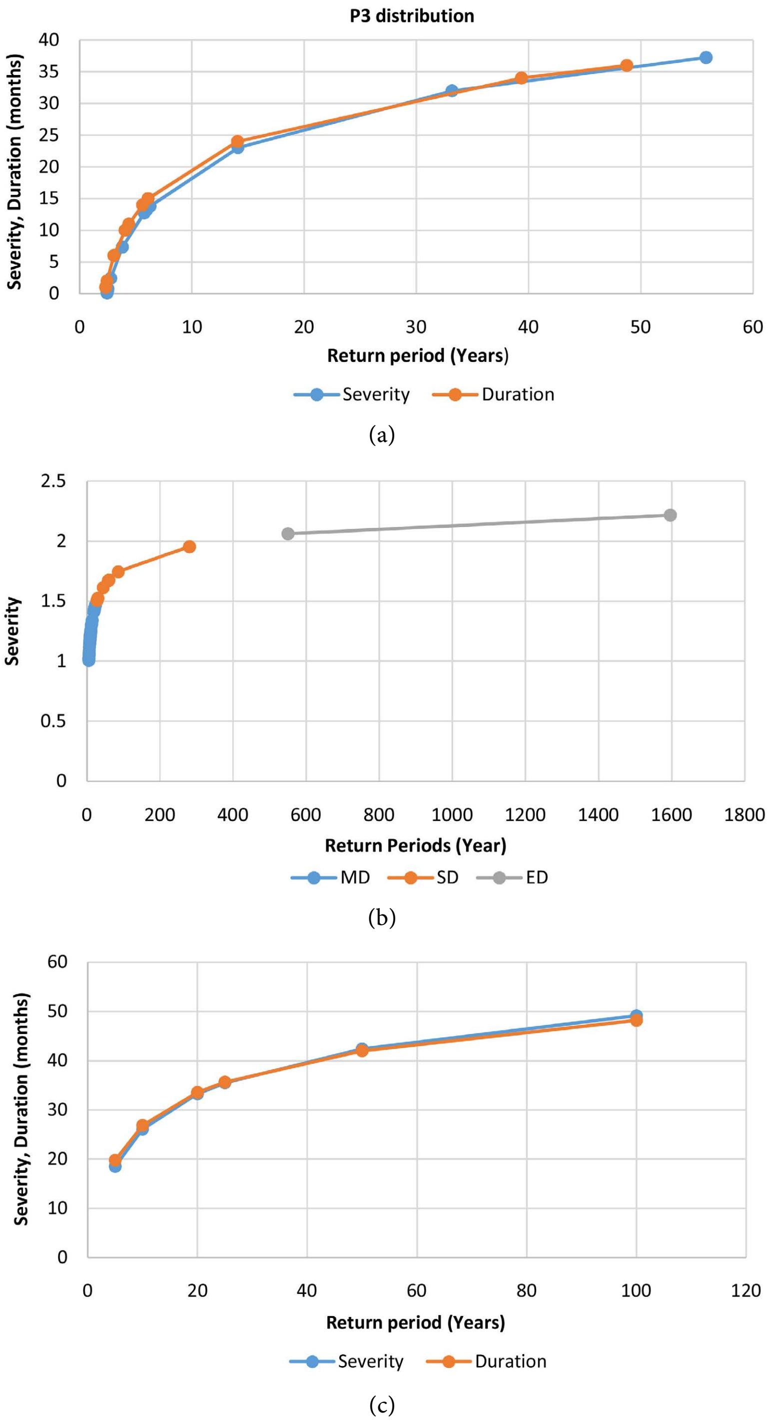


Figure 7. Predicted severities with various return periods.

Similarly, severities with 5, 10, 20, 25, 50, and 100 year return periods were computed for Bamako area, and the durations at which they may occur in the future were also estimated using the P3 distribution over Bamako. The results revealed that higher severities occurred with higher durations and lower severities with shorter durations with respect to increase or decrease in the return period **Figure 7(c)**. Previous studies such as (Sahana et al., 2020; Adarsh et al., 2018 and Cavus & Aksoy, 2020) stated that when the return period increases, the drought severity is likely to increase owing to the physical process of the drought. In addition, the return periods of moderate, severe and extreme droughts using SPI-12 were computed as shown in **Figure 7(b)**. The results showed that moderate droughts using the 12-month SPI drought series ranged from 5.2 to 23.2 years, severe droughts ranged from 27.3 to 281 years and extreme droughts from 549.7 to 1596.4 years, respectively, with 1-month duration. This is clear that at shorter duration such as 1-month, the return period of highest severities is higher than at longer duration. Findings of this study revealed that Bamako is prone to experience severe severity droughts with shorter and higher durations (1, 2, 6, 10-month) over time in average every 2.5 to 3.8 years. As many people in Bamako depend on direct groundwater resources, public awareness programs should be deliberate and implemented with a perfect understanding of local perspectives and needs. Local drought risk could be reduced by focusing on educating and training people. Scientists and planners must work together to promote the development of systems that are appropriate, pertinent, comprehensible, affordable and people-centered in order to enhance drought monitoring and early warning systems (UNISDR, 2009). Drought monitoring to enhance national level early warning system for local farmers is already established in Mali (UNISDR, 2009). We recommend the continuing establishment of networks to support the sharing of basic climate information and early warning systems across various regions of Mali especially in Bamako where groundwater dependency is growing.

4. Conclusion

Lack of precipitation for an extended period of time has its effects on water availability and the state of the environment. Drought therefore poses enormous risk on societies and the environment. In this study, rainfall variability related to drought forecasting was assessed using various parametric probability distributions and non-parametric Mann-Kendall trend test over the study area (Bamako). The SPI for different timescales revealed that Bamako experienced several historical droughts during the period 1991-2020. The years of historical drought detected in this study were from extreme droughts once in 2002 and 2015, to severe droughts in 1993, 2002, 2003, 2013 and 2015 using the 12-month SPI. The results further indicated that using the non-parametric Mann-Kendall trend test, a trend was observed in annual rainfall series but was not significant at 5% and 10% significance levels. The return periods of severity droughts were calculated based on the best fitted distribution which is P3 distribution, the result indicated that Bamako is prone to experience frequent severe severities with shorter and higher durations in the future. The return periods of severities associated with 1, 2, 4, 6, and 10-month duration were computed and severities for 5 - 100 years return periods were also estimated using the P3 distribution. The results showed that the 5, 10, 20, 25, 50, and 100 years return periods have 18.51, 26.08, 33.25, 35.50, 42.38, and 49.14 severities, respectively, while durations associated to these severities are 19.8, 26.9, 33.5, 35.6, 42, and 48.2 months, respectively.

Some of the limitations of this study are that only the SPI was used to identify drought over the study area. An efficient management of groundwater resources during drought cannot therefore be overemphasized. To add more useful information on drought related to meteorological conditions such as evapotranspiration, future investigations should consider the standardized precipitation and evapotranspiration index (SPEI) indicator for drought evaluation. Severity drought and duration are often characterized by joint behavior of mutually correlated random variables the use of univariate frequency distribution to describe the return periods of the drought severity and duration may lead to underestimation or overestimation of associated risk of events. Future investigations should also consider the bivariate method for return periods computation focusing either by drought duration or severity exceeding a specific value T_{DS} ($d \geq D$ or $s \geq S$) or by drought duration and severity T'_{DS} ($d \geq D$ or $s \geq S$). These two forms of return periods are generally computed using copula-based approach.

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Conflicts of Interest

The authors declare they have no competing interests.

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