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Research Article

Investigating Effective Reconnaissance Drought Index Ability to Reproduce Drought Signature over the Massili Basin (Burkina Faso)

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Abstract

Drought is a significant natural hazard particularly in arid and semi-arid regions where water resources management is already challenging. Burkina Faso, a landlocked country located in the Sahel region, is highly vulnerable to drought due to its arid climate. The country has experienced recurrent droughts since the 1970s, with significant impacts on its population and economy. To develop effective drought mitigation strategies, a comprehensive understanding of drought characteristics is required. This study investigates historical long-term drought trends in the Massili basin located in central Burkina Faso. For this purpose, drought features has been analyzed based on the Effective Reconnaissance Drought Index (eRDI) at various months of accumulation. To calculate the Effective Reconnaissance Drought Index for the Massili Basin, monthly precipitation (Prct), minimum temperature (Tmin), and maximum temperature (Tmax) data spanning from 1960 to 2021 were obtained from the National Meteorological Agency of Burkina Faso. The Potential evapotranspiration (ETP) was estimated using the Hargreaves method. Our findings indicate that under eRDI-3, 1964 (1.86), 2020 (1.53), and 2021 (0.63) are the wettest years, while 1963 (-0.65) and 1998 (-0.76) are the driest. Under eRDI-12, a significant portion of the values falls within the range of -0.14 to 0.03. In the case of eRDI-24, a substantial number of the values cluster between -0.08 and 0.08. This distribution highlights near-normal drought conditions (-0.99 to 0.99) as the most frequent occurrence within the watershed. The desertification of the Sahel area has been a topic of discussion for decades. However, these findings of this study reinforce the prevailing belief in a partial re-greening of the Sahel region.

Keywords

Meteorological Drought, Kernel Density, Probability Density Function, Massili

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1. Introduction

Climate change refers to a long-term shift in global or regional climate patterns. Pervasive effects of climate change include extreme events such as floods and drought. Indeed, as stated by scholars some regions have experienced floods whereas others are experiencing droughts [1-3]. [4] defined drought as a complex and poorly understood natural hazard with a broader impact on human populations than any other. Nontheless, drought definitions can be categorized into two primary types: conceptual and operational. Conceptual definitions provide a general understanding of drought as a prolonged period of insufficient precipitation that has significant impacts on the environment and human activities. In contrast, operational definitions focus on practical applications, establishing criteria for determining drought onset, severity, and termination to inform response and mitigation strategies. In arid and semi-arid areas where securing sufficient water for basic human needs is a persistent challenge, drought has been discussed extensively [5-7]. Drought severely impacts the three pillars of sustainable development which are economy, society, and environment. It severely diminishes water availability, compromising food security and hindering economic development, particularly in sectors reliant on hydropower. Burkina Faso has been challenged by recurring droughts since the 1970s. As stated by [8], the country has experienced a significant shift in annual rainfall. The most severe droughts in Burkina Faso occurred in 1973-1974 and 1983-1984. Since 1991, the country has experienced about seven major droughts, including those in 2011-2012, 2014, and 2020 [9]. These droughts have led to significant production losses, as highlighted by [10], and ultimately impact malnutrition rates by contributing to increased food prices, food shortages, and reduced food consumption [11, 12]. A variety of drought indices, including the Net Water Balance Index (NWBI), The Vegetation Condition Index (VCI) and the Percent Normal has been employed for drought monitoring worldwide. The Net Water Balance Index (NWBI) developped by [13] quantifies dryness or wetness over various time periods based on precipitation and evapotranspiration. This index is estimated by normalyzing the difference betweem precipitation and the evapotranspiration. The Vegetation Condition Index (VCI) introduced by [14] estimates drought based on data derived from satellite-based Advanced Very High Resolution Radiometer (AVHRR). The principle of VCI index is based on the establishment of a relationship between vegetation and climate by identifying drought onset, intensity, duration, and impact on vegetation. The Percent Normal refers to a meteorological drought index that estimates precipitation deviation from its long-term mean. The Percent Normal calculates drought on various timescales by dividing the current precipitation by the normal. A significant limitation of this index is its inability to succesfully reproduce complex drought dynamics influenced by factors beyond precipitation. The eRDI was selected for this study to analyse drought conditions across Massili basin. This drought index estimates water deficit based on Precipitation and Potential evapotranspiration of a given area. The eRDI is more sensitive and suitable for detecting droughts in changing environmental conditions as it incorporates potential evapotranspiration. It provides a more comprehensive assessment of drought conditions, as it accounts for the water demand of the atmosphere, which is a critical factor in understanding drought dynamics.

2. Material and Methods

2.1. Study Area

The Massili basin located in central Burkina Faso extends between longitudes 1°15' West and 1°55' West and latitudes 12°17' North and 12°50' North. The watershed covers approximately an area of 2612 km^2 and is drained by the Massili River that is one of the main tributaries of the Nakambe River. The watershed is predominantly flat, with roughly 27% covered by tree and shrub savannas and 59% occupied by farmland. The basin falls within the North Sudanese agro-ecological zone, characterized by an average annual rainfall of 700 to 900 mm and a dry season lasting 6 to 7 months. Rainfall distribution in the basin is uneven both spatially and temporally, with the peak rainfall typically occurring between August and September.

2.2. Climatic Datasets

To estimate the Effective Reconnaissance Drought Index (eRDI) for the Massili Basin, precipitation (Prct), minimum temperature (Tmin), and maximum temperature (Tmax) data at a monthly time step for the period 1960 to 2021 was collected from the National Meteorological Agency of Burkina Faso (ANAM-BF). Basic statistics of these observed records are compiled in Table 1. The data underwent quality control to ensure its suitability for scientific research.

Table 1. *Summary of basic statistics of monthly precipitation, mini-mum and maximum Temperature of Ouagadougou.*

	Year	Month	Prcp	Tmax	Tmin
Min.	1990	1.00	0.00	29.50	14.30
1st Qu	1975	3.75	0.00	33.00	20.00
Median	1990	6.50	22.65	35.20	22.70
Mean	1990	6.50	65.32	35.27	22.32
3rd Qu	2006	9.25	110.40	37.23	24.60
Max.	2021	12.00	452.60	42.00	32.00

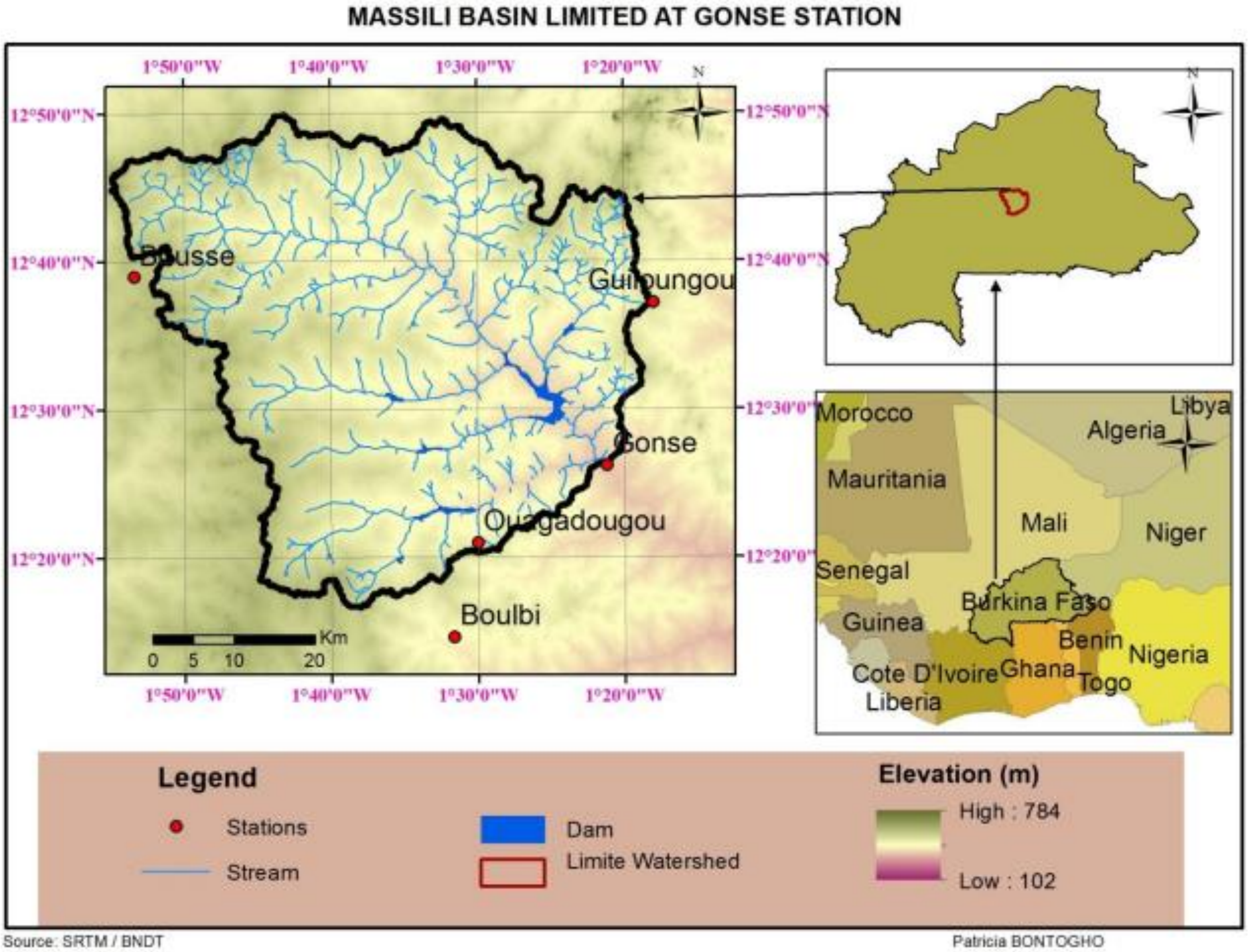


Figure 1. Location of Massili basin limited at Gonse station.

2.3. Methodology

2.3.1. Effective Reconnaissance Drought Index

Effecive Reconnaissance drought index developped by [15] has been applied widely for drought related studies [16, 17]. This method was selected for this study based on its ability to reproduce drought signature in semi-arid and arid areas [18, 19]. The eRDI method is commonly used in semi-arid and arid regions, as demonstrated by studies conducted by [20] and [21].

The Effective Reconnaissance Drought Index (eRDI) is expressed as:

$$a_i = \frac{PA_i}{ETP_i} \quad (1)$$

Where

ai stands for the value o the Effective Reconnaissance Drought Index at month i

PAi represents the accumulated precipitation at month i

ETPi represents the potential evapotranspiration at month i

In order to estimate the potential evapotranspiration (ETPi), the Hargreave method introduced by [22] was adopted. Mainly based on monthly minimum and maximum temperature, the potential evapotranspiration of Hargreaves (PETHG) in a given period (mm), is expressed as:

$$PET_{HG} = 0.0023 * (T_{mean} + 17.8) * \left(\sqrt{T_{max} - T_{min}}\right) * R_a \quad (2)$$

Where:

PET_{HG} is the potential evapotranspiration of Hargreaves method

Ra represents the extra-terrestrial radiation and is related to the latitude of the study area

Tmean, Tmax and Tmin are the mean, maximum and minimum temperatures respectively.

Positive values of eRDI depict wet periods while negative values depict dry periods. Table 2 below shows different categories of drought severity as understood within eRDI concepts.

Table 2. *Classification of Effective Reconnaissance Drought Index (eRDI) categories.*

eRDI range	Category label
≥ 2.0	Etremelywet
1.5 to 1.99	Very wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderate drought
-1.5 to -1.99	Severe drought
≤ -2.0	Extreme drought

2.3.2. Trend Detection

Many scholars have documented a broad range of trend estimators. In this study, we adopted the most common methods, namely the Man kendall test and Sen's slope, to detect positive or negative trends in the different time series of Reconnaissance Drought Index. Mann Kendall test is defined as a non-parametric trend method that identify monotonic trend (increasing or decreasing) in a dataset. Linear regression fits a straight line to the data and calculates the slope to assess the strength and direction of the trend.

2.3.3. Probability Density Function

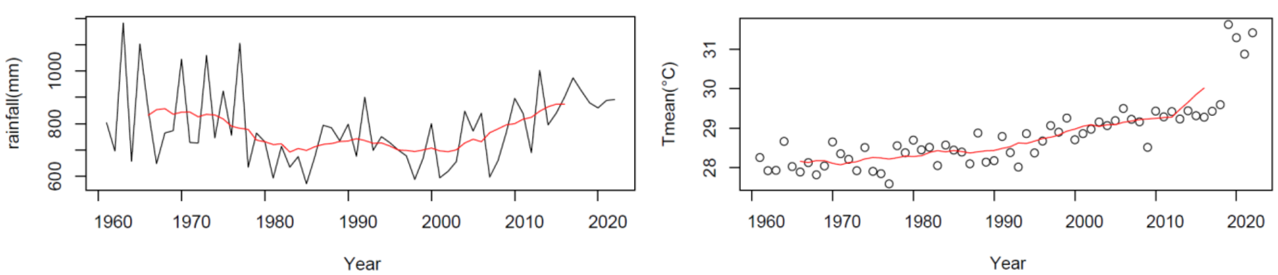
Parametric and nonparametric probability density estimation are the main methods to obtain a smooth Probability density function (PDF) from data as stated by [23]. This study makes used of the nonparametric probability density estimation, particularly kernel density estimation (KDE), to achieve a smooth PDF. Kernel Density is a non-parametric method, which estimate the probability density function (PDF) of a random variable based on a sample of data. Kernel density provides a smooth curve representation of the data's distribution. It determines therefore the shape and spread of the density estimate around a given point. Common kernel functions include Gaussian, Epanechnikov, and rectangular [24-26].

The kernel function is expressed as:

$$\int_{-\infty}^{\infty} k(x)dx = 1 \tag{3}$$

3. Results and Discussion

The rainfall time-series plots of Massili basin depicted in figure 2a) show that the watershed has experienced a gradual increase in annual rainfall, especially since the early 2000s. This trend contrasts with a significant decrease during the 1970s and 1980s. The basin witnessed the highest annual rainfall in 1962 (1183.2mm) and the lowest in 1984 (571mm), highlighting the study area's susceptibility to extreme weather events. Figure 2b) displays the scatter plot of the mean temperature. Alongside the increasing rainfall, this figure depicts a substantial rising trend in the long-term mean temperatures. Therefore, the Massili basin is experiencing the effects of climate change as reported by [27] and [28]. The combination of increased rainfall and higher temperatures could lead to a higher risk of flooding, especially in areas with poor drainage, and increased evaporation rates, potentially offsetting the benefits of more rainfall. These changes can affect water availability for ecosystems and human use, alter local ecosystems, and impact agricultural productivity, increasing water resource management challenges.



a) Yearly rainfall b) Yearly Tmean

Figure 2. *a) annual rainfall variability within Massili Basin (1960-2021); annual mean Temperature variability within Massili basin (1960-2021).*

Figure 3a below illustrates the frequency distribution of the eRDI at 3 months accumulation over the Massili basin. As stated by [29], a frequency distribution organizes a time series dataset into groups based on value ranges and counts the number of data points falling within each group. A substantial portion of the eRDI values ranges from -1 to -0.31. Based on the eRDI categories reported in table 2, this distribution implies that near normal (-0.99 to 0.99) to moderate drought (-1.0 to -1.49) are the most recorded within the watershed. Extremely wet periods were scarce in the area, with such conditions only identified in the years 1962 (3.38), 1964 (3.28), 2012 (3.45), 2016 (3.23), and 2020 (3.82). The frequency distribution of drought based on the eRDI method at 6 months accumulation is described in figure 3b). A substantial portion of the eRDI values ranges from -0.82 to -0.37. This distribution highlights near normal drought (-0.99 to 0.99), as the most frequent. The years 1964 (1.86), 2020 (1.53) and 2021 (0.63) are identified as the wettest whereas 1963 (-0.65) and 1998 (-0.76) are the driest. The frequency distribution of drought based on eRDI method at 12 months accumulation indicates that a substantial portion of the eRDI values range from -0.14 to 0.03 as shown in figure 3c). This distribution highlights near normal drought (-0.99 to 0.99) as the most frequent. Similarly, the frequency distribution of drought 24 months accumulation as described in figure 3d), indicate that a substantial portion of the eRDI values range from -0.08 to 0.08. This distribution highlights near normal drought (-0.99 to 0.99) drought as the most frequent.

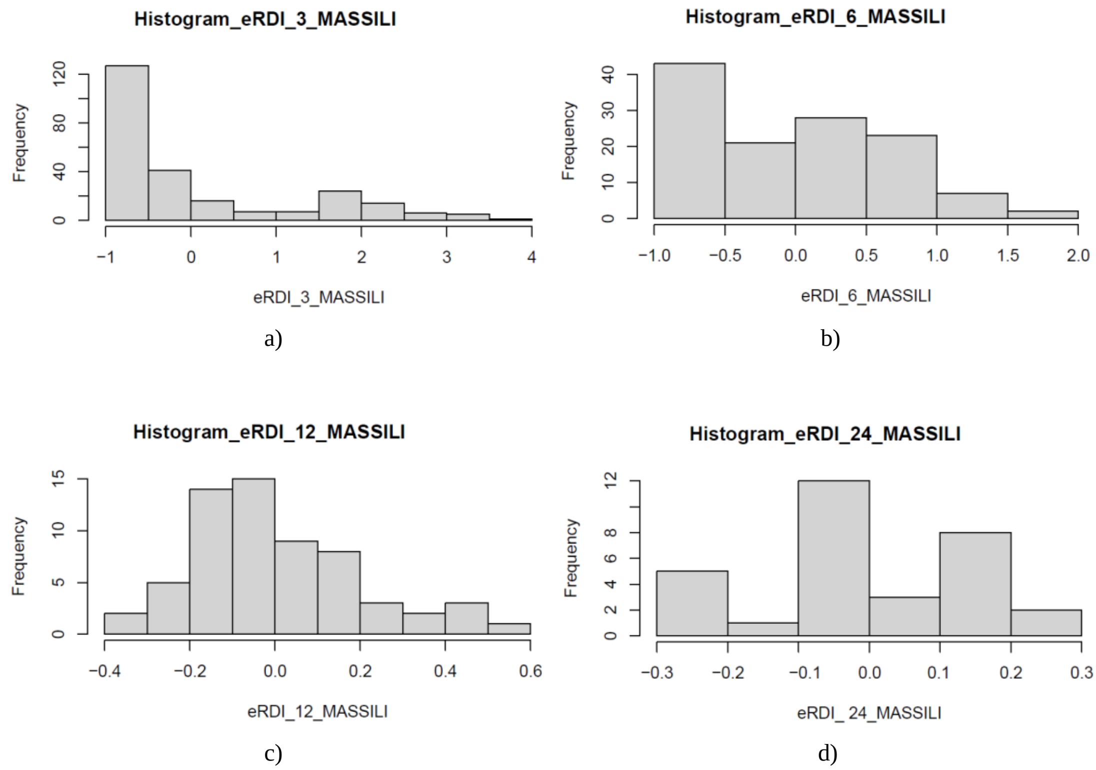
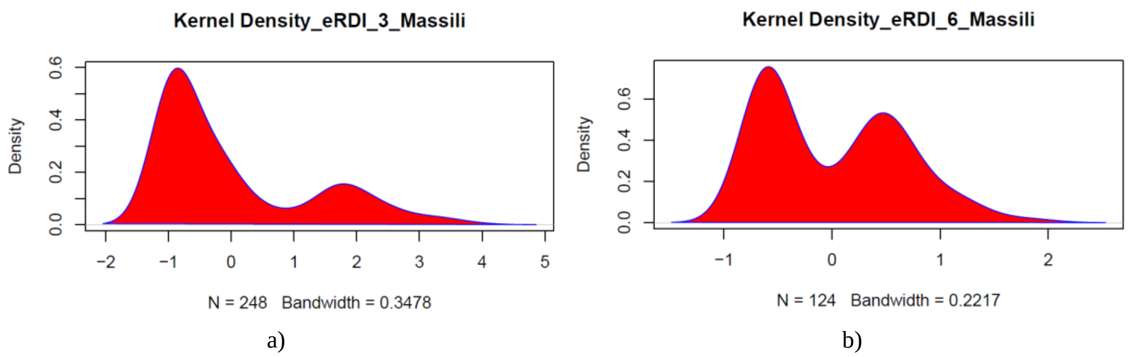


Figure 3. *a) Frequency distribution of eRDI at 3 months accumulation; b): Frequency distribution of eRDI at 6 months accumulation; c): Frequency distribution of eRDI at 12 months accumulation; d): Frequency distribution of eRDI at 24 months accumulation.*

Figure 4 shows the bivariate Probability density function of drought intensity and duration estimated by KDE at various month accumulation. The bandwidth of the kernel is a free parameter that significantly impacts the resulting estimate. In eRDI with a 3-month accumulation, a bandwidth of 0.34 is considered optimally smoothed. For eRDI_6, eRDI_12, and eRDI_24, the optimally smoothed bandwidths are 0.22, 0.07, and 0.06, respectively.



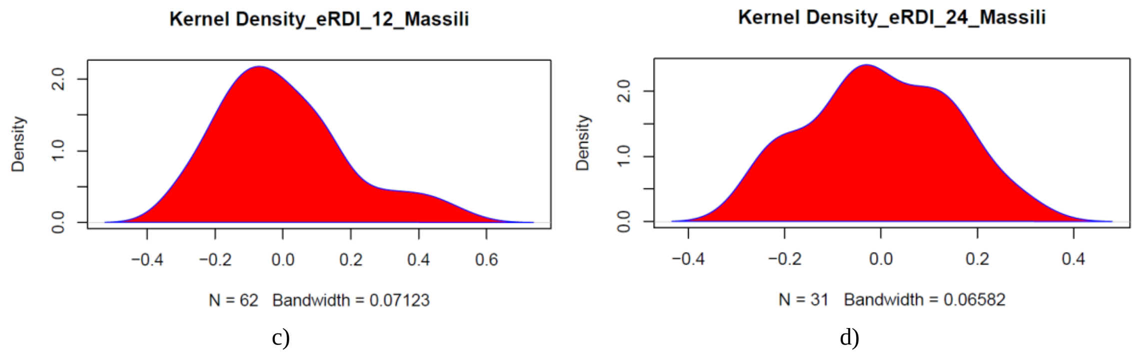


Figure 4. *Kernel density for eRDI at various time scale over Massili basin.*

Table 3 indicates the Z parameter and the Sen's slope values for eRDI time at various months' accumulation. A value of Z equal to 0.43397, 0.76886, 1.5612 and 2.1440 has been identified for eRDI-3, eRDI-6, eRDI-12 and eRDI-24 respectively. A Man kendall tau value of 0. 02301 (eRDI-3), 0. 05812 (eRDI-6), 0.17073 (eRDI-12) and 0.3428571 (eRDI-24) is found. Additionaly, sen's slope tau of 0.00006, 0.00071, 0.00138 and 0.00424 is recorded for eRDI-3, eRDI-6, eRDI-12 and eRDI-24 respectively. The eRDI time series accros all accumulation periods (eRDI-3, eRDI-6, eRDI-12, and eRDI-24) exhibit positive trends indicating a general upward trajectory in the eRDI values over time. The significance of the trends, as measured by the Mann-Kendall tau and Sen's slope values, increases with longer accumulation periods. This suggests that the positive trend becomes more pronounced and statistically significant when considering longer-term eRDI data. In addition, the Sen's slope values, which represent the rate of change, are higher for longer accumulation periods. The eRDI values are increasing at a faster rate for longer-term eRDI compared to shorter-term eRDI. These findings suggest that drought is decreasing within the watershed over time.

Table 3. *Man kendall and Sen's slope estimators on eRDI at differents months accumulation.*

	Man Kendal		**Sen's Slope**	
	z	**tau**	**z**	**slope**
eRDI-3	0.43397	0.02301	0.43397	0.00006
eRDI-6	0.76886	0.05812	0.76886	0.00071
eRDI-12	1.5612	0.17073	1.5612	0.00138
eRDI-24	2.1440	0.34285	2.1440	0.00424

4. Conclusion

Understanding of drought frequency and severity is crucial for financial institutions and governments. Information on this helps them anticipate potential losses and mitigating uncertainties caused by extreme drought events, by doing so, these entities can make informed decisions and implement effective strategies to protect their interests. This study used the eRDI approach to analyze agricultural drought frequency in the Massili Basin. The Mann-Kendall (MMK) test and Sen's slope test were employed to detect changes, magnitude, and severity of drought. The results suggest a moderate drought trend indicating that a relatively low drought risk is experienced Massili Basin. The study emphasizes the need for short-term and long-term strategies to develop effective drought early warning systems. The research provides information for decision-makers to implement drought early warning systems. Overall, the study contributes to a better understanding of drought dynamics in the Massili Basin and provides valuable insights for developing effective drought management strategies. Future research could explore the spatial variability of the drought across different parts of the basin and the impact of changes on groundwater resources.

Abbreviations

ANAM-BF	National Meteorological Agency of Burkina Faso
AVHRR	Advanced Very High Resolution Radiometer
eRDI	Effective Reconnaissance Drought Index
ETP	Potential Evapotranspiration
KDE	Kernel Density Estimation
MMK	The Mann-Kendall
NWBI	Net Water Balance Index
PDF	Probability Density Function
Prct	Precipitation
Tmin	Minimum Temperature
Tmax	Maximum Temperature
VCI	The Vegetation Condition Index

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Author Contributions

Tog-Noma Patricia Emma Bontogho: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Writing – original draft

Michelline Marie Regina Kansole: Writing – review & editing

Mercy Apuswin Abarike: Writing – review & editing

Mamounata Kabore: Writing – review & editing

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Data Availability Statement

The data that support the findings of this study can be found at the National Meteorological Agency of Burkina Faso.

Conflicts of Interest

The authors declare no conflicts of interest.

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