



RESEARCH ARTICLE

CONTRIBUTION OF FREQUENCY ANALYSIS TO THE PREDETERMINATION OF FLOODS IN THE NAZINON WATERSHED AT DAKAYE IN BURKINA FASO

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INTRODUCTION

Floods constitute one of the most frequent and destructive natural hazards worldwide, inflicting severe material damage and substantial economic losses. These events are driven by a complex interplay of hydrometeorological factors, including temperature variations, precipitation intensity, snowmelt, soil saturation, surface runoff, and freeze-thaw cycles. In recent decades, urban areas have become increasingly vulnerable to flooding, resulting in significant human casualties and property damage. In Africa, the primary driver of floods is the intensification of extreme rainfall events. This trend is particularly pronounced in West Africa, one of the regions most susceptible to the impacts of climate change (IPCC, 2007). Following the prolonged droughts of the 1970s and 1980s, the region has witnessed a resurgence of flood events, causing widespread socio-economic and environmental disruption (Amoussou et al., 2008). In 2009, catastrophic floods affected several West African nations—including Senegal, Mali, Benin, Ghana, and Burkina Faso—leading to extensive human and material losses (OCHA and Earth, 2013). In Burkina Faso, an unprecedented rainfall of approximately 263 mm on September 1, 2009, triggered flooding across 11 of the country's 13 regions (CONASUR, 2009), with major urban centers such as Ouagadougou and Bobo-Dioulasso severely impacted. More recently, on September 12, 2022, torrential rains submerged the Nazinon bridge on National Road No. 6, disrupting a critical transportation link between Ouagadougou and the Ghanaian border. A significant barrier to effective flood risk management in the region is the limited availability of quantitative data on water resources and their spatial-

ABSTRACT

Flood risk remains a constant threat to populations, prompting growing interest in water sciences. Within this context, the present study, "Contribution of Frequency Analysis to the Predetermination of Floods in the Nazinon Watershed at Dakaye", aims to implement a suitable frequency model for flood prediction. The methodology involved analyzing precipitation variability, characterizing the hydrological regime, and understanding watershed behavior. A frequency analysis was then applied to maximum flow rates. The sample was constructed using the annual maximum method. Basic assumptions of frequency analysis were tested, followed by calibration and validation of various models to identify the best-fitting distribution. Rainfall analysis in the Nazinon watershed revealed an upward trend. However, the annual maxima method failed to meet the stationarity assumption. Among the tested distributions, Gumbel's law provided the best fit. This model enabled the estimation of return periods of 2, 5, 10, 20, 50 and 100 years using the method of moments. In terms of probability, a flood with a 100-year return period has a 1% chance of occurring in any given year. These quantiles are essential for designing hydraulic structures and can be used with a safety coefficient to ensure resilience. This study highlights the importance of frequency analysis in flood prediction and infrastructure planning, especially in regions experiencing increasing rainfall variability.

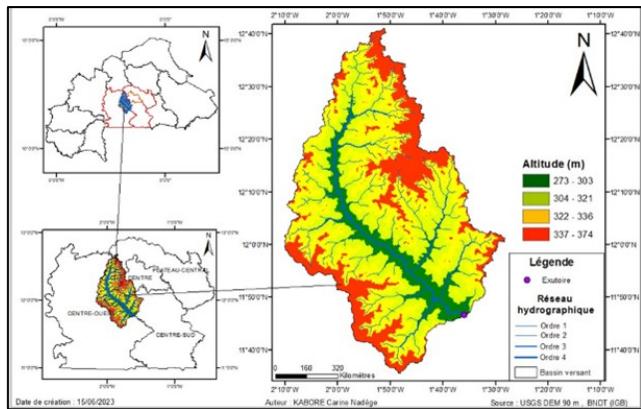
temporal variability. This knowledge gap hampers sustainable development planning and underscores the urgent need for robust early warning systems and proactive risk mitigation strategies. In this context, frequency analysis emerges as a vital tool for characterizing watershed behavior and forecasting extreme flood events. This study seeks to apply appropriate frequency models to estimate extreme flood quantiles in the Nazinon basin, focusing on the Dakaye hydrometric station. The objective is to support evidence-based decision-making by identifying the most suitable statistical model, calibrating its parameters, and estimating flood quantiles for a range of return periods.

MATERIALS AND METHODS

MATERIALS

Study area: Our study area focuses on the Nazinon River basin, which covers a surface area of 11,370 km². It is a national sub-basin of the Nakambé and, together with the Mouhoun, forms part of the international Volta River basin. The Nazinon watershed at the Dakaye outlet—central to this study—is located between latitudes 11°46.052' North and 11°46.640' North, and longitudes 1°36.032' West and 1°36' West. The Dakaye hydrometric station, situated within the Nazinon basin, lies across the Centre-South, Centre, Central Plateau, and Centre-West regions of Burkina Faso. Five distinct types of soil formations can be identified within the Nazinon basin at the Dakaye

hydrometric station. The soils are generally poor in quality, with low water retention capacity, making them largely unsuitable for agricultural activities. The vegetation consists of a designated forest reserve. This herbaceous formation is characterized by an annual grass cover, overlaid with a sparsely distributed woody layer composed of shrubs or small trees (Sani Oumarou, 2008). The climate of the Nazinon basin at Dakaye is classified as Sahelian, characterized by low annual precipitation. The rainy season typically extends from June to September, with peak rainfall occurring predominantly in August. Temperatures can reach a maximum of 43°C in April, while minimum values drop to around 14°C in January (DEIE, 2016). The climate is influenced by a dry air flow originating from the northeast to the east. There is considerable variability in the distribution of annual rainfall, accompanied by a slight upward trend.



Data

Hydrometric Data: To characterize the hydrological regime of the Nazinon watershed at Dakaye, a time series of daily discharge data spanning the period from 1980 to 2021 was obtained from the Directorate for Water Studies and Information (DEIE). These data were used to perform statistical analyses aimed at the preliminary estimation of flood events within the watershed.

Climatic Data: Standardized precipitation indices were processed using a chronological series of rainfall data from the Ouagadougou-Aero synoptic station, provided by the National Meteorological Agency (ANAM), covering the period from 1980 to 2021. These data enabled an assessment of the homogeneity of rainfall patterns within the watershed.

Softwares: The Khronestat software was used to detect break periods and the HYFRAN software was employed for the statistical analysis of discharge data.

METHODS

Data Quality Control: The discharge time series provided by the Directorate for Water Studies and Information (DEIE) spans the period from 1980 to 2021, offering a sufficiently long record for statistical analysis. However, the dataset contains several gaps due to missing data. Specifically, no records are available for the years 1992, 1993, 2002, 2004, 2005, and 2015, reflecting periods during which the Dakaye station was not operational. This discontinuity can be attributed to various factors, including the absence of personnel, lack of maintenance, inaccessibility of the site, and financial constraints. Initially, the data—originally organized by calendar year—were restructured to facilitate analysis. Subsequently, the rate of missing data was calculated, revealing year-to-year variability. In certain years, the gap rate reached 100%, indicating complete station inactivity. The average rate of missing data across the series is approximately 21%, which is substantial and likely to influence the reliability of the study (see Table 1). To ensure the robustness of subsequent analyses, only the years during which the Dakaye station was actively monitored will be considered.

Breakpoint Periods Detection: Annual rainfall data from the Ouagadougou-Aero synoptic station were analyzed using the Khronestat software to detect potential breakpoints associated with non-stationarity.

Table 1. Classification of Missing Data Rates

Rate of missing data	Classification
1% 2%	Négligeable
5%10%	Faible
10%-25%	Modéré
25%-50%	Élevé
>50%	Excessif

In general, a breakpoint is defined as a change in the probability distribution of a time series at a given—often unknown—point in time (Ardoin-Bardin, 2004). Khronestat includes several statistical tests, notably the non-parametric Pettitt test (Pettitt, 1979), the Bayesian method of Lee and Heghinian, and Hubert's segmentation method. For each of these tests, the null hypothesis (H_0) corresponds to the absence of a breakpoint at a 1% significance level. These tests are particularly sensitive to changes in the mean, and when the null hypothesis of series homogeneity is rejected, an estimate of the breakpoint date is provided. In this study, the Pettitt test was selected due to its recognized robustness and statistical power.

In cases where a breakpoint is detected within historical time series, it is advisable to calculate the variation between the pre-break and post-break periods. This variation reflects either a downward trend (deficit) or an upward trend (surplus), and is characterized by:

$$T = \frac{\text{Map} - \text{Mav}}{\text{Mav}} * 100$$

$$W = \sum_{i=1}^{n-1} (x_i x_{i+1}) + (x_1 x_n)$$

Map and Mav represent the mean values of the time series before and after the breakpoint, respectively. If the surplus is positive, it indicates an upward trend; conversely, a negative value reflects a downward trend (OUEDRAOGO, 2020).

Time Series Constitution: The statistical estimation of extreme flood discharges can be performed using two main approaches: the annual maximum method and the peak-over-threshold (POT) method. For short time series—typically ranging from 10 to 20 years—the POT method is recommended (Javelle, 2001). Given the nature of our dataset, which spans more than 20 years, we adopted the annual maximum method. This approach involves constructing a data series by extracting the highest daily mean discharge value for each year. Its primary advantage lies in its simplicity of implementation. However, it has the drawback of retaining only one value per year—the annual maximum—potentially overlooking multiple significant flood events in years with high flood activity. Conversely, it may include relatively minor events in years with low hydrological activity. As a result, the sample may lack homogeneity.

Independence: A series is considered as independent when it consists of a collection of events that, taken pairwise, satisfy the condition of statistical independence and the occurrence of one event does not influence the probability of occurrence of the other. The Wald-Wolfowitz runs test was employed, as it is considered robust (Thorsten, 2018). Let x_1, x_2, \dots, x_n be a sequence of observations from the time series. The test is used to compare the following two hypotheses:

- **Null hypothesis (H_0):** The sequence of observations is random and independent.
- **Alternative hypothesis (H_1):** The sequence of observations is not random, indicating a lack of independence.

$H_0 : x_1 = x_2 \dots x_n$... 55 are independent et $H_1 : x_1 \neq x_2 \dots x_n$ are not independent. The Wald–Wolfowitz test statistic is calculated as follows:

Homogeneity: A sample of a random variable is considered homogeneous when its constituent data originate from the same probability distribution and are collected under similar conditions. In this study, the Wilcoxon test was used, as it is recognized for its robustness (Thorsten, 2018). This non-parametric test allows for comparisons between two subsamples to determine whether their means differ significantly.

Considering a data series denoted respectively x_1, x_2, \dots, x_n et $x_{n+1}, x_{n+2}, \dots, x_m$, whose means are M_1 et M_2 , the Wilcoxon test allows the comparison of these two hypotheses: $H_0: M_1 = M_2$ et $H_1: M_1 \neq M_2$. The null hypothesis (H_0) states that the data are homogeneous, whereas the alternative hypothesis (H_1) indicates that the data are not homogeneous. The test statistic is expressed as follows:

$$V = \frac{W - 0.5(n+1)+0.5}{\sqrt{Var(W)}}$$
 with $W = \sum_{i=1}^m RI_s(R_i) * S(R_i)$

$S(R_i)$ is a multiplicative factor equal to 0 if the data are recorded before the change, and equal to unity if the data are recorded after

Stationarity: The Mann–Kendall test, considered as a robust test (Thorsten, 2018) was used. Indeed, it is a non-parametric test that can, a priori, detect trends that are not necessarily linear in the data series. This test is based on the correlation between the ranks of a time series and their order. The null hypothesis states that there is no trend. To this end, for each term in the series, the number of preceding terms that are smaller is calculated. The test statistic is expressed by the following equation:

$$S = \sum_{i=1}^n \frac{1}{n-1}$$

$$S = \sum 1/n-1 ; i=1 \sum \text{signe}(x_j - x_i) \quad nj=i+1 \text{ with } \text{signe}(x) = \{ -1 ; 0 ; 1 \}$$

Selection of Distributions: The annual maximum discharges were evaluated using HYFRAN software, which allows the fitting of numerous statistical distributions to data series that meet the assumptions of independence, homogeneity, and stationarity. Frequency analysis is a statistical prediction technique that examines past events, representative of a given process (hydrological or otherwise), to estimate their probabilities of future occurrence. This approach relies on the construction of a frequency model, an equation that characterizes the statistical behavior of the process and quantifies the likelihood of events of a given magnitude. The method is inherently challenging because hydrology is a historical science: past events, which are rarely reproducible, form the basis for simulating unobserved values beyond the available record. In this study, the principal probability distributions considered include the Generalized Extreme Value (GEV) distribution, the Gumbel distribution, the Pearson Type III distribution, and the Log-Pearson Type III distribution. Previous research has further demonstrated that the Normal (Gaussian) distribution is more appropriate for modeling average values, whereas the Gumbel distribution provides a superior representation of extreme events.

Estimation of Model Parameters: The estimation of model parameters, also referred to as calibration or specification, consists in determining the parameters of the probability distributions under consideration. The method of moments was employed; this statistical technique estimates the parameters of a distribution—such as the mean, variance, and skewness coefficients—by equating certain theoretical moments (which depend on these parameters) with their empirical counterparts. The method of moments is considered a “natural” and straightforward approach. It generally produces estimators of comparable or even superior quality to those obtained via the maximum likelihood method. However, a difficulty arises in the case of small samples, since higher-order moments tend to be biased (Meylan et al., 2012). Let \mathcal{M} denote a parametric family of probability distributions, and let \mathcal{S} be a sample of observations of the random variable. Within this family, a specific distribution is selected by assigning particular values to the parameters m_1, m_2, \dots, m_p , such that:

The theoretical moments of the distribution are set equal to the corresponding empirical moments, calculated from the sample values. This leads to a system of unknown equations with, which requires explicit formulation of the relationships between the parameters and the theoretical expressions of the moments. For many probability distributions, this method yields relatively simple results and is therefore widely applied. However, it tends to assign considerable weight to extreme values (Bois et al., 2007).

Statistical Distributions Comparison Criteria: To select the model that best fits the sample, the Akaike Information Criterion (AIC) proposed by Akaike (1974) and the Bayesian Information Criterion (BIC) introduced by Schwarz (1978) were applied. These criteria aim to strike a balance between sufficient parameterization to adequately fit a probability distribution to the observations and minimal complexity of the model (Bobée et al., 1999). They also allow for ranking statistical distributions according to the principle of parsimony, with the best fits corresponding to the lowest criterion values (Bobée et al., 1999). In the general case, the AIC is expressed as: $AIC = 2 \log(L) + 2k$ where L is the maximized likelihood and k is the number of free parameters in the model. Similarly, the Bayesian Information Criterion is designed to select the best-fitting model (among a set of candidate models) for data series. It is based on the likelihood function and is closely related to the AIC. The BIC is given by:

Période de retour	Qualification de l'évènement pluvieux
Plus de 100 ans	Très exceptionnel
30 à 100 ans	Exceptionnel
10 à 30 ans	Très anormal
6 à 10 ans	Anormal
Moins de 6 ans	Normal

$$BIC = 2 \log(L) + k * \log(n)$$

Where L is the maximized likelihood of the estimated model and n is the number of observations.

Model Validation Using the Chi-Square Test: Once the adjustment model has been selected, it must be subjected to a series of tests to verify the adequacy of the fitted distributions to the observed sample values.

Table 2. Distributions parameters

Distributions	Density de probabilité	Domain of definition	Number of parameters
Gumbel	$f(x) = \frac{\alpha^\lambda}{\Gamma(\lambda)} x^{\lambda-1} e^{-\alpha x}$	$x > 0$	2
GEV	$f(x) = \frac{1}{\alpha} [1 - \frac{k}{\alpha} (x - u)]^{\frac{1}{\lambda}}$	$x > \mu + \frac{\alpha}{k}$ Si $k > 0$	3
Pearson3	$f(x) = \frac{\alpha^\lambda}{\Gamma(\lambda)} (x - m)^{\lambda-1} \exp[-\alpha(x - m)]$	$x > m$	3
Log Pearson3	$f(x) = \frac{\alpha^\lambda}{x \Gamma(\lambda)} (\ln x - m)^{\lambda-1} \exp[-\alpha(\ln x - m)]$	$x > e^m$	3

In this study, the Chi-square test, developed in the late 19th century by the British mathematician and statistician Karl Pearson, was applied. This statistical method evaluates the correspondence between an observed sample distribution and a theoretical distribution. The test also serves to determine whether independence exists between two qualitative variables. It compares the observed frequencies in the sample with the expected theoretical frequencies. The differences between observed and expected frequencies are squared to ensure positivity, then divided by the expected frequencies and summed to obtain the Chi-square test statistic.

The Chi-square statistic is calculated as:

$$X^2 = \sum [(O - E)^2 / E]$$

where:

X^2 : Chi-square test statistic

O: observed frequencies

E: expected frequencies

A high value of the Chi-square statistic indicates a significant difference between observed and expected frequencies, suggesting that the variables under study are not independent. Conversely, a low value suggests independence between the variables.

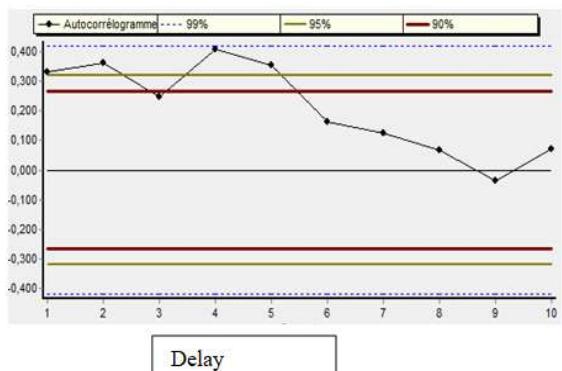
Estimation of Quantiles for Return Periods: Studies conducted by Koudamilor et al. (2017) demonstrated that extreme rainfall events tend to fit the Gumbel distribution more effectively, with a 95% confidence interval. Accordingly, the Gumbel distribution (1958) was applied to daily rainfall heights to characterize the return periods of extreme rainfall events. This approach was used to assess whether extreme rainfall episodes—often responsible for floods—could be classified as extreme events. The return period of an event is defined as the inverse of its annual exceedance probability (Mohimont and Demerée, 2016). The Vandiepenbeeck classification (1997) was utilized to characterize rainfall events according to different return period ranges, from normal to very exceptional. The classification is showed into Table 3. For the estimation of quantiles, return periods of 2, 5, 10, 20, 50 and 100 years will be considered.

RESULTS AND DISCUSSION

Data Quality Control: The rank correlation and autocorrelation tests applied to the annual rainfall data at the watershed station indicate that, at confidence levels of 99% and 95%, the data do not exhibit randomness. Consequently, the presence of a trend, as verified by the rank correlation test, is confirmed. Two breakpoint periods have been detected as illustrated in table 4. Indeed, changes have been observed from 1990 to 2008 with a mean value of 709,179 mm and from 2009 to 2017 where the average rainfall was 871,222 mm.

Table 4. Breakpoint period

Début	Fin	Moyenne	Ecart type
1980	2008	709,179	86,201
2009	2017	871,222	94,907



The independence of annual maxima was verified using the Wald-Wolfowitz test and accepted at the 5% significance level. Stationarity was assessed with Kendall's test, which concluded in favor of acceptance at the 5% significance level. Thereby confirming the absence of any trend in the data. The Wilcoxon homogeneity test applied to the annual maximum discharges also led to the acceptance of the null hypothesis (the data are homogeneous) at the 5% significance level, thus supporting the conclusion that the dataset is homogeneous. The results of the Wald-Wolfowitz, Kendall, and Wilcoxon tests are summarized in the table 5 below. The p-values of Wald-Wolfowitz, Kendall and Wilcoxon are high than significance threshold (5%). Then, null hypothesis (H_0) can't be rejected. So we accept the null hypothesis.

Table 5. Basis hypothesis test

Tests	Wald_Wolfowitz	Kendall	Wilcoxon
Statistics	$U = 0,0271$	$K = 2,62$	$W = 0,289$
P-value	0,978	0,057	0,773
H_0	Accepted	Accepted	Accepted

The fitting of annual maxima using the method of moments enabled the construction of adjustment curves for candidate probability distributions. Calibration results indicate that, within the annual maxima framework, the Gumbel, Generalized Extreme Value (GEV), Pearson Type III, and Log-Pearson Type III distributions provide the most satisfactory fits to the dataset. The adjustment curves of these four distributions exhibit close similarity across the sample, suggesting that each offers a reasonable representation of the observed data. The method of moments was applied to estimate the parameters of the probability distributions fitted to the annual maximum discharges. Results of the estimated parameters are showed in table 6.

Table 6. Distributions parameters

Distributions	Nmber of Parametres	Parameters
Gumbel	2	$\mu = 23.87$; $\sigma = 16.44$
GEV	3	$\mu=24.18$; $\sigma=17.74$; $\xi=0.063$
Pearson3	3	$\mu=2.23$; $\sigma=0.067$; $\xi=0.11$
Logpearson3	3	$\mu=6.05$; $\sigma=4.15$; $\xi=2.10$

Where μ is the location, σ the scale and ξ the shape parameters. These parameters will be used to estimate the quantiles for different return period

Table 7 presents the results of the identification of the best fitted distributions using Bayesian Information Criterion (BIC) and the Akaike Information Criterion (AIC). In fact, many authors (Nili et al., 2021; Flowers-Cano and Ortiz-Gómez, 2021; Kasali and Adeyemi, 2022) have used the AIC and BIC criteria in their studies to identify the best fitted model

Table 7. Distributions criteria

Distributions	XT	P(Mi)	P(Mi x)	BIC	AIC
Gumbel	99.504	16.67	41.57	322.706	318.708
GEV	94.928	16.67	5.45	326.769	322.018
Pearson 3	94.346	16.67	6.94	326.286	321.536
Log Pearson	90.613	16.67	28.52	323.459	319.539

Where XT is the quantile for a given return period, $P(Mi)$ is a priori probability, $P(Mi|x)$ is a posteriori probability. Since the distribution that best fits a sample according to the BIC and AIC criteria is the one with the lowest values, the comparison indicates that the Gumbel distribution provides the most appropriate fit, with a BIC of 322.706 and an AIC of 318.708

Fitting validation and quantiles estimation: The validation of the frequency model applied to the annual maxima was carried out using the Chi-square test at the 5% significance level. The chi-square statistic obtained shows that the probability of observing such a deviation between the observed and expected values, under the

assumption of a good fit, is 11%. Since this probability exceeds the 5% significance threshold, the null hypothesis cannot be rejected. It can therefore be concluded that the model provides a satisfactory fit to the dataset.

Table 8. Fitting of Probability Distributions

Distribution	Statistics	p-value	H ₀
Gumbel	X ² =8,89	0,1136	Accepted

The results of this test compiled in table 8 confirmed that the Gumbel distribution provides an acceptable fit to the data. Based on the comparison criteria of AIC and BIC, the Gumbel distribution was identified as the most appropriate model for the sample. This distribution was subsequently employed to fit the annual maximum discharges using the method of moments. As a result of this statistical analysis of the series, the quantiles corresponding to return periods of 2, 5, 10, 20, 50 and 100, years were determined and are presented in table 9 below.

Table 9. Estimated quantiles of return periods

Return periods T (years)	Estimated Quantiles (m ³ /s)	Confidence Interval (95%)
2	29,9	23,6-36,2
5	48,5	37,9-59,2
10	60,9	46,5-75,3
20	72,7	54,5-90,9
50	88	64, 8-111
100	99,5	72,5-127

The statistical fitting of the annual maximum discharges indicates that for return periods of 100, 50, 20, 10, 5, and 2 years, the corresponding quantiles are 99.5 m³/s, 88 m³/s, 72.7 m³/s, 60.9 m³/s, and 48.5 m³/s, respectively. In terms of occurrence probability, a return period of 100 years corresponds to a 1% chance of being exceeded in any given year. The results of the various tests indicate that, at the watershed scale, the analyzed rainfall series exhibit breakpoints. According to Pettitt's test, a breakpoint occurred in 2008 at the Ouaga-Aéroport station. The Lee and Heighian test as well as Hubert's test also confirm this same breakpoint date. However, these findings contradict a similar study conducted on the Nakanbé at the Ouagadougou-Aero station (Bonkoungou, 2020), which did not detect any breakpoint during the period 1987–2016 at the same station. This discrepancy may be explained by the length of the series considered. The deficit/exceedance calculated at the station level yields a positive value (22.85), indicating an upward trend in precipitation. Frequency Model Fitting of Annual Maxima results denoted that the Gumbel distribution demonstrates superior performance relative to the others and was therefore selected as the most appropriate model for annual maxima. This outcome aligns with the principles of extreme value theory, which emphasize the suitability of the Gumbel distribution for modeling maximum discharge values. Furthermore, these findings corroborate those of Sawadogo W. (2022), who conducted a hydrological study of the Pongolenga dam catchment in the commune of Komsilga, Kadiogo Province, Central Region, and Kirakoya A.F. (2020), who analyzed the hydrological regime of the Nakanbé at Wayen. The fitted Gumbel distribution yielded quantile estimates that increase consistently with the return period, reflecting the expected statistical behavior of extreme discharges. The highest quantile, associated with a 1000-year return period, is 137 m³/s, while the lowest, for a 2-year return period, is 48.5 m³/s. This monotonic progression confirms both the reliability of the frequency analysis and the suitability of the Gumbel distribution for modeling annual maxima in the dataset. Interpreting return periods in terms of exceedance probability is essential for risk assessment. For instance, the 100-year flood, with a quantile of 99.5 m³/s, corresponds to a 1% probability of occurrence in any given year. Although this probability may appear small, the cumulative likelihood of such an event over the lifespan of hydraulic structures becomes significant. This underscores the importance of incorporating long-return-period quantiles into design

considerations. From an engineering perspective, the estimated quantiles provide critical reference values for the design of flood protection works, including levees, spillways, and retention basins. The choice of design flood depends on the acceptable level of risk, economic constraints, and the strategic importance of the infrastructure. While return periods of 20–50 years may suffice for ordinary protective structures, critical infrastructure often This underscores the importance of incorporating long-return-period quantiles into design considerations. From an engineering perspective, the estimated quantiles provide critical reference values for the design of flood protection works, including levees, spillways, and retention basins. The choice of design flood depends on the acceptable level of risk, economic constraints, and the strategic importance of the infrastructure. While return periods of 20–50 years may suffice for ordinary protective structures, critical infrastructure often Results from the estimations of quantiles for these different return periods could be used as reference data for the design of flood protection structures along the Nazinon river.

CONCLUSION

The performance validation of statistical distributions demonstrated that the Gumbel law, applied through the annual maxima method, provides the most suitable representation of flood events in the study area. The analysis revealed, for instance, that the 100-year flood is estimated at 99.5 m³/s, corresponding to a 1% probability of occurrence in any given year, while the largest flood observed in the basin has a return period of approximately 80 years. The principal limitation of this study lies in the issue of missing data, as uncertainties introduced by data infilling compound those already inherent in observed records. This challenge is widespread across West Africa, where since the late 1980s the hydrometric network has declined, with gauging stations often abandoned or monitored irregularly. Despite these constraints, the study contributes to updating knowledge on flood prediction in the Nazinon watershed. By relying on recent datasets, it confirms that the Gumbel distribution remains one of the most robust statistical models for forecasting maximum discharges in this basin, and thus provides a recommended tool for hydraulic development programs and projects. Moreover, for the design and construction of flood protection infrastructure in this region, these findings should be carefully integrated into planning and decision-making processes.

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

REFERENCES

- Albergel J. (1988.). Génèse et prédetermination des crues au BURKINA FASO : du m² au km² : étude des paramètres hydrologiques et leur évolution.
- Ambroise B., I. G.-p.-4. (s.d.).
- Bezak N., B. M. (2014). Comparison between the peaks-over-threshold method and the annual maximum method for flood frequency analysis. Hydrological Sciences Journal. 59(5) : 959-977.
- Fairouze, T. H. (2009-2010). Les pluies exceptionnelles sur les villes du BURKINA FASO : cas de la ville de OUAGADOUGOU. OUAGADOUGOU: 2iE.
- Hosking J. R. M., W. J. (1998). Estimation of the generalized extreme-value distribution by the method of probability-weighted moments. Technometrics, 27(3) : 251-261.
- Kouider A. (2003.). Analyse fréquentielle locale des crues au Québec. Université du Québec, Institut national de la recherche scientifique, p.

Lang M., O. T. (1999). Towards operational guidelines for over-threshold modeling. *Journal of hydrology*, 225(3-4) : 103-117.

Meylan P., F. A.-C. (2008). Hydrologie fréquentielle : une scienceprédictive: PPUR presses polytechniques,p.

Musy A., H. C. (2014). Hydrologie : Presses polytechniques et universitaires romandes, p.

N., A. B.-D. (, 2010.). Inondation du 1er Septembre 2009 au BURKINA FASO. Evaluation des dommages, pertes et besoins de construction, de reconstruction et de relèvement.

OUEDRAOGO. (2020). Modélisation de l'offre et de la demande en eau dans un contexte de changement climatique dans le bassin supérieur de Nakanbé : application du modèle WEAP à la gestion intégrée des ressources en eau p.21-38.

Scarrott C., M. A. (2012). A review of extreme value threshold estimation and uncertainty quantification. *REVSTAT-Statistical Journal*, 10(1) : 33-60.

SOUANEF N. (2015.). Analyse fréquentielle des débits max de crues de l'Oued Abiod. Université Mohamed Khider-Biskra, p.
