Journal of Flood Risk Management

WILEY

CIWEM Chartered Institution of Water and Environmental Management Journal of Flood Risk Management

ORIGINAL ARTICLE OPEN ACCESS

Flood Frequency Analysis in West Africa

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Received: 21 March 2024 | **Revised:** 14 October 2024 | **Accepted:** 23 November 2024

Funding: The financial support was provided by the AFD/IRD project CECC.

Keywords: flood frequency analysis | GEV | GMLE | regional envelope curve | West Africa

ABSTRACT

Devastating flood events are recurrently impacting West Africa. To mitigate flood impacts and reduce the vulnerability of populations, a better knowledge on the frequency of these events is crucial. The lack of reliable hydrometric datasets has hitherto been a major limitation in flood frequency analysis at the scale of West Africa. Utilising a recently developed African database, we perform a flood frequency analysis on the annual maximum flow (AMF) time series, covering 246 river basins in West Africa, between 1975 and 2018. Generalized extreme value (GEV) and Gumbel probability distributions were compared to fit AMF time series with the L-moments, Maximum Likelihood (MLE) and Generalized Maximum Likelihood (GMLE) methods. Results indicated that the GEV distribution with the GMLE method provided the best results. Regional envelope curves covering the entire West African region with unprecedented data coverage have been generated for the first-time providing insights for the estimation in flood quantiles for ungauged basins. The correlation between flood quantiles and watershed properties shows significant correlations with catchment area, groundwater storage, altitude and topographic wetness index. The findings from this study are useful for a better flood risk assessment and the design of hydraulic infrastructures in this region, and are a first step prior to the development of regional approaches to transfer the information from gauged sites to ungauged catchments.

1 | Introduction

West Africa is highly vulnerable to climate change. The region is expected to experience unprecedented changes in both temperature and extreme precipitation patterns (IPCC 2014; Niang et al. 2014; Gautier, Denis, and Locatelli 2016; Sylla et al. 2016; Serdeczny et al. 2017; Adefisan 2018; Ahokpossi 2018; Akinseye et al. 2020; Ilori and Ajayi 2020; Muthoni 2020; Opoku et al. 2021). This vulnerability stems from West African countries limited economic and institutional capacities to cope with and adapt to climate variability (Roudier et al. 2011; Sultan and Gaetani 2016; Zougmoré et al. 2016; Lalou et al. 2019; Fitzpatrick et al. 2020). Climate variability accentuates the frequency, intensity and impact of extreme events, such as storms, floods and droughts (Kunkel 2003). In particular, catastrophic floods have hit many West African countries in recent years and there is a concern about a potential increase in flood hazard in this region (Di Baldassarre et al. 2010; Hounkpè et al. 2015; Chun et al. 2021; Tramblay, Rouché, et al. 2021; World Bank 2021).

Acquiring comprehensive insights into the frequency of extreme events is crucial for climate change adaptation and risk management (Katz, Parlange, and Naveau 2002). Frequency analysis involves estimating the occurrence probability of an extreme event using probability distributions (Cunnane 1988; Hosking and Wallis 1997; Rahman et al. 2013; Hamed and Rao 2019; Faulkner et al. 2020; Chahraoui, Touaibïa, and Habibi 2021; Malik and Pal 2021; Gogoi and Patnaik 2023). It is a widely used engineering method in fields where risk assessment and management are critical (Gaume 2018). It is

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commonly used in hydrology to evaluate flood risk, including assessing the likelihood of flood events and determining the feasibility and cost-effectiveness of hydraulic infrastructure like dams, bridges and dikes (Dalrymple 1960; Farquharson, Meigh, and Sutcliffe 1992; Castellarin, Burn, and Brath 2001; Reis and Stedinger 2005; Kidson and Richards 2005; Newman et al. 2021; Yan et al. 2021). Hydraulic infrastructures are indeed designed based on the magnitude and exceedance probability of extreme events, such as a 100-year flood, to mitigate the associated risks (Pan and Rahman 2022). Thus, flood frequency analysis involves identifying a statistical model capable of estimating the exceedance probability of flood events at a specific location (Meylan, Favre, and Musy 2008; Hu et al. 2020). However, in Africa, observed discharge time series rarely span the design flood return period used in hydrologic engineering (Tramblay, Rouché, et al. 2021). According to the USGS Bulletin 17C Guidelines (England Jr et al. 2019), a minimum record of 10 years is required to perform flood frequency analysis. Thus, estimating flood quantiles with long return periods often requires a certain degree of extrapolation (Kidson and Richards 2005; Rahman et al. 2013; Ibeje and Ekwueme 2020; Lawrence 2020; Zhou et al. 2021). However, uncertainties arise in extrapolation due to several factors, such as sample size, choice of the probability distribution, parameter estimation algorithm and non-stationarity. The longer the extrapolation period, the greater the uncertainties (Wilcox et al. 2018), hence the need to quantify these uncertainties (Shimizu, Yamada, and Yamada 2020).

Due to the significant economic and environmental impacts of flood hazards (Wadsworth 1999; Wang, Jiang, and Chen 1999; ICHARM 2009; CRED 2012; EM-DAT 2015; Tramblay, Villarini, and Zhang 2020; UNDRR 2020, 2023; Buchenrieder, Brandl, and Balgah 2021; Tanoue et al. 2021; Balgah et al. 2023; Dossoumou et al. 2023; Lawanson, Proverbs, and Ibrahim 2023), flood frequency analysis (FFA) has become a major concern and interest among hydrologists in recent decades (Bobée and Rasmussen 1995; Ahmed et al. 2023). FFA is based on extreme value theory (EVT) (Fisher and Tippett 1928; Embrechts, Klüppelberg, and Mikosch 1997; Coles 2001), which suggests that the extremes of a random variable are asymptotically close to one of three types of extreme value distributions (EVD): the Gumbel (Gumbel 1958), Fréchet (Fréchet 1927) and Weibull (Weibull 1951) distributions. Two methods are commonly used to construct a series of extreme values (Salas, Obeysekera, and Vogel 2018; Sarailidis and Tsiougkos 2018): Peaks-Over-Threshold (POT) (Hosking and Wallis 1997; Lang, Ouarda, and Bobée 1999) and Block-Maxima (BM) (Gumbel 1958). The POT approach involves isolating extreme values from the rest of the observations using a threshold (Kumar, Sharif, and Ahmed 2020; Shimizu, Yamada, and Yamada 2020). However, setting an appropriate threshold and ensuring the independence of sampled values are major limitations of the POT method (Bezak, Brilly, and Šraj 2014; Guru and Jha 2015). The BM approach is comparatively easier to implement due to its simplicity (Pan and Rahman 2022). With the BM method, the observation period is divided into non-overlapping intervals of equal length, from which the maximum value is extracted for each block (Engeland, Hisdal, and Frigessi 2004; Ferreira and de Haan 2015). The sampled maxima are treated as independent random variables as the BM approach considers only one extreme event per block (Caissie et al. 2022). General distributions that include all of the three limiting distributions mentioned above are available (Papalexiou and Koutsoyiannis 2013): the General Extreme Value (GEV) distribution for the Block-Maxima approach and the Generalized Pareto (GP) distribution (Arnold 2008) for POT.

Stationarity is one of the underlying assumptions of frequency analysis; in a stationary context, the variable of interest has a time-invariant probability density function (PDF) (Milly et al. 2008). However, in the context of global warming-driven environmental changes (Lee et al. 2023), the stationarity assumption needs to be verified (Milly et al. 2008; Debele, Strupczewski, and Bogdanowicz 2017; Salas, Obeysekera, and Vogel 2018). The most usual approach to check for non-stationarity is to use a probability distribution whose parameters are not constant but instead vary based on one or several covariates (Cunderlik and Burn 2003; Rigby and Stasinopoulos 2005; Serinaldi and Kilsby 2015; Marra et al. 2019). Most often, a linear relationship between the location parameter of the distribution with time, or other covariates, is typically employed to account for the non-stationary behaviour of time series in flood frequency analysis (Coles 2001; López and Francés 2013; Hounkpè et al. 2015; Lu et al. 2020; Chen, Papadikis, and Jun 2021; Anzolin et al. 2023; Bossa et al. 2023). Very few studies have focused on non-stationary flood frequency analysis in West Africa (Tramblay et al. 2014; Hounkpè et al. 2015; Dègan et al. 2017; Bossa et al. 2023), compared to the South African region where several studies have introduced non-stationary probabilistic modelling to improve flood frequency analysis in this region (Johnson, Smithers, and Schulze 2021; Mukansi 2024).

In developing countries, including West Africa, hydroclimatic data are typically very scattered (Xu and Singh 1998; Amoussou et al. 2014; Bodian, Dezetter, and Dacosta 2015; Aryee et al. 2018; Bodian et al. 2020; Tramblay, Villarini, et al. 2021). Consequently, most studies on flood frequency analysis in West Africa are limited to the catchment scales with a small number of basins, where data could be collected. Some of these studies focus on local frequency analysis at a few locations (Amoussou et al. 2014; Ehiorobo and Uso 2014; Olukemi et al. 2014; Hounkpè et al. 2015; Ntajal et al. 2016; Wilcox et al. 2018; Ibeje 2020; Osei et al. 2021; Bossa et al. 2023), while others explore regionalization (Komi et al. 2016; Faye 2019; Ekeu-Wei, Blackburn, and Giovannettone 2020; Ibeje and Ekwueme 2020). The common limitations of these studies lie in the relatively small number of stations used, with small study areas. Local hydrographic variability can be masked by these limitations, leading to inaccurate results and limiting regional applications. The main objective of this study is to apply local frequency analysis to a large set of catchments in West Africa, using the recently developed ADHI database (Tramblay, Villarini, et al. 2021). After a description of the study area and data used in Section 2, Section 3 details the methodology employed, including trend and autocorrelation tests, fitting of candidate probability distributions and correlation analysis. Results and discussions are presented in Section 4. Finally, conclusions and perspectives are given in Section 5.

2 | Study Area and Data

2.1 | Study Area

West Africa extends from the Atlantic coast of Senegal (18° W) to the east of Chad (25° E) and from the Gulf of Guinea (4° N) to the north of the Sahel (25° N), covering about one-fifth (1/5) of the African continent (Satgé et al. 2020). It covers a wide range of ecosystems, bioclimatic regions and habitats, from deserts in the north to tropical rainforests in the south (Le Houérou, Evenari, and Goodall 1986; Bocksberger et al. 2016; Merem et al. 2017; Nicholson 2018; Couvreur et al. 2021). West Africa can be divided into three climatic zones according to the seasonal oscillation of the Inter-Tropical Convergence Zone (ITCZ) (Nicholson 2008, 2009; Akinsanola et al. 2015; Mul et al. 2015; Sule and Odekunle 2016; Biasutti 2019; Gbode et al. 2023): (i) the Sahelian zone, characterized by an average annual rainfall of 150–600 mm; (ii) the Sudanian zone, which forms a broad belt south of the Sahel, with average annual rainfall ranging from 600 to 1200 mm; and (iii) the Guinean zone, characterized by an average annual rainfall ranging from 1200 to 2200 mm. Except for the southern regions of the coastal countries stretching from Liberia to Nigeria, which experience two rainy seasons (a lengthy one followed by a shorter one), much of West Africa exhibits a bimodal rainfall pattern, with a wet season and a dry season, influenced by the West African monsoon (Rodríguez-Fonseca et al. 2015; Nicholson 2018). Almost half of the African continental watersheds, including 11 major transboundary river basins, are located in West Africa (Niasse 2004).

2.2 | Data

The data was obtained from the African Database of Hydrometric Indices (ADHI) built by Tramblay, Villarini, et al. (2021). This database provides hydrological indices computed from different data sources including 1466 hydrometric stations with daily discharge time series that span at least 10 years between 1950 and 2018. The ADHI database also contains several physiographic features describing the watersheds. Table 1 provides names, abbreviations and references for these watershed properties. For West Africa, the ADHI database includes 441 stations located in different countries. The area of the West African catchments in the database varies from 95 to 2,150,000 km^2, and the daily discharge series exceeds 44 years of record for some stations, with an average length of 19 years. The block-maximum (BM) approach was used to create data series used in flood frequency analysis. Annual maximum flow (AMF) was extracted from the daily streamflow records for the period from 1975 to 2018. To handle challenges posed by the missing data in the ADHI database, we have carefully examined the hydrographs at each station year-by-year. If values were missing near the flood peak, we excluded that year from the analysis, as the missing data could have included the Annual Maximum Flow (AMF) for that year. This approach follows the sampling method outlined by Wilcox et al. (2018). This check has enabled us to ensure that no AMF was extracted during a period with a lot of missing data. The selection of watersheds was based on three main criteria: (i) the length of the available time series, (ii) the regulation of catchments (Figure S1) and (iii) the size of watershed areas. Watersheds not influenced by dams, with a minimum record length of 10 years, and an area less than 150,000 km^2 were considered. Applying these criteria, a total of 246 stations were selected from the West Africa ADHI database. The AMF series of retained stations have an average temporal depth of 23 years,

TABLE 1 | Catchment properties.

Description	Abbr.	References
Curve number	CN	(Ross et al. 2018) https://doi.org/10.1038/sdata.2018.91
Available water capacity	AWC	(Wieder 2014) https://doi.org/10.3334/ORNLDAAC/1247
Bulk density	BD	
% Clay	Clay	
% Gravel	Gravel	
% Sand	Sand	
% Silt	Silt	
Groundwater depth	GD	(MacDonald et al. 2012) https://doi.org/10.1088/1748-9326/7/2/024009
Groundwater productivity	GP	
Groundwater storage	GS	
Maximum altitude	MA	(Lehner and Grill 2013) https://doi.org/10.1002/hyp.9740
Mean slope	Slope	
Mean altitude	Altitude	
Topographic Wetness Index	TWI	(Sørensen, Zinko, and Seibert 2006) https://doi.org/10.5194/hess-10-101-2006
% Forest	Forest	ESA CCI LandCover http://www.esa-landcover-cci.org/
% Urban	Urban	
% Cropland	Cropland	
% Cropland irrigated	CI	
% Grassland	Grassland	
% Shrubland	Shrubland	
% Sparse	Sparse	
% Bare land	BL	
Area	Area	
Mean annual precipitation	Prec	(Harris et al. 2020) https://doi.org/10.1038/s41597-020-0453-3
Mean annual temperature	Temp	
Mean annual potential evapotranspiration	PET	

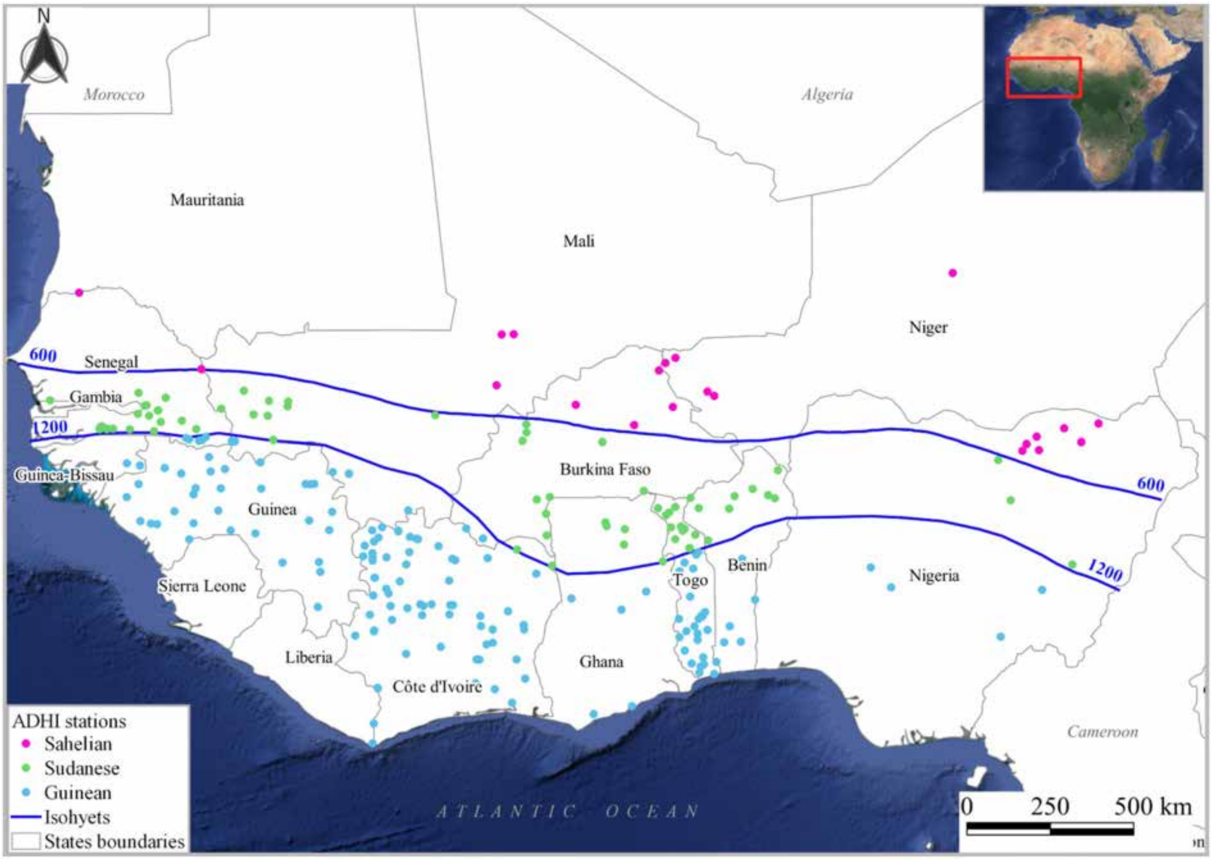

FIGURE 1 | Location of 246 ADHI watersheds selected for the study, the blue lines represent isohyets delimiting West Africa climatic regions, and the grey lines indicate the borders of West African countries.

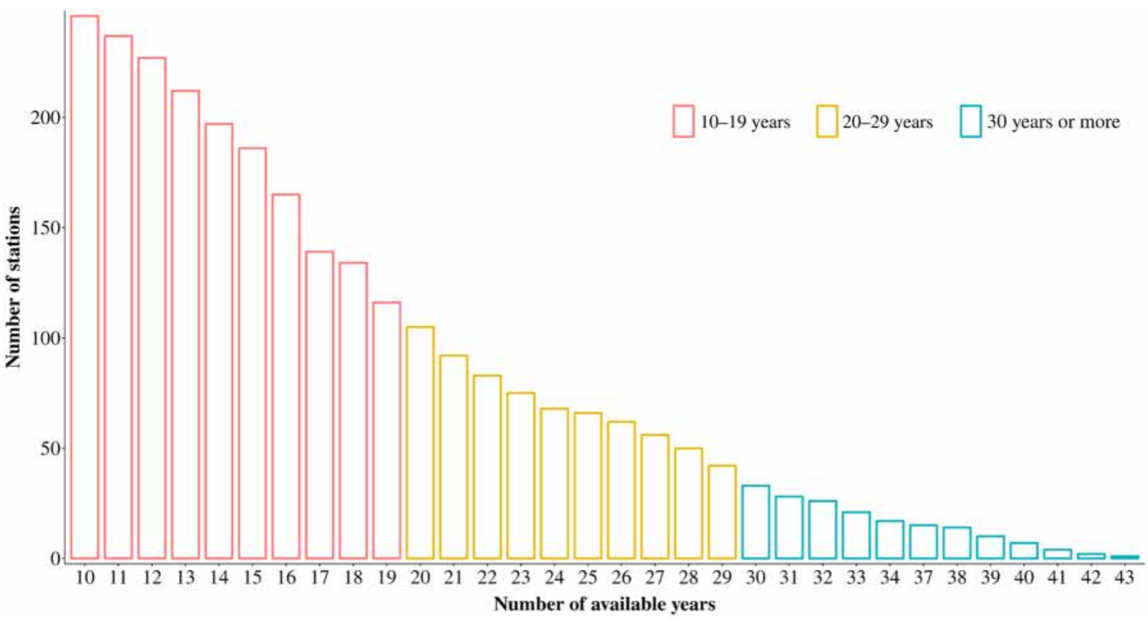

FIGURE 2 | Distribution of hydrometric stations selected based on the number of years of available data. Stations are classified into three categories according to AMF record length: 10–19 years (red), 20–29 years (yellow) and at least 30 years (blue).

with the longest series spanning 43 years. Figure 1 shows the spatial distribution of the selected stations, with 63% of them located in the Guinean zone. The Sudanian and Sahelian zones account for 27% and 10% of selected stations, respectively. Most selected basins (70%) have an area of less than 10,000 km^2. Figure 2 shows the number of hydrometric stations according to the number of data points available, providing an overview of the temporal coverage of hydrometric data in West Africa.

3 | Methodology

Flood frequency analysis is applied through a six-step process (Meylan, Favre, and Musy 2008): (i) construction of a series of extreme values, (ii) verification of the assumptions underlying frequency analysis through the application of statistical tests on the sample of extreme values, (iii) selection of several extreme value distributions to fit the data series, (iv) estimation of the distributions' parameters, (v) comparison of the distributions based on goodness-of-fit (GOF) tests (Takara and Takasao 1988) and (vi) estimation of flood quantiles.

3.1 | Independence and Homogeneity Tests

Two statistical tests were applied to the annual maximum discharge time series at 0.05 significance level. The Wald-Wolfowitz independence test (Wald and Wolfowitz 1940) was used to detect autocorrelation in the annual maximum series, while the non-parametric Mann–Kendall trend test (Mann 1945; Kendall 1975) was employed to assess the stationarity assumption. However, the results of simultaneous multiple tests should be interpreted globally, to account for the presence of spatial cross-correlations or spatial clusters in the data, which increase the number of rejections of the null hypothesis than expected by the significance level (Farris et al. 2021). To assess the significance of the detected local trends by the Mann-Kendall test on a regional level, the False Discovery Rate (FDR) procedure (Hochberg and Benjamini 1995) was implemented. The FDR procedure aims to reduce the proportion of false positives among the null hypothesis local rejections (Wilks 2006). Given the p-values for each grid point, the FDR test rejects the local null hypothesis at sites where the corresponding p-value is below a regional significance level (α_{global}, set at 0.05 for consistency with local trend analysis). If at least the null hypothesis is rejected at one grid point, trends detected are regionally significant (Wilks 2016).

3.2 | Candidate Probability Distributions

Two extreme value distributions were assessed: the GEV (Generalized Extreme Value) and the Gumbel. The GEV distribution is a three-parameter model, whereas the Gumbel distribution has two parameters. These two distributions are selected since they are the most commonly used for flood frequency analysis. It is worth noting that when the shape parameter (ξ) of the GEV equals 0, it becomes identical to the Gumbel distribution (Martins and Stedinger 2000; Smirnov, Ma, and Volchenkov 2020). Equations (1) and (2) present the cumulative distribution functions (CDFs) of the two probability distributions. Some studies have argued that both the location and scale parameters should be varied proportionally to capture the impact of climate change (Stedinger and Griffis 2011; Prosdocimi and Kjeldsen 2021; Jayaweera et al. 2023). However, researchers often opt to model only the location parameter as a covariate-dependent function, as this added complexity could significantly complicate the model parameters estimation process and would require large datasets for reliable parameter estimates (Coles 2001; Cheng et al. 2014; C. Zhang et al. 2023). Furthermore, previous research has indicated that estimating the GEV shape parameter (ξ) is challenging, especially in a stationary context (Martins and Stedinger 2000; Papalexiou and Koutsoyiannis 2013; Carney 2016; Ragulina and Reitan 2017). Therefore, it is impractical to assume smooth variation of shape parameters over time or as a function of covariates in non-stationary models (Coles 2001; Rohmer, Thieblemont, and Le Cozannet 2021). Thus, to account for non-stationarity in flood frequency analysis here in, we have expressed the location parameter (μ) of the two distributions as a linear function of time, denoted as $\mu(t)$, leaving the other parameters constant.

$$F(x; u, \alpha, \xi) = exp\left\{ -\left[1 - \xi\frac{(x-u)}{\alpha}\right]^{1/\xi} \right\} \quad \kappa \neq 0 \tag{1}$$

$$F(x; \xi, \alpha) = exp\left\{ -exp\left[-\frac{(x-u)}{\alpha} \right] \right\} \quad \kappa = 0 \tag{2}$$

where x, u, α and ξ are the data, location, scale and shape parameters, respectively, and $(u + \alpha/\xi) \le x < \infty$ if $\xi < 0; -\infty < x < \infty$ if $\xi = 0; -\infty < x \le (u + \alpha/\xi)$ if $\kappa > 0$.

3.3 | Fit of Probability Distributions

Three parameter estimation methods were used to fit probability distributions to AMF series: L-moments (LM) (Hosking 1990), Maximum Likelihood (MLE) (Fisher 1992) and Generalized (Penalized) MLE (GMLE) (Martins and Stedinger 2000). The fitting was carried out in the R environment (R Core Team 2022) using the extRemes v2.0 library (Gilleland and Katz 2016). This package implements the three fitting methods mentioned above and also allows the integration of covariates in a non-stationary context. According to Martins and Stedinger (2000), the MLE method is unstable in estimating GEV parameters for small samples. They recommend the use of a Bayesian prior distribution, to constrain the GEV shape parameter within a reasonable range of values. They used a beta distribution (with shape parameters $p = 6$ and $q = 9$) as a prior, which constrains the values of the shape parameter in the interval [−0.5, +0.5]. This restriction results in the GMLE method. However, the authors recommend improving this prior when regional information is available to develop a more informative prior distribution. This improvement was successfully applied in the United Kingdom (Howard 2022) and North Africa (Tramblay et al. 2024). In this work, a normal prior distribution is adopted to develop a more informative prior for the shape parameter of the GEV distribution.

3.4 | Assessing Goodness-of-Fit (GOF) of Probability Distributions

To compare the probability distributions, the Akaike information criterion (AIC) (Akaike 1974) and the Bayesian information criterion (BIC) (Schwarz 1978) were used. The mathematical expressions for these criteria are provided in Equations (3) and (4). The joint use of these performance metrics to find models favoured by both criteria makes model selection more efficient (Kuha 2004; Phillips, Samadi, and Meadows 2018; Cheng, Du, and Ji 2020; Lu et al. 2020; Razmkhah, Fararouie, and Ravari 2022). In addition to the AIC and BIC criteria, the models were also compared based on uncertainties associated with the estimation of flood quantiles. A normalised uncertainty range, defined as the ratio of the difference between the upper (97.5%) and lower (2.5%) bounds of the confidence interval and the estimated quantile was computed (Metzger et al. 2020; Tramblay et al. 2024). Confidence intervals were computed using the bootstrap percentile method (Ialongo 2019), implemented in the R-extRemes (v2.0) library (Gilleland and Katz 2016; Gilleland 2020). This method is easy to apply, regardless of the complexity of the model, and is based strictly on available information, with no underlying assumptions about data distribution (Serinaldi and Kilsby 2015).

$$AIC = -2log(L) + 2k \tag{3}$$

$$BIC = -2log(L) + k \cdot log(N) \tag{4}$$

where k is the number of free parameters in the model, L is the maximum likelihood, and N is the sample size.

3.5 | Correlation Between Flood Quantiles and Catchment Properties

Understanding the relationship between flood quantiles and catchment properties provides valuable information for flood risk management and forecasting (Stein et al. 2021; Titley et al. 2021). Such an analysis helps identify key catchment properties (e.g., area, slope, soil type) that significantly impact flood behaviour. Incorporating these factors into predictive models improves their accuracy, leading to better flood forecasts and more targeted flood mitigation strategies (Filipova et al. 2022). In this work, we focused on the 20-year flood and the maxima of the AMF series for the correlation analysis. The 20-year flood is chosen here as it balances the rarity of extreme events (considering data length limitations) with the uncertainty of estimated return periods, making it a reliable metric for comparative studies (Dawson et al. 2005; Tramblay and Somot 2018; Slater et al. 2021; Griffin et al. 2022; Han et al. 2022). The Spearman's correlation coefficient was used to investigate the relationship between flood quantiles and catchment properties. Spearman's correlation is the non-parametric equivalent of Pearson's correlation, which is based on the assumption of normality of observations (Hauke and Kossowski 2011; de Winter, Gosling, and Potter 2016). Thus, it is more suitable for hydrological data, which often exhibit skewed distributions. A principal component analysis (PCA) (Greenacre et al. 2022) was also carried out to analyse the correlation between the different physiographic characteristics of watersheds. PCA is a dimensionality-reduction (DR) approach that is used to condense a multivariate dataset while preserving most of its variance (Bharadiya 2023; Krzyśko et al. 2024). This reduction is done by transforming the original variables into a new set of variables known as principal components (PCs) (Liu et al. 2023; Dorabiala, Aravkin, and Kutz 2024). PCs are linear combinations of the original variables and are ranked according to the amount of variance they explain in the data. The first principal component (PC-1) is the linear combination of variables that captures the greatest amount of variation in the data.

4 | Results and Discussion

4.1 | Independence and Homogeneity Tests

Testing for autocorrelation and trends in AMF time series is crucial for ensuring the reliability of flood frequency analysis results. The proportion of stations where the assumptions of independence or homogeneity are rejected for each climatic zone and each statistical significance level is given in Table S1. Autocorrelation is detected in 17 AMF series at 0.05 level. Such series are excluded from the remainder of the analysis. Figure 3 shows the spatial distribution of trends detected by the Mann–Kendall test. A significant trend is detected in the AMF series of 29 out of 234 independent time series (at 0.05 level), with 17 downward trends and 12 positive trends. Thus, non-stationary frequency models have been applied for these 29 AMF series. Figure 3 reveals no discernible spatial pattern in the identified trends, even though the study area features three different climatic zones. To assess the regional significance of trends detected by the Mann–Kendall test, the FDR procedure was implemented with global significance thresholds of 0.05, for consistency with local trend analysis. Among 29 significant local trends, only 5 are field significant at 0.05 level. These results suggest that the local significant trends detected are not spurious trends or artefacts of multiple tests but reflect real hydrological changes in West Africa. The findings from the study of Tramblay, Villarini, and Zhang (2020) indicate statistically significant increasing trends in flood occurrences in Africa between 1950 and 2010, particularly in the western and southern regions. As the AMF series we have used falls within the period 1975–2018, our results are consistent with those of Tramblay, Villarini, and Zhang (2020), using a much longer period, starting in 1950, to analyse trends and change points in floods across Africa. The results of Ekolu et al. (2022) also show significant decadal variability of floods in sub-Saharan Africa, explaining aperiodic upward and downward trends.

4.2 | Fitting of Frequency Models in a Stationary Context

Martins and Stedinger (2000) recommend improving the prior distribution of the GEV shape parameter in the GMLE method when regional information is available. As depicted in Figure 4, the original prior from Martins and Stedinger (2000) is inappropriate for West Africa. Thus, a normal distribution, fitted to the GEV shape parameter values estimated by the L-moments method (Hosking 1990) on 98 AMF series spanning at least 20 years, is employed as a prior distribution for the GMLE method in this study. Figure 3 shows that the distribution of shape parameter values obtained with the new regional prior using a normal distribution (with a mean of −0.24 and a standard deviation of 0.16) is more similar to that obtained with the L-moments. The new regional normal prior was used for the remainder of the analysis.

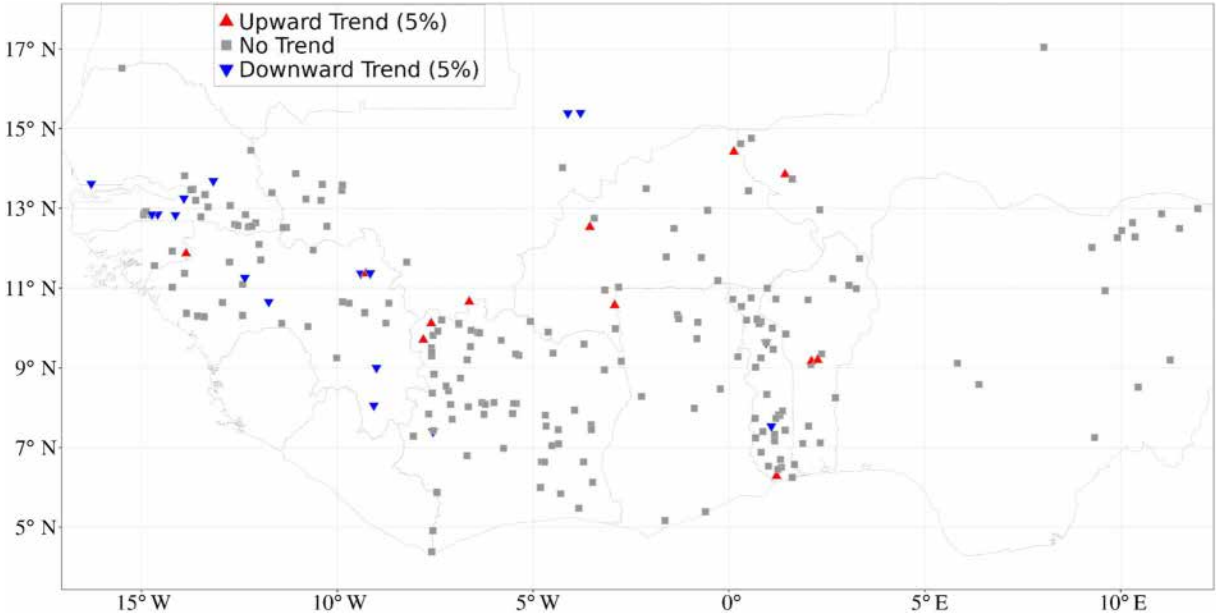

FIGURE 3 | Spatial distribution of trends detected by Mann–Kendall test at 0.05 statistical significance level in West Africa. The red (blue) upward (downward) triangles represent significant positive (negative) trends and the grey points represent no trend. The grey lines indicate the borders of West African countries.

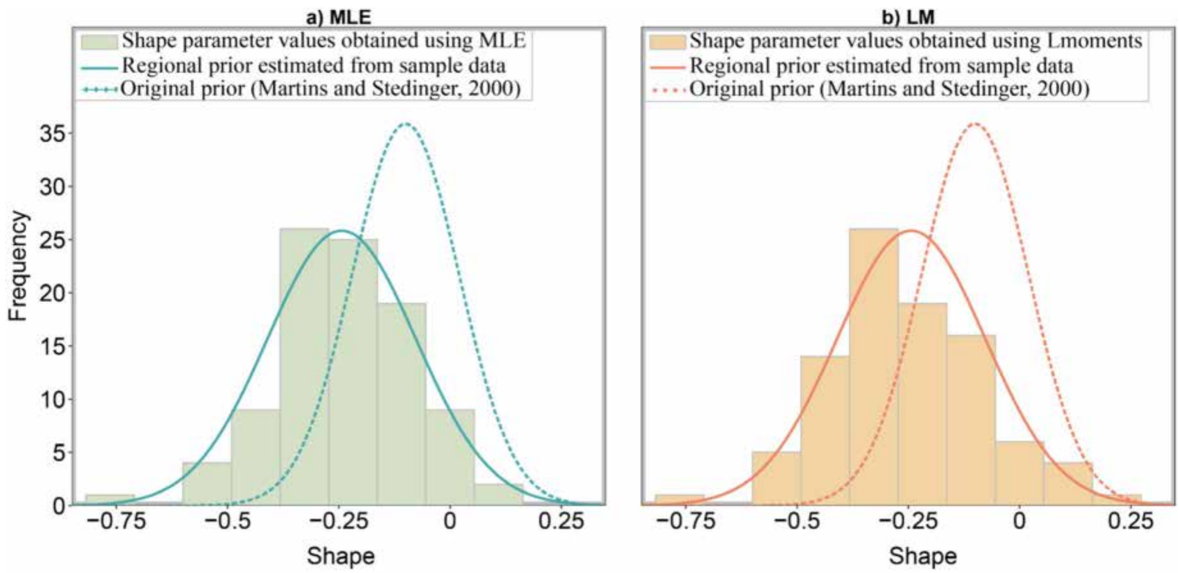

FIGURE 4 | Histograms shape parameter values of the GEV distribution fitted with (a) MLE and (b) LM methods to the series of annual maxima from 96 stations with more than 20 years of data, with the Martins and Stedinger (2000) prior distribution (dashed line) and the new regional prior (solid line).

To select the probability distribution that fits best at each site, the goodness-of-fit of the GEV and Gumbel distributions are compared based on the AIC and BIC criteria. Figure 5 displays the best distribution in each station according to the AIC and BIC criteria for each parameter estimation method (LM, MLE and GMLE). Our evaluation of the frequency models shows that, overall, in a stationary context, the GEV is the model that best fits the AMF series in the study area. The GEV obtained the lowest AIC and BIC values at 90% of stations when fitted with the GMLE method, whatever the criterion considered (Figure 5a,d). BIC scores were also more favourable for the GEV model when fitted with the LM (L-moments) method at 92% of stations (Figure 5f). However, according to the AIC criterion, the Gumbel model fits best at 60% of stations using the same method (Figure 5c). AIC and BIC scores are fairly balanced between the two distributions with the MLE method (Figure 5b,e). In terms of statistical methodology, these results are consistent with those of Rahman et al. (2013) in Australia, who evaluated 15 probability distributions fitted with several parameter estimation methods, including the GEV and Gumbel, over 127 watersheds with at least 40 years of annual maxima discharges. Their results show that the GEV fits better than the Gumbel distribution according to the AIC and BIC criteria. The results of Beskow et al. (2015) and Back and Bonfante (2021) in Brazil, who applied frequency analysis to more than 200 series

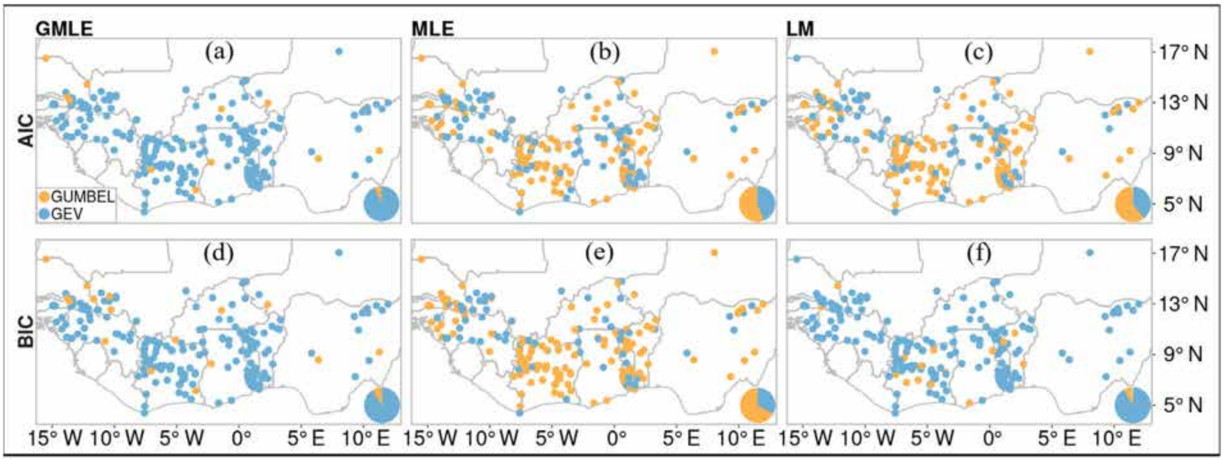

FIGURE 5 | Best distribution in each station according to AIC and BIC criteria and parameter estimation methods (GMLE, LM and MLE) in a stationary context. The pie charts show the proportion of sites where each distribution is selected. Panels (a), (b) and (c) show the selection of distributions based on the AIC criterion, and panels (d), (e) and (f) show the selection of distributions based on the BIC criterion. The blue and orange points respectively represent stations for which the GEV and Gumbel distribution are best suited. The grey lines indicate the borders of West African countries.

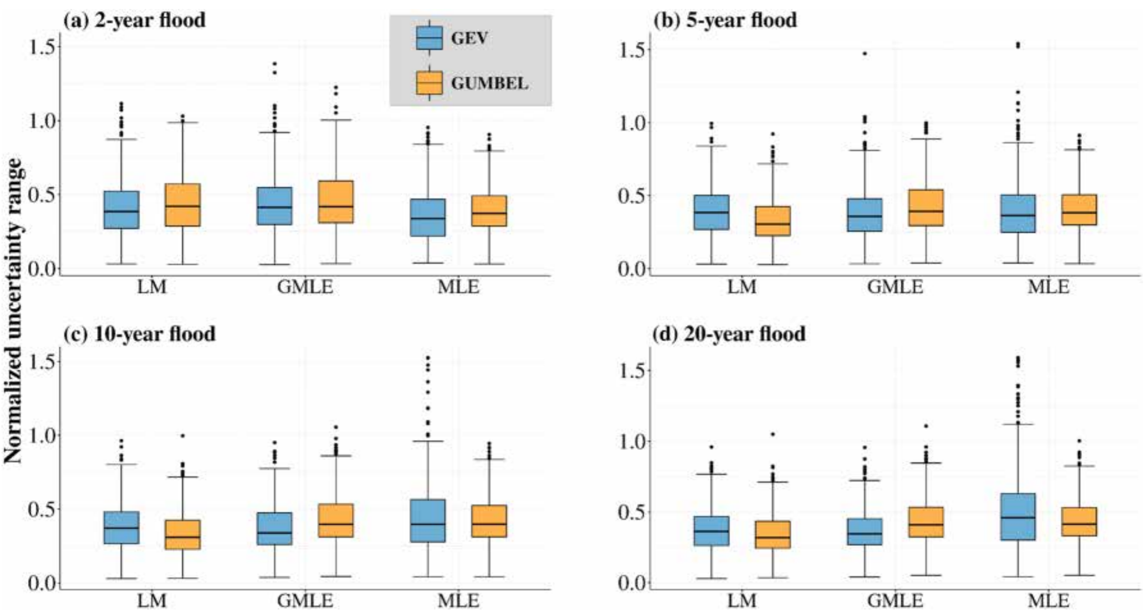

FIGURE 6 | Uncertainties in stationary flood quantile estimation for various return periods: (a) 2-year, (b) 5-year, (c) 10-year and (d) 20-year, using both GEV and Gumbel distributions, fitted with the LM, MLE and GMLE methods. The blue and orange boxplots represent respectively the normalized uncertainty distributions for the GEV and Gumbel distributions.

of annual precipitation maxima, also show a predominance of the GEV at most stations.

To assess the robustness of the frequency models, a normalised uncertainty range, defined as the ratio of the difference between the upper (97.5%) and lower (2.5%) bounds of the confidence interval and the estimated quantile was computed. Due to data availability challenges, flood quantiles for return periods up to 20 years are estimated for stations with record length falling between 10 and 29 years, and the 50-year flood quantile is computed only for stations with at least 30 data points.

Figure 6 shows the comparison of model uncertainties in stationary flood quantiles estimation. Considering the GMLE method, the GEV distribution produces the lowest estimation bias for all return periods. For the MLE method, the Gumbel distribution becomes more robust than the GEV as the return period increases from the 10-year return period. Model performances are fairly balanced when considering the LM method, with highly variable uncertainties depending on the return period. The differences in performance between the GMLE and MLE methods can probably be explained by the improvement of GMLE initial prior with regional information (Martins and

Stedinger 2000). The GMLE method might be preferred to MLE in situations where the sample size is relatively small, as it can provide more stable parameter estimates by incorporating additional information in estimating the GEV shape parameter.

The relationship between record lengths and mean normalised uncertainty was investigated, to analyse the impact of sample size on the robustness of the fitted distributions. Figure 7 shows that whatever the parameter estimation method considered (LM, MLE and GMLE), uncertainty in quantile estimation decreases for all distributions as the sample size increases. For the GMLE method, for example, considering the 20-year return period, when the length of the AMF series increases from 11 to 43 years, the normalised uncertainty falls from 0.52 to 0.17 and from 0.63 to 0.22 for the GEV and Gumbel distributions, respectively. An analysis of the slopes of the linear fitting lines (Table S2)

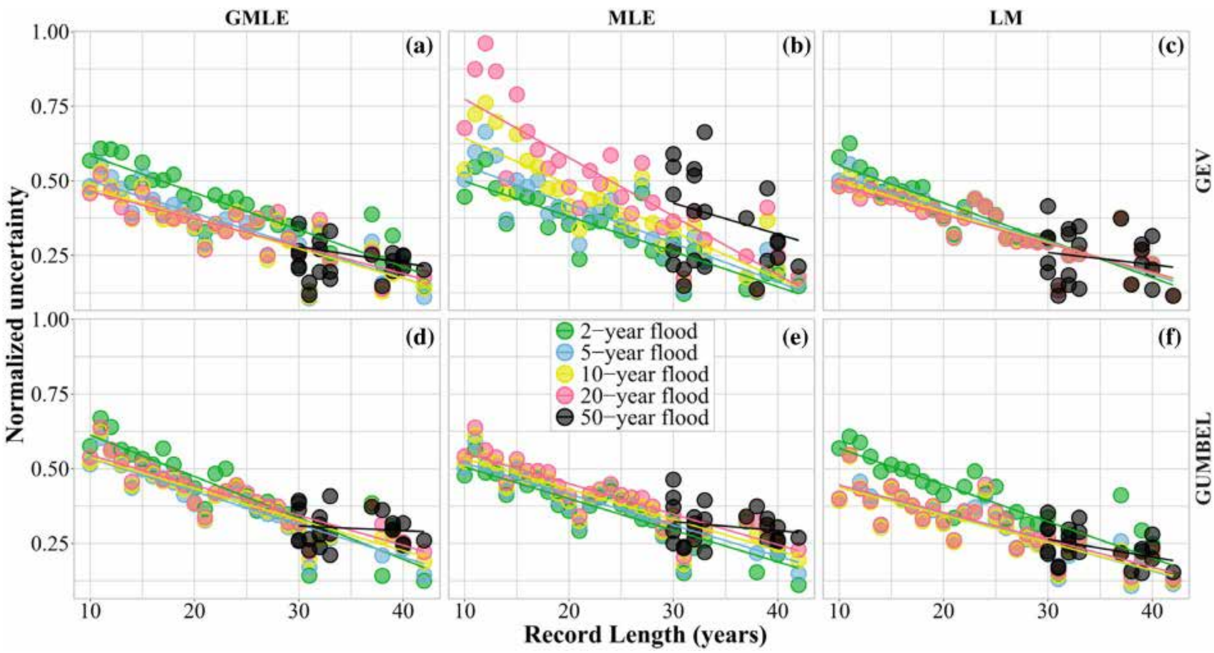

FIGURE 7 | Scatter plot of AMF series lengths and normalized uncertainty range for 2-, 5-, 10-, 20- and 50-year floods, computed with six models: (a) GEV-GMLE, (b) GEV-MLE, (c) GEV-LM, (d) Gumbel-GMLE, (e) Gumbel-MLE and (f) Gumbel-LM. The thin continuous lines represent a linear fit between normalized uncertainty and AMF series lengths, illustrating the general trend in the relationship between the two variables.

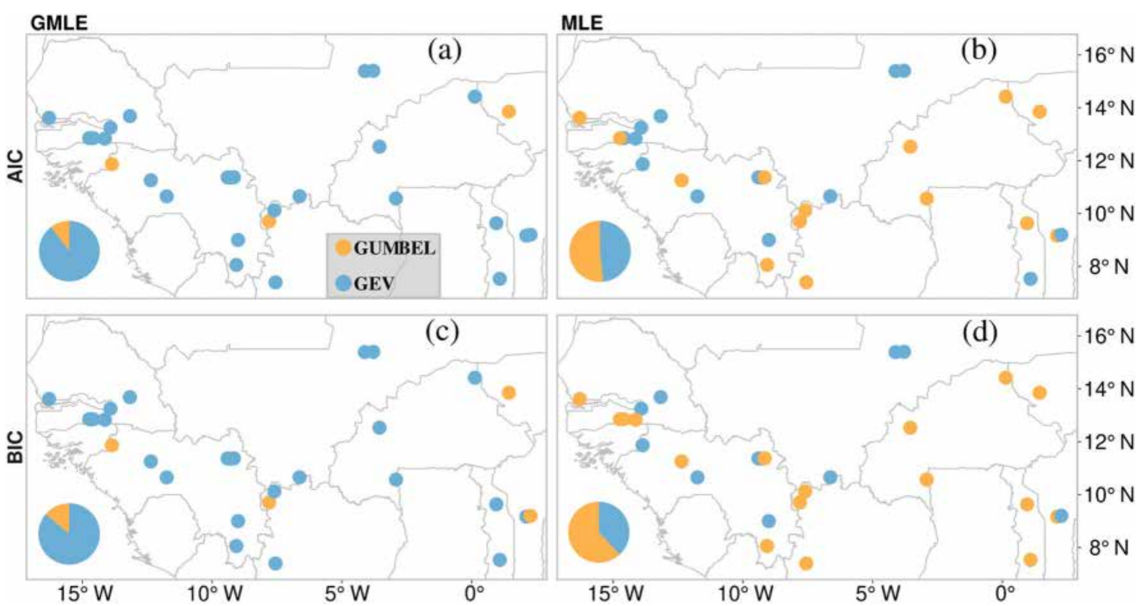

FIGURE 8 | Best distribution in each station according to AIC and BIC criteria and parameter estimation methods (GMLE and MLE) in a non-stationary context. The pie charts show the proportion of sites where each distribution is selected. Panels (a) and (b) show the selection of distributions based on the AIC criterion, and panels (c) and (d) show the selection of distributions based on the BIC criterion. The blue and orange points respectively represent stations for which the GEV and Gumbel distribution are best suited. The grey lines indicate the borders of West African countries.

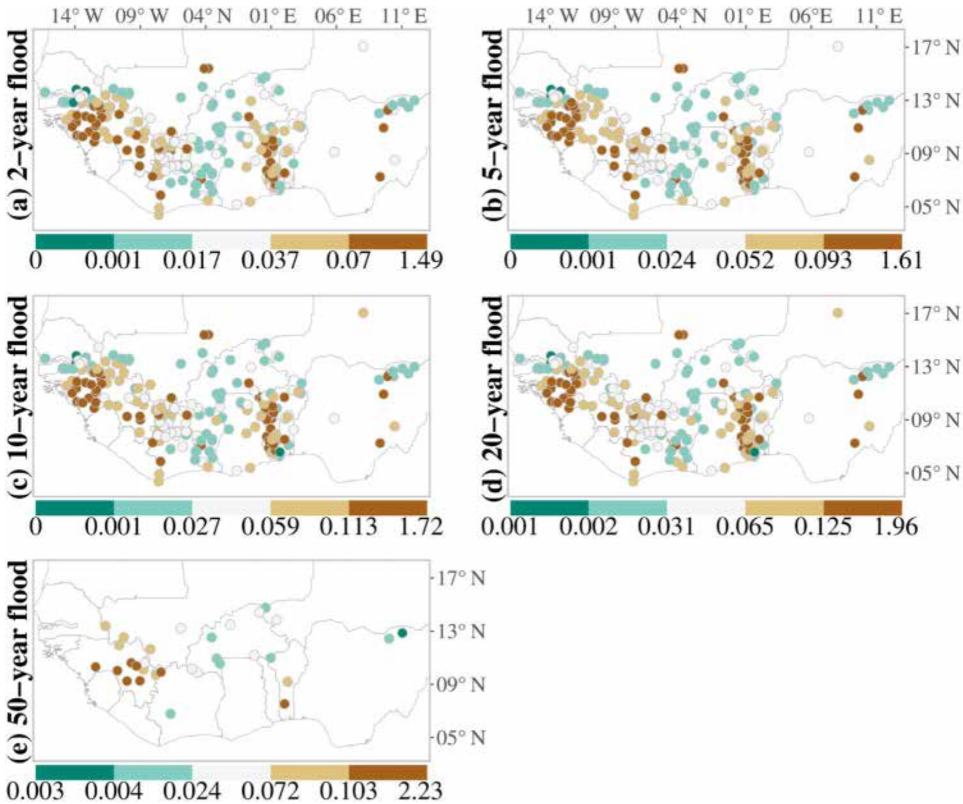

FIGURE 9 | Spatial distribution of (a) 2-year flood, (b) 5-year flood, (c) 10-year flood, (d) 20-year flood and (e) 50-year flood quantiles in West Africa. Quantiles were estimated using the GEV distribution fitted with the GMLE method and normalised by catchment area. The grey lines indicate the borders of West African countries.

shows that of the three parameter estimation methods, the MLE method is the most sensitive to record length, particularly with the GEV distribution (Figure 7b). For instance, considering the 20-year flood as an illustration, the slopes for the GEV distribution are −0.869, −1.788 and −0.881 for the GMLE, MLE and LM methods, respectively. Similarly, for the Gumbel distribution, the slopes are −0.975, −0.997 and −0.802 for the GMLE, MLE and LM methods, respectively. There are subtle differences between the slopes obtained using the GMLE and LM methods. These results demonstrate the impact of sample size in the estimation of frequency model parameters (Hosking and Wallis 1997; Martins and Stedinger 2000; Moretti and Mendes 2003; Papalexiou and Koutsoyiannis 2013; Serinaldi and Kilsby 2015; Hu et al. 2020; Metzger et al. 2020), and hence in the estimation of design values (Marra et al. 2019).

4.3 | Fitting of Frequency Models in Non-Stationary Context

Fitting frequency models in a non-stationary context can be challenging but is essential to determine whether non-stationary distributions do provide more reliable forecasts of hydrological variables (Serinaldi and Kilsby 2015). The Mann–Kendall trend test, applied at the 0.05 significance level, detected significant trends in 29 AMF time series (Figure 2). A comparison between non-stationary GEV and Gumbel distributions, fitted with the MLE and GMLE methods is shown in Figure 8. According to the AIC and BIC criteria, the GEV-GMLE model (Figure 8a,c) fits best at 86% of the stations with trend-dependent AMF series. With the MLE method, the AIC score is balanced between the two distributions (Figure 8b), and Gumbel distribution is more adequate at 62% of the stations according to the BIC criterion (Figure 8d). However, whether non-stationary quantiles and, in particular, at the end of the records, are statistically different from the stationary quantiles is an important question to address. Figure S2 shows the results of the comparison between stationary and non-stationary models, by overlapping confidence interval ranges of flood quantiles, calculated using the bootstrap percentile method. We find confidence intervals overlap in most stations, suggesting no significant difference between stationary and non-stationary quantiles. Such results are consistent with previous studies testing the uncertainties in quantile estimation in stationary and non-stationary contexts (Serinaldi and Kilsby 2015). Therefore, the stationary GEV distribution, fitted with the GMLE method, is here identified as the best frequency model for estimating flood quantiles in West Africa.

4.4 | Quantiles and Return Periods of Annual Peak Flood

4.4.1 | Spatial Distribution of Flood Quantiles

If a stationary model yields confidence intervals that overlap with those produced by non-stationary models, the added complexity of non-stationary models becomes less relevant (Serinaldi and Kilsby 2015). Thus, we have identified the stationary GEV distribution, fitted with the GMLE method, as the best frequency model for estimating flood quantiles in West Africa. However, the choice of the stationary GEV to compute flood quantiles in the region does not preclude the use of the non-stationary GEV for specific cases where one would like to account for the trend in AMF time series. After the selection of the best-suited probability distribution, the main aim of flood frequency analysis is to estimate flood quantiles and return periods. The spatial distribution of flood quantiles in West Africa is shown in Figure 9. The quantiles were estimated using the GEV-GMLE model and normalised by catchment area to allow comparison of flood magnitudes across watersheds. For AMF series with significant trends, we have selected the flood quantile from the last year (Figure S8) of the fitting period (Faulkner et al. 2020; Xavier et al. 2020; Hesarkazzazi et al. 2021), to avoid the underestimation of the true magnitude of floods due to improper handling of positive trends in the data (Faulkner et al. 2020; Hecht et al. 2022). As shown in Figure 9, there are no distinct spatial patterns in flood quantiles distribution in West Africa, consistent with the high regional climatic diversity (Emetere 2016; Ilori and Ajayi 2020; Muthoni 2020; Gbode et al. 2023). However, the highest specific discharges are mostly concentrated in the western part of the region and the basins located in Benin. These results suggest that flood quantiles are rather a function of the physiographic properties of catchments than spatial proximity.

4.4.2 | Regional Envelope Curves (RECs)

Knowledge of flood quantiles is essential in hydrologic engineering to design infrastructure and manage associated risks (Herschy 1998; Li, Wang, and Li 2013). However, this knowledge is a major challenge in ungauged sites. The development of empirical regional envelope curves (RECs) is a traditional approach to flood estimation in ungauged catchments (Castellarin 2007; Rodier and Roche 1984). A regional envelope curve (REC) represents the upper limit of floods observed in a region (Castellarin, Vogel, and Matalas 2005). It is obtained by plotting, in a log–log space, a scatterplot of specific discharge against the catchment area. The REC represents the line encompassing all observations within the scatterplot (Padi, Baldassarre, and Castellarin 2011). Regional envelope curves have been developed for the whole world (Rodier and Roche 1984), for Africa (Padi, Baldassarre, and Castellarin 2011), and for some specific African regions (Farquharson, Meigh, and Sutcliffe 1992; Tramblay et al. 2024). However, no regional envelope curve has been developed for the entire West African region with a set of stations representative of the region. Figure 10 shows the regional envelope curves for maxima of the AMF series (Figure 10a) and 20-year flood (Figure 10b) for the entire West Africa region, with the corresponding equations for each curve. It is completed by Figure S3, which shows the regional envelope curves developed for the 10-year flood (Figure S3a), 20-year flood (Figure S3b) and 50-year flood (Figure S3c). These RECs provide a robust, efficient and straightforward tool for flood forecasting in West Africa given the scarcity of gauging stations in most catchments, contributing to improved resilience and safety in vulnerable communities. However, the high variability of the scatter plots suggests uncertainties associated with inferring peak flows based solely on watershed area. This variability can be potentially attributed to differences in the physiographic characteristics of the watersheds (rainfall variability, land use, slope, shape of the watershed, etc.), that affect runoff generation and peak discharge.

On the envelope curves shown in Figure 10, it is important to highlight the particularity of the Katsina-Ala at Katsina-Ala (ADHI-325) and Agbla (ADHI-641) watersheds. These stations are the two that intersect the envelope curve. The areas of these catchments are approximately 17,000 and 480 km^2, respectively for the Katsina-Ala at Katsina and Agbla bassins. The high specific discharges of these watersheds can be explained by their location s in the Guinean zone, which receives abundant rainfall throughout the year, with an annual average between 1200 and 2200 mm (ECOWREX 2018; Ilori and Ajayi 2020; Gbode et al. 2023). This region is also known for its rugged terrain with steep slopes (Orange 1990), which have a significant influence on flooding. To investigate whether this behaviour could be explained by the presence of outliers or the presence of isolated very extreme events, Figures S5 and S6 show the details of the fitting of the GEV distribution to the AMF series of these stations using L-moments (LM), with four diagnostic plots (two Q–Q plots, a return level plot and a density plot). These diagnostic plots show that there are no outliers in the AMF series of

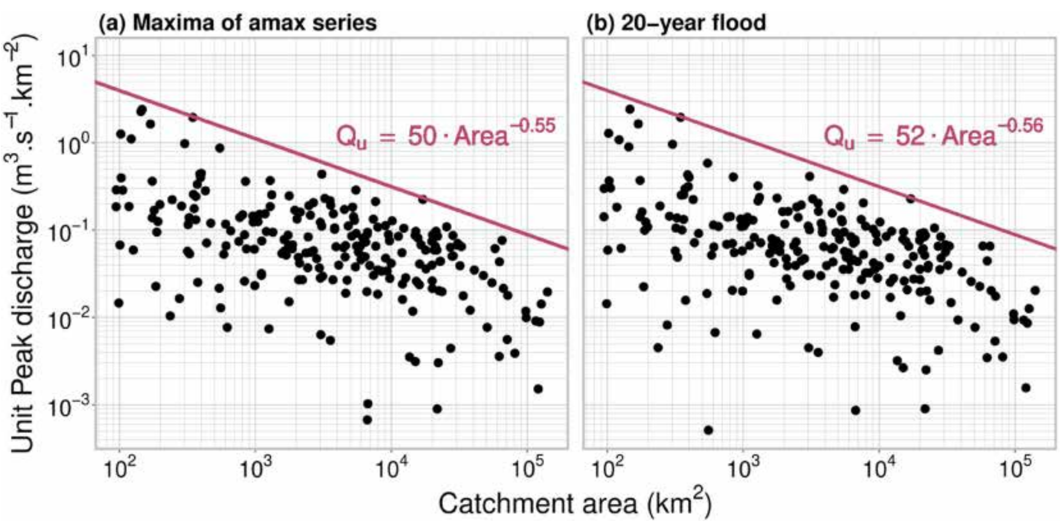

FIGURE 10 | Regional envelope curve (REC) of maximum specific discharge in West Africa: (a) maxima of the AMF series and (b) 20-year flood. The black points represent scatterplots of specific discharge against the catchment area and the red lines represent RECs.

the two watersheds, and they also show a good fit of the GEV distribution in both stations. This suggests that the high specific discharges observed in both watersheds represent a typical hydrological response that may be influenced by the geographical and climatic conditions of the Guinea region, highlighting the importance of considering regional characteristics when analysing hydrological data.

4.4.3 | Correlation Between Flood Quantiles and Catchment Properties

To examine the potential drivers of spatial variations in flood quantiles, a Spearman rank correlation was performed. As shown in Figure 11, the strongest correlation (significant at 0.05 level) is noted with catchment area ($\rho = 0.73$), followed by maximum altitude (MA), topographic witness index (TWI) and geological properties (GD and GP), which have a correlation coefficient (ρ) greater than 0.5. These results are consistent with those of Tramblay et al. (2024), who performed the same correlation analysis in North Africa. Their results show that overall, correlations with flood quantiles are stronger with physiographic and geological properties (GD, GP and GS) of watersheds, than with climatic variables (precipitation, temperature, evapotranspiration). Ahn and Merwade (2016) also investigated the relationship between flooding and geomorphic characteristics in Indiana (United States) and found that geomorphic factors, particularly watershed length, significantly influence the severity of flooding. As the geology of a watershed determines the quantity of water in groundwater and influences both the runoff and the groundwater flow, this can explain the strong correlation between flood quantiles and geological properties. Principal component analysis (PCA) was also carried out to examine the correlations between watershed properties. The results, as shown in Figure S4, reveal that variables with a strong correlation with flood quantiles are also highly correlated with each other. For instance, some land cover types (cropland and grassland) and soil properties (sand, bulk density and porosity) are also correlated with temperature (Temp) and evapotranspiration (PET). Land use impacts significantly the absorption of solar radiation, surface temperature, evaporation rates, soil heat transmission, and so on, that could explain these dependencies (Pal and Ziaul 2017; Hua and Ping 2018). For instance, transforming vegetative cover into other land uses such as cropland could lead to higher surface temperatures (Y. Zhang, Odeh, and Ramadan 2013; Sahana, Ahmed, and Sajjad 2016; Akomolafe and Rosazlina 2022). Changes in land use categories could be also significant factors affecting flood dynamics (Teklay et al. 2019; Wang et al. 2020).

5 | Conclusions

Local frequency analysis was applied to annual maxima flow series from 246 hydrometric stations across West Africa, thus providing the largest flood frequency analysis in this region. The trend analysis, performed using the non-parametric Mann–Kendall test, revealed some local significant trends, albeit without any strong discernible spatial pattern for the time period considered. The GEV and Gumbel distributions were fitted to the AMF series using three parameter estimation methods: L-moments, Maximum Likelihood and Generalized (Penalized) Maximum Likelihood. The original prior distribution of the GMLE method was adjusted as recommended by Martins and Stedinger (2000), to develop a more informative prior distribution adapted to the West African context. Thus, a normal distribution with a mean of −0.24 and a standard deviation of 0.16 was used as a new prior distribution of the GEV shape parameter in the GMLE method. The GEV distribution fitted with the GMLE method was selected as the best distribution in most stations based on the AIC and BIC evaluation criteria. In addition, stationary and non-stationary quantiles computed for stations with trend-dependent AMF series have

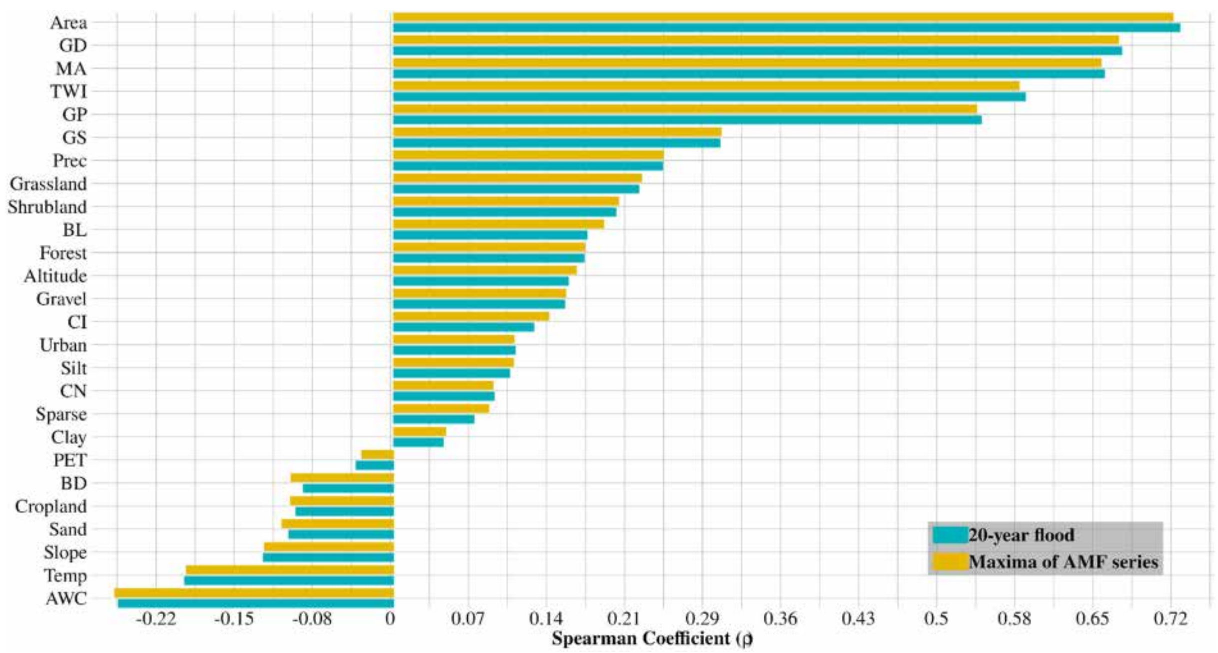

FIGURE 11 | Correlations between watershed properties and flood quantiles. The blue and orange bars represent respectively the 20-year flood and maximum of AMF series for each station.

fairly comparable and overlapping confidence intervals, suggesting that there is no significant difference between them. However, further analysis is necessary to explore and evaluate various non-stationary models in greater detail for this region. Flood quantiles (2-year, 5-year, 10-year, 20-year and 50-year) were then estimated, and regional envelope curves have been proposed for West Africa, to estimate maximum floods as a function of watershed area. Regional envelope curves are a simple and robust tool for the design of hydraulic infrastructure that are notably useful for engineering purposes. They offer a comprehensive framework for estimating maximum floods based on watershed area.

The Block-Maxima approach to sample floods that have been applied in the present work can produce short sample sizes when the data records are not long enough. However, it is well known that record length influences the robustness of model parameters and quantiles estimation (Martins and Stedinger 2000; Moretti and Mendes 2003; Papalexiou and Koutsoyiannis 2013; Serinaldi and Kilsby 2015; Hu et al. 2020; Metzger et al. 2020). This increases the uncertainty in design value estimation in areas where data are scattered (Marra, Amponsah, and Papalexiou 2023). Yet, in the context of West Africa, access to hydrometric data remains an issue and several gauges have been removed and, in many cases, only old records are available. Recent studies about non-asymptotic probability distributions suggested that they provide a sound alternative to block maxima sampling to maximise the information used and reduce uncertainties in model inference (Miniussi, Marani, and Villarini 2020; Mushtaq et al. 2022; Hu et al. 2023). Furthermore, flood frequency analysis at ungauged sites is crucial for water resources and risk management. The regional envelope curve is a simple and robust tool, but it only gives a general overview of the maximum flood observed in a region, taking into account the differences in catchment size (Rodier and Roche 1984). In addition, the envelope curve only determines maximum floods for a given catchment area and not their probability of occurrence (Castellarin, Vogel, and Matalas 2005). Regional flood frequency analysis (RFFA) is a methodology frequently used to estimate flood quantiles at ungauged sites (Desai and Ouarda 2021; Pan et al. 2023). It would therefore be interesting to perform RFFA in West Africa, using the correlations observed between watershed properties and flood quantiles (Figure 11) as a basis, to develop a regional approach for flood quantiles estimation in ungauged catchments.

Acknowledgements

The financial support of the AFD/IRD project CECC is gratefully acknowledged. The authors wish also to thank the various basins agencies in West Africa who contributed to the data collection.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The ADHI dataset containing the annual maximum time series is available at: https://doi.org/10.23708/LXGXQ9. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.