Original Research Article

Probability Distribution Analysis of Annual Maximum Precipitation in the Niger Delta: A Critical Step Towards Effective Flood Risk Management

ABSTRACT

Aims: The study aimed to analyze historical maximum precipitation data from seven cities in the Niger Delta to assess vulnerability to extreme rainfall events, identify optimal probability distribution models for future predictions, and provide insights for flood risk management strategies.
Study Design: This is a retrospective analytical study based on historical precipitation data.
Place and Duration of Study: The study was conducted across seven major cities in the Niger Delta region of Nigeria, utilizing data collected over several decades.
Methodology: Historical maximum precipitation data were statistically analyzed to determine the best-fit probability distribution models. The Kolmogorov-Smirnov (KS) test and Mean Squared Prediction Error (MSPE) were used to validate the suitability of distributions, including Log-Normal, Normal, Log-Pearson III, and Generalized Extreme Value (GEV) for each city. Return periods of 10, 25, 50, and 100 years were calculated to predict future precipitation trends and assess flood risks.
Results: Significant variations in annual maximum precipitation were observed across the cities, with Calabar recording the highest peak at 4062.7mm. The Log-Normal distribution was the best fit for Akure and Calabar, while the Normal distribution best described rainfall in Benin City. Log-Pearson III was optimal for Owerri, Umuahia, and Uyo, and GEV best fitted Port Harcourt's data. High P-values (>0.87) indicated good model fits across the cities. Return period analysis suggested greater risks of extreme precipitation events in coastal cities like Calabar and Port Harcourt.
Conclusion: The study underscores the importance of tailored, city-specific flood management strategies in the Niger Delta to mitigate the impact of extreme rainfall events, particularly in the face of climate change.

Keywords: Niger Delta, Precipitation, Flood risk, Probability distribution, Return period, Climate change

1. INTRODUCTION

1.1 Background

The Intergovernmental Panel on Climate Change (IPCC) projects that the frequency and intensity of heavy precipitation events will increase in the 21st century, leading to significant socio-economic impacts globally [1]. This intensification of extreme rainfall events is linked to a warming climate, with evidence suggesting that the likelihood of heavy precipitation increases with each increment of global warming [2]. Intense precipitation events present a major risk globally to populations and built environments, often leading to flood, inundation, landslides and other disasters.

In the Niger Delta region of Nigeria, floods have become a recurring disaster [3], primarily occurring during the peak of the rainy season between June and September. The link between rainfall and flooding in the Niger Delta is undeniable. The region's low-lying terrain [4] coupled with its extensive network of rivers and creeks, makes it particularly vulnerable to flooding during periods of intense rainfall [5]. Flooding in the Niger Delta, particularly along major river basins like the Niger and Benue, is a perennial issue with devastating consequences. These floods have a significant impact on the region's socio-economic landscape, often resulting in widespread displacement, loss of life, and extensive damage to property and infrastructure. One of the most severe flood events in recent history occurred in 2012, affecting over seven million people and resulting in hundreds of fatalities [6]. The floods were triggered by exceptionally high rainfall levels, which overwhelmed the region's rivers and tributaries, causing them to overflow their banks.

1.2 Study Area

The Niger Delta is a vast wetland situated in southern Nigeria. The Niger Delta is the region at the southernmost tip of Nigeria. It lies between latitude 3°N and 6°N and longitude 5°E and 8°E [7]. It covers an expansive area of approximately 70,000 square kilometers [8] and constitutes about 7.5% of Nigeria's total land mass. The physical geography of the Niger Delta is characterized by diverse landscape. The upper delta plain is dominated by freshwater swamps and rainforests, transitioning into the lower delta plain with its characteristic mangrove swamps and numerous islands. The coastal zone features barrier islands that protect the delta's 450km coastline. This varied terrain creates a complex network of creeks, rivers, and estuaries, forming an intricate hydrological system. Topographically, the Niger Delta is predominantly flat, with an average elevation of less than 10 meters above sea level. Some areas lie as low as 2 meters above sea level, making the region particularly vulnerable to flooding and sea-level rise. The northern sections of the delta gradually rise to elevations of up to 300 meters, forming a transition zone to the inland regions, (Fig. 1).

The climate of the Niger Delta is characterized as tropical monsoon [9], with notably high rainfall intensity compared to other regions in Nigeria. The area experiences two distinct seasons: a long rainy season spanning from March to November, and a shorter dry season from December to February. Annual rainfall is exceptionally high, varying from 2,000 mm in inland areas to over 4,000 mm in coastal regions. The most intense rainfall in the region occurs between June and October, coinciding with the West African Monsoon. Rainfall patterns in the Niger Delta are significantly influenced by the Intertropical Convergence Zone (ITCZ) [10, 11, 12]. The movement of the ITCZ northwards and southwards throughout the year brings about the distinct wet and dry seasons. The hydrology of the Niger Delta is complex and dynamic, influenced by several interacting factors. These include local rainfall patterns, discharge from the Niger River and its tributaries and tidal influences from the Atlantic Ocean.

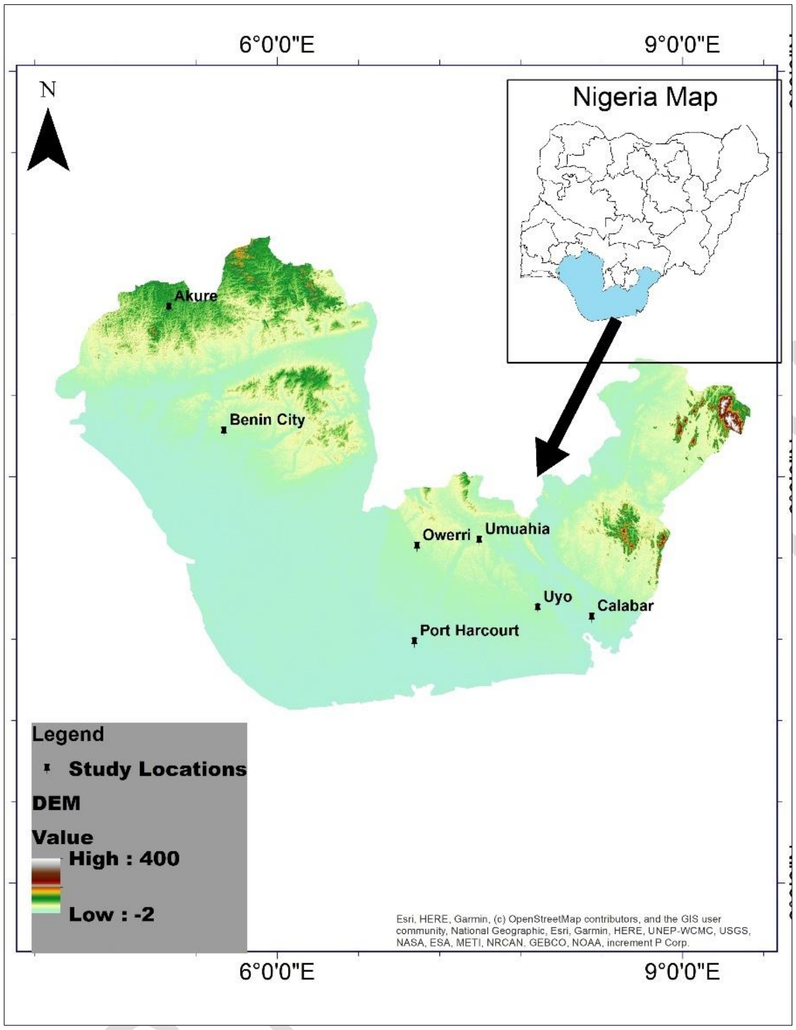

Fig. 1. Digital Elevation Model (DEM) of the Niger Delta showing the selection study stations.

1.3 Study Rationale

The Niger Delta region of Nigeria faces significant challenges due to the variability and intensity of rainfall patterns. This variability, marked by areas experiencing heavier rainfall than others, has led to an increase in severe flooding events in recent times. Understanding and accurately predicting rainfall patterns is crucial for effective water resource management and flood mitigation in the region.

Statistical models utilizing historical rainfall data and probability distributions are essential tools for predicting future precipitation trends and assessing the potential impact of extreme rainfall events. However, the changing climate poses a challenge, as the frequency and intensity of heavy rainfall are expected to deviate from historical norms.

Rainfall analysis, particularly the use of probability distributions and annual maximum rainfall data, is essential for informed decision-making in water resources engineering. Researchers often analyze precipitation data by examining its specific distribution characteristics rather than forcing it to fit a predetermined model, as no single distribution fully captures the complex patterns.

This study evaluates various probability distributions to represent annual maximum rainfall in the Niger Delta, addressing a critical research gap. By identifying the most suitable models, this research aims to enhance understanding of local rainfall patterns, ultimately informing decision-making processes for flood mitigation and water resource management in the region.

1.4 Literature Review

Accurate estimation of return periods for extreme rainfall events is crucial for effective water resource management and disaster mitigation. Consequently, modeling these events using appropriate probability distributions has been a focal point of hydrological research. A variety of distributions, including the Generalized Extreme Value (GEV), Pearson Type III (P3), Log-Pearson Type III (LP3), Gumbel, and Lognormal, have been extensively applied in this context. Studies across different regions have yielded varying results regarding the best-fitting distribution for rainfall data. While gamma and Weibull distributions effectively modeled rainfall in Dois Vizinhos, Brazil [13], a broader spectrum of distributions, such as Beta, Dagum, Wakeby, Pareto, Log-Pearson 3, GEV, and Generalized Gamma (4P), were found suitable for the Kyrenia region of Northern Cyprus [14]. Other studies have explored the applicability of Lognormal, Loglogistic, and Johnson distributions in mountainous Vietnam [15] and investigated the regional and temporal variability of distributions in Ethiopia [16]; while [17] concluded that different cities of Pakistan indicate different probability distributions which increased the uncertainty and instability to the hydrological processes.

Within Nigeria, several studies have focused on identifying the most appropriate probability distribution functions for modeling rainfall patterns. [18] compared multiple distributions across 20 stations, finding Log-Pearson Type III as the best fit for half of the stations. [19] evaluated GEV and Generalized Pareto (GPA) for annual and partial series data, respectively, in Makurdi metropolis. [20] compared LN, PT3, and EVT I distributions for a watershed in Akwa Ibom state, while [21] determined GPA as the most suitable model for estimating rainfall magnitudes at various return periods in Southwest Nigeria. These studies underscore the importance of selecting appropriate probability distributions based on the specific characteristics of the study area and the rainfall parameters being analyzed.

2. MATERIAL AND METHODS

The primary data source for this study was the Nigerian Meteorological Agency (NIMET), which provided annual precipitation records for seven cities in Niger Delta. The dataset spanned approximately five decades, with slight variations in the exact period for each location. Benin City, Calabar, Port Harcourt, and Owerri had data available from 1972 to 2022, while Akure's records began in 1981, Umuahia's in 1980, and Uyo's in 1977, all extending to 2022. To ensure data integrity and consistency, rigorous preprocessing was undertaken. This included thorough quality checks to identify and address any missing values or outliers in the dataset. Annual rainfall totals were meticulously calculated from the monthly maximum rainfall data provided by NIMET. The processed data was then formatted to ensure compatibility with the analytical software used in subsequent stages of the study.

The block maxima approach, a fundamental method in extreme value theory, was adopted for this study. This approach involves dividing the data into non-overlapping periods (blocks) of equal size and selecting the maximum value from each block for analysis. In this case, annual maximum precipitation was chosen as the block size, aligning with common practice in hydrological studies [22].

Specifically, the top 21 maximum annual rainfall values were selected for analysis from each city's historical precipitation record. This selection process ensures that only the most extreme events are considered, which is crucial for understanding the behavior of rare and potentially catastrophic rainfall events. The choice of 21 years balances the need for a sufficiently large sample size to ensure statistical robustness with the practical limitations of data availability. This timeframe is long enough to capture a range of climate variability, including potential effects of large-scale climate patterns such as El Niño Southern Oscillation (ENSO) or the West African Monsoon, which can influence rainfall patterns in the Niger Delta region.

The core analytical tool employed in this research was the Terrestrial and Remote Sensing Analysis (TeReSA) software, developed by the Centre de recherche sur l'environnement alpin (CREALP). TeReSA, an R-based tool designed for environmental data analysis, was particularly suited for this hydro-meteorological study due to its specialized functions for processing and analyzing rainfall data. The crux of the statistical analysis involved computing and mapping Probability Distribution Functions (PDFs) for each of the seven cities. A range of distribution functions were considered, including Normal, Log-Normal, Generalized Extreme Value (GEV), Gumbel, Exponential, Pearson Type III, and Log-Pearson Type III distributions.

To determine the best-fitting distribution for each city's rainfall data, several goodness-of-fit tests were applied. The Mean Square Prediction Error (MSPE) was calculated to measure the average squared difference between predicted and observed values. The Kolmogorov-Smirnov (KS) statistic was employed to quantify the maximum distance between the empirical distribution function of the sample and the cumulative distribution function of the reference distribution. Additionally, the *P*-value of the Kolmogorov-Smirnov test was computed to indicate the probability of obtaining test results at least as extreme as the observed results, assuming the null hypothesis is correct. The selection of the most appropriate distribution for each city was based on a combination of these metrics, with preference given to models exhibiting the lowest MSPE and KS statistic values, along with the highest *P*-value from the KS test. The final phase of the methodology involved a comprehensive interpretation of the analytical results. This process aimed to identify the best-fitting probability distribution for each city's rainfall pattern, estimate return periods for extreme rainfall events, and assess the spatial variability of rainfall patterns across the seven cities Table 1 presents the geographical coordinates and elevations of the seven selected stations in the Niger Delta region. These stations represent major urban centers across the area, offering a comprehensive view of rainfall patterns in the region. The stations span from Akure to Calabar, thus, covering a significant portion of the Niger Delta. Elevations range from as low as 20 meters above sea level in Port Harcourt to 350 meters in Akure, reflecting the diverse topography of the region.

Table 1. Geographical coordinates and elevation of selected stations in the Niger Delta

Station	Latitude (°N)	Longitude (°E)	Elevation (meters)
Akure	7.2571	5.2058	350
Benin City	6.3350	5.6037	88
Calabar	4.9757	8.3417	32
Owerri	5.4891	7.0176	75
Port Harcourt	4.8156	7.0498	20
Umuahia	5.5250	7.4922	148
Uyo	5.0377	7.9128	70

Selecting the appropriate probability distribution model is crucial for accurately modeling extreme rainfall events. This study considered several commonly used distribution models in extreme rainfall analysis, each with unique characteristics suited to different rainfall patterns. For detailed equations and further explanations of these models, refer to the following sources in Table 2.

Table 2: Distribution models and further sources of equation and explanations

Model	Probability distribution function (PDF)	Range	Further sources of explanation
Normal	$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\ \left[\frac{-1}{2}\langle\frac{x-\mu}{\sigma}\rangle\right]^2$	$-\infty < x < +\infty$	[23]
Log Normal	$f(x) = \frac{exp\left[\frac{-1}{2}\left(\frac{\ln(x-\gamma)-\mu}{\sigma}\right)^2\right]}{(x-y)\sigma\sqrt{2\pi}}$	$\gamma < x < +\infty$	[24][25]
Pearson Type 3	$f(x) = \frac{\lambda^\beta\,(x-\gamma)^{\beta-1}e^\lambda\,(x-\gamma)}{x\Gamma(\beta)}$	$\gamma < x < +\infty$	[26]

Log-Pearson Type 3	$f(x) = \frac{1}{x\mathrm{I}\beta\mathrm{I}\Gamma\,(a)}\left[\frac{\ln(x)-\gamma}{\beta}\right]^{a-1} exp\left[-\frac{\ln(x)-\gamma}{\beta}\right]$	$0 < x \le e^{\gamma}\beta < 0$ $e^{\gamma} \le x < +\infty\ \beta > 0$	[27]
Exponential	$f(x) = \beta e^{-\beta x}, x \ge 0$	$\beta > 0$	[28]
Gumbel	$(x) = \frac{1}{a} exp\left[\pm\frac{x-b}{a} - \exp\left(\pm\frac{x-b}{a}\right)\right]$	$-\infty < x < +\infty$	[28]
Generalized Extreme Value (GEV)	$f(x) = exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\delta}\right)\right]^{-\frac{1}{\xi}}\right\}$	$1 + k\frac{(x-\mu)}{\sigma} > 0\ for\ k \ne 0$ $-\infty < x < +\infty\ for\ k = 0$	[29]

Goodness-of-Fit Tests

Goodness-of-fit tests are statistical methods used to determine how well a sample distribution matches a specified theoretical distribution. Inferences on probability distribution of population are made based on parameter estimates calculated from small representative samples. The goodness-of-fit test provides a statistical hypothesis on the theoretical probability distribution functions fit to the observed sample points and whether there are any notable differences between theoretical and empirical data points. In this research, the Kolmogorov-Smirnov test is used to decide if a sample comes from a population with a specific distribution. It is one of the most useful and general methods for comparing two samples, as it is sensitive to differences in both location and shape of the empirical cumulative distribution functions (ECDF) of the two samples.[30,31] and others have extensively discussed the steps and procedures involved in computing the KS statistic.

The Mean Square Prediction Error

The Mean Square Prediction Error is a simple but effective indicator of the goodness-of-fit of a distribution. It is calculated as the expected value of the squared difference between the fitted values and the (unobservable) distribution:

$$MSPE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x_i})^2$$

where n is the size of the sample, x_i are the observations and $\hat{x_i}$ the predictions made with the probability distribution[30].

Return Period

The return period (T) (sometimes called the recurrence interval) is an estimation of the likelihood of an event such as flood or extreme precipitation to occur over an extended period and is a means of expressing the exceedance probability [32]. T is a measure of the probable time interval between the occurrence of a given event and that of an equal or greater event [33]. If a hydro meteorological variable (X) equal to or greater than x occurs on the average once in T years, then the probability of occurrence P(X ≥ x) of such a variable is shown in the following Eq.n

$$P = \frac{1}{T}(X \ge \mathrm{X})\ or\ T = \frac{1}{P}(X \ge X)$$

3. RESULTS AND DISCUSSION

3.1. Analysis of maximum precipitation

Figure 2 illustrates the maximum annual precipitation trends for the selected stations in the Niger Delta. An analysis of historical maximum precipitation data from seven cities in the Niger Delta provides valuable insights into the region's vulnerability to extreme rainfall events. Among the cities studied, Calabar emerged as a significant peculiarity, experiencing exceptionally high annual maximum precipitation. The city recorded a remarkable peak of 4062.7mm in 2012, a figure that substantially surpasses the maximum readings from other locations in the study. This extreme value underscores Calabar's particular vulnerability to intense rainfall events and highlights the urgent need for robust flood management strategies in the area. Other cities in the study, including Port Harcourt, Uyo, Benin City, Owerri, and Akure, also experienced notably high annual maximum precipitation, often exceeding 2000mm. Port Harcourt, while not reaching Calabar's extreme levels, consistently showed high precipitation levels, frequently surpassing 2000mm annually. Interestingly, Umuahia and Uyo exhibited distinct periods of clustered high-intensity rainfall, particularly noticeable in the mid-1990s and mid-2000s. This pattern suggests the influence of specific climatic shifts or localized meteorological conditions during these periods, warranting further investigation into the underlying causes.

When compared to the study by [34], the rainfall patterns observed in this research are consistent with their findings, especially regarding the high variability in rainfall across cities. For instance, while [34]. reported an average rainfall of 2906mm in Calabar with a 13% variability, this study recorded an extreme peak of 4062mm in 2012, highlighting the significant year-to-year differences. Similarly, Port Harcourt and Uyo, which showed significant rainfall in this analysis, were also identified by [34] with average rainfalls of 2305mm and 2556mm, respectively, confirming the cities' susceptibility to heavy precipitation events. These similarities underscore the consistent challenge of managing rainfall variability and flood risks across the Niger Delta region.

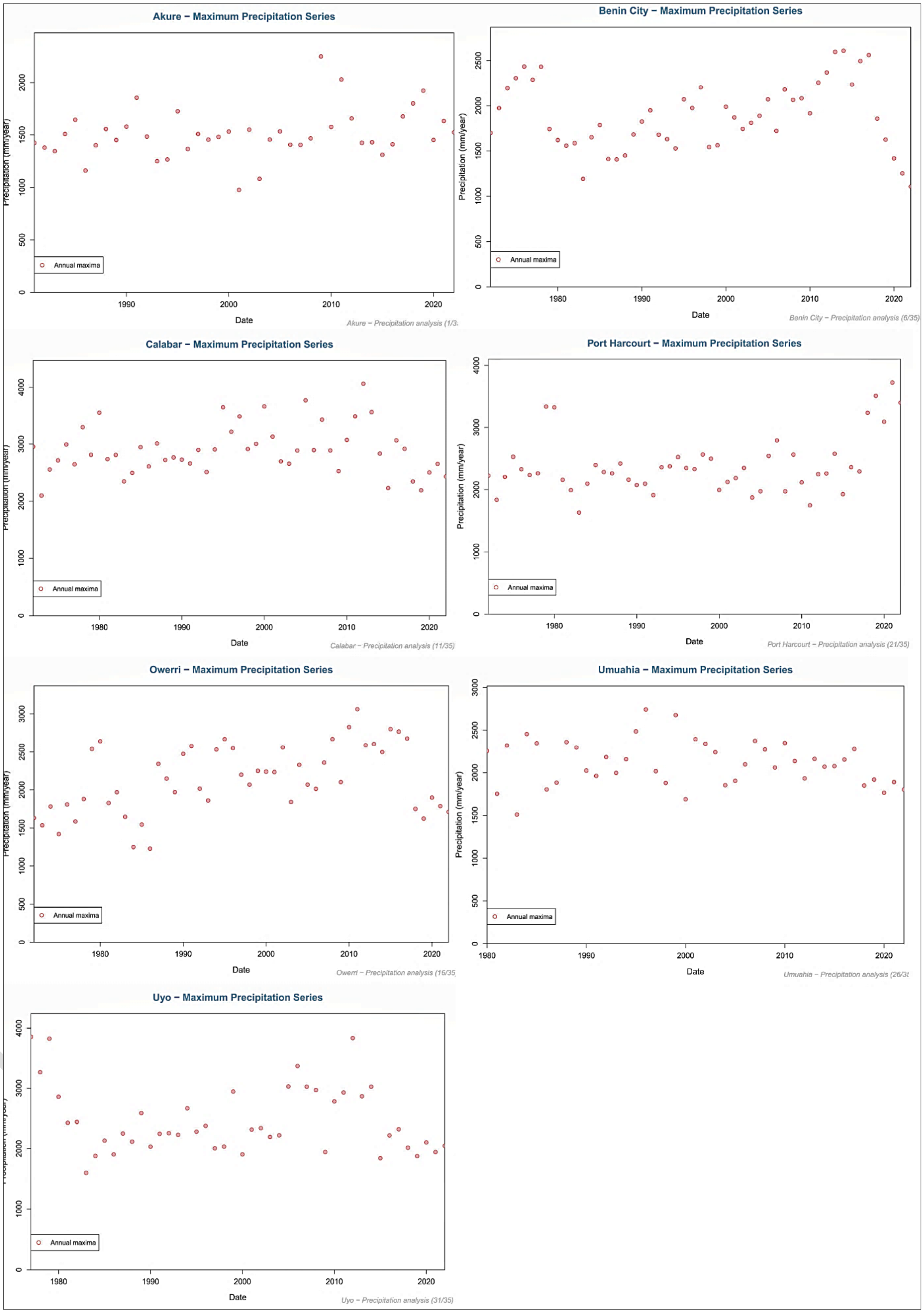

Fig. 2. Maximum annual precipitation trends in selected stations in the Niger Delta

3.2. Analysis of Probability Distribution Function

Figure 3 presents the precipitation distribution functions (PDF) for the selected study stations. the probability distribution function assessment metrics provide quantitative measures of how well each distribution fits the observed data. The KS test assesses the overall agreement between the theoretical distribution and the empirical data, while the MSPE quantifies the average squared difference between predicted and observed values. Lower values of the KS and MSPE indicate a better fit. The results of these tests are summarized in Table 3 below

Table 3. Rainfall Distribution Model Fit Assessment for selected stations in the Niger Delta

City	Best-Fit Distribution	KS Statistic	*P*-value	MSPE
Akure	Log-Normal	0.119	*.93*	189000
Benin City	Normal	0.07843	*.998*	520000
Calabar	Log-Normal	0.09804	*.97*	649000
Owerri	Log-Pearson III	0.09804	*.97*	652000
Port Harcourt	GEV	0.1176	*.88*	592000
Umuahia	Log-Pearson III	0.06977	*.99997*	255000
Uyo	Log-Pearson III	0.08696	*.995*	1040000

The analysis revealed diverse best-fit distributions across the seven cities, reflecting the complex rainfall patterns in the Niger Delta region. In Akure, the Log-Normal distribution emerged as the best fit, with a KS statistic of 0.119 and a *P*-value of 0.93. This suggests that the annual maximum rainfall in Akure tends to be positively skewed, which is common for precipitation data. The relatively high *P*-value indicates a good fit, although the KS statistic is the highest among the seven cities, suggesting that the fit, while adequate, may not be as strong as in some other locations.

Interestingly, Benin City's rainfall data was best described by a Normal distribution, with a KS statistic of 0.07843 and a remarkably high *P*-value of 0.998. This is somewhat unusual for rainfall data, which typically exhibits positive skewness. The excellent fit suggests that Benin City's annual maximum rainfall patterns are more symmetrically distributed than is typical for such data. Calabar, like Akure, was best fitted by a Log-Normal distribution, with a KS statistic of 0.09804 and a *P*-value of 0.97. This aligns with the expectation of positively skewed rainfall data and indicates a good fit to the observed data. The Log-Pearson III distribution provided the best fit for Owerri's data, with a KS statistic of 0.09804 and a *P*-value of 0.97. This distribution is often used in hydrology due to its flexibility in modeling skewed data. The high *P*-value suggests a good fit to the observed data. Port Harcourt's rainfall data was uniquely best described by the Generalized Extreme Value (GEV) distribution, with a KS statistic of 0.1176 and a *P*-value of 0.88. This distribution is particularly well-suited for modeling extreme events, suggesting that Port Harcourt may experience more extreme rainfall events compared to the other cities studied. The *P*-value, while still indicating a good fit, is the lowest among the seven cities. The Log-Pearson III distribution provided an excellent fit for Umuahia's data, as evidenced by the very high *P*-value of 0.99997 and the lowest KS statistic (0.06977) among all cities. This suggests that the Log-Pearson III distribution very accurately represents the rainfall patterns in Umuahia. Uyo's rainfall data was also best fitted by the Log-Pearson III distribution, with a KS statistic of 0.08696 and a high *P*-value of 0.99501. Notably, Uyo has the highest MSPE value (1,040,000) among all cities, suggesting that while the distribution fits well, there may be higher variability or more extreme events in the data.

The comparative analysis reveals interesting patterns across the seven cities. The prevalence of Log-Normal and Log-Pearson III distributions indicates that rainfall data in most cities is positively skewed, which is typical for precipitation data. The exception is Benin City, where the Normal distribution suggests more symmetrical rainfall patterns. The GEV distribution's best fit for Port Harcourt suggests this city may be more prone to extreme rainfall events compared to the others.

All cities show high *P*-values (greater than 0.87), indicating good fits for their respective best-fit distributions. Umuahia stands out with an almost perfect fit (*P*-value= 0.99997). However, MSPE values vary significantly

across cities, from 189,000 (Akure) to 1,040,000 (Uyo). This suggests varying levels of predictive accuracy, with some cities' rainfall patterns being more challenging to predict than others.
In comparison to the study by [35], the results present some similarities and differences in the best-fit distributions across the cities. Both studies identify the Generalized Extreme Value (GEV) distribution as the best fit for Port Harcourt, highlighting its suitability for modeling extreme rainfall events in the city. However, for Benin City, while this study identifies the Normal distribution as the best fit, [35] recommend the Pearson III distribution, reflecting a different interpretation of the rainfall data.

3.3. Analysis of annual rainfall return period

Figure. 4 presents the return period analysis for annual maximum precipitation for the selected stations. Coastal cities like Calabar and Port Harcourt showed the highest predicted precipitation amounts for long return periods. For instance, Calabar is predicted to experience 4007mm of precipitation for a 100-year return period according to the Log-Normal model, while Port Harcourt is expected to see 3280mm based on the Gumbel model. In contrast, inland cities such as Akure and Benin City generally displayed lower predicted precipitation amounts, with Akure expecting 2116 mm and Benin City 2962 mm for a 100-year return period. Cities situated between the coast and inland areas, including Owerri, Umuahia, and Uyo, exhibited moderate precipitation predictions. A notable pattern emerged when examining short return periods of less than 10 years. In these instances, there was generally close agreement between all models and observed data across all cities, suggesting higher confidence in predictions for more frequent precipitation events. However, as the return period increased, especially beyond 100 years, significant divergence between models became apparent in all locations.
The higher predicted precipitation amounts for coastal cities like Calabar and Port Harcourt, especially for extreme events, suggest these areas may face an elevated risk of severe flooding compared to inland cities. The variations in precipitation predictions across cities indicate that flood risk and necessary mitigation strategies need to be tailored to specific locations within the Niger Delta, rather than applying a uniform approach across the region. While the analysis provides more confidence in predictions for frequent events due to the good agreement between models for shorter return periods, it also highlights the need for adaptive and robust flood management strategies that can accommodate a range of potential scenarios. The substantial increases in precipitation from 10-year to 100-year return periods across all cities underscore the potential for more severe extreme events in the future, possibly aligned with climate change projections.

Table 4. Estimated rainfall (mm) for various return periods in selected Niger Delta stations

Return Period (years)	Akure (LN)	Benin City (N)	Calabar (LN)	Owerri (LN)	Port Harcourt (G)	Umuahia (G)	Uyo (G)
10	1808.3	2362.5	3449.8	2759.5	2473.6	2535.9	3130.1
25	1940.9	2635.4	3689.9	3055.8	2799.3	2769.7	3514.9
50	2031.6	2802.8	3853.8	3263.9	3041.0	2943.2	3800.4
100	2116.9	2962.5	4007.5	3463.2	3280.8	3115.4	4083.8

(LN = Log-Normal, N = Normal, G = Gumbel)

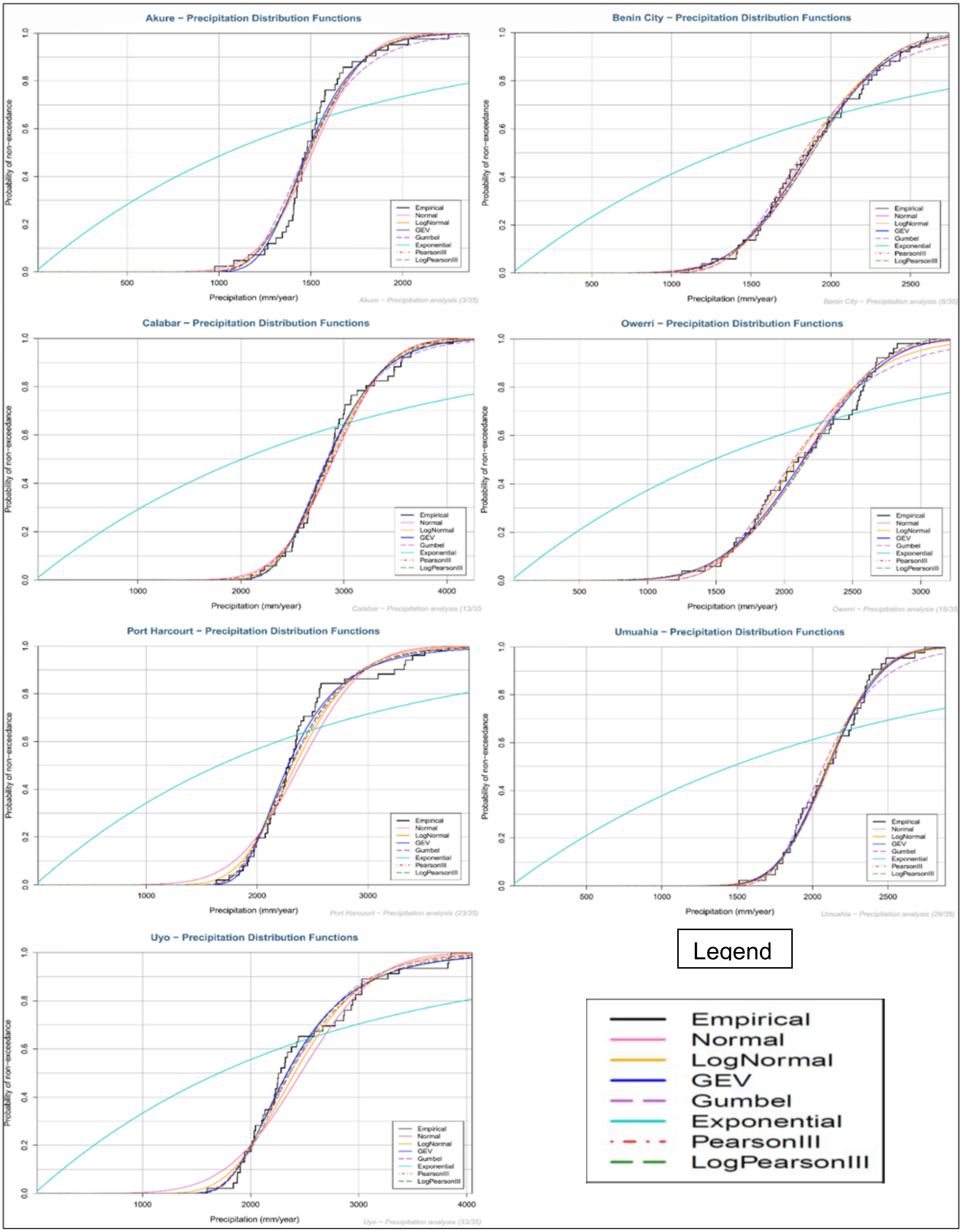

Fig. 3. Precipitation Distribution Functions for selected study stations in the Niger Delta

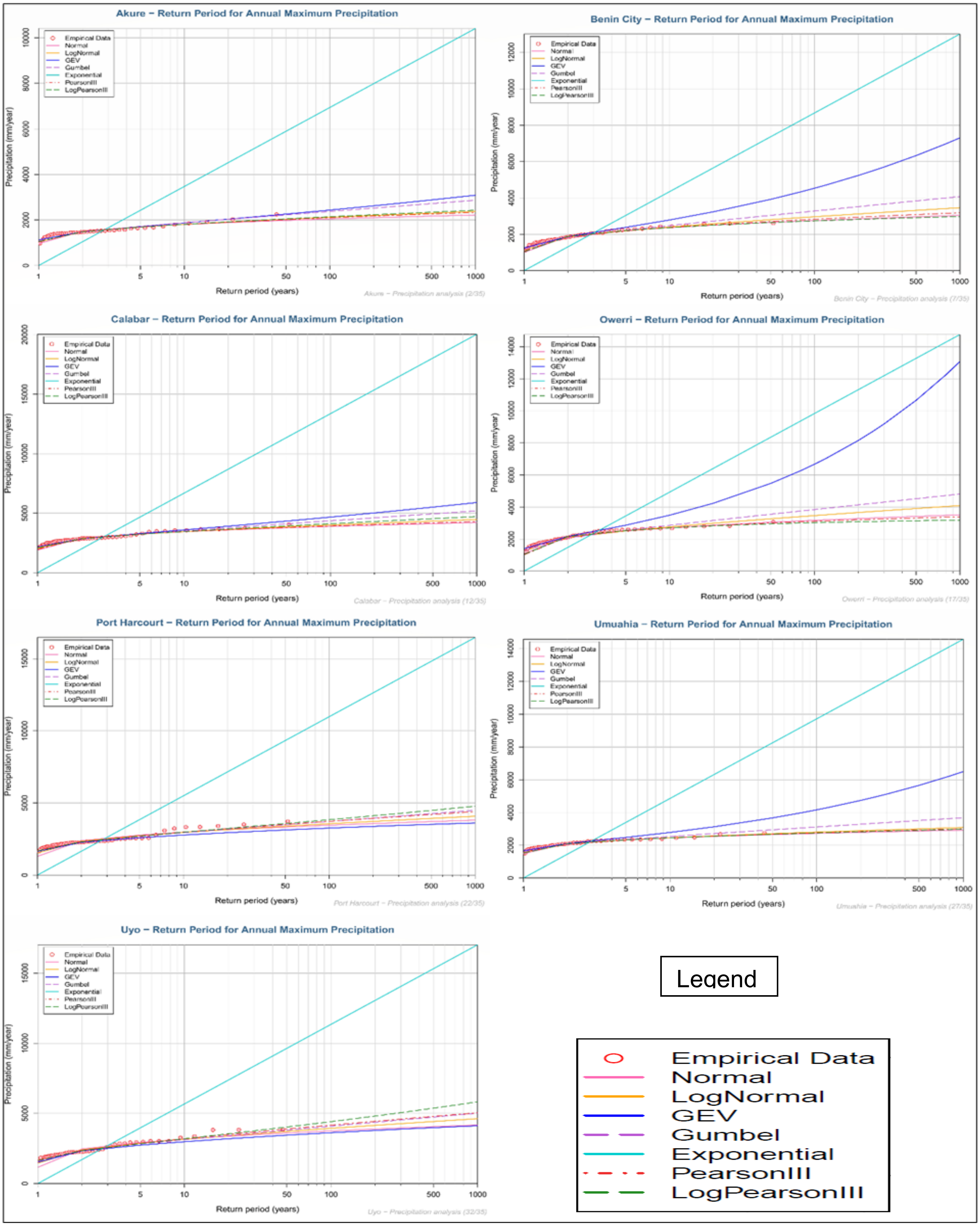

Fig. 4. Return Period Analysis for Annual Maximum Precipitation for selected stations in the Niger Delta

3.4. Implications for Flood Risk Management in the Niger Delta

The variation in best-fit rainfall distributions across the seven major cities in the Niger Delta region has important implications for flood risk management and infrastructure design. These differences in statistical patterns highlight the need for city-specific approaches, rather than relying on a one-size-fits-all strategy for the entire region. For example, the Generalized Extreme Value (GEV) distribution observed in Port Harcourt suggests this city may require particular attention to planning for extreme precipitation events. In contrast, the wide range of annual maximum rainfall seen in Uyo indicates a vulnerability to both moderate and high-intensity rainfall occurrences. Predictive models should also be used cautiously in Uyo, given the high margin of error identified by the study.

The variety of best-fit distributions across the cities underscores the inherent complexity of rainfall patterns in the Niger Delta. This complexity demands location-specific hydrological analyses to properly inform urban planning, water infrastructure design, and flood mitigation strategies. An overly generalized approach is unlikely to be effective. Certain cities face heightened flood risks based on their rainfall characteristics. Calabar emerges as the highest-risk area, with Benin City, Owerri, Port Harcourt, and Uyo also demonstrating moderate to high vulnerability. Owerri and Umuahia, in particular, show high variability and potential for clustered extreme precipitation events, making them prone to episodic flooding. Even Akure, with the lowest rainfall intensities, has experienced historical flooding.

These findings emphasize the crucial need for tailored, adaptive flood management policies in each of the Niger Delta cities. Infrastructure design standards, drainage systems, and other water-related projects must be based on the specific statistical patterns observed in that locale. As climate change continues to alter precipitation regimes, such granular, location-based analyses will become increasingly important for sustainable urban development and climate resilience planning in the region.

4. CONCLUSION

This study's analysis of annual maximum precipitation in seven Niger Delta cities reveals significant spatial variability in rainfall patterns, emphasizing the need for location-specific approaches to hydrological modeling and flood risk management. The diversity of best-fit probability distributions - ranging from Log-Pearson III and Normal to Generalized Extreme Value (GEV) - underscores the complexity of precipitation regimes in the region.

Key findings include distinct regional variations in rainfall patterns and intensity, the importance of selecting appropriate probability distributions for accurate flood risk assessment and infrastructure planning, and significant differences in return period estimates, highlighting varying levels of flood risk among the cities. These results have profound implications for urban planning, infrastructure design, and water resource management in the Niger Delta, suggesting a one-size-fits-all approach would be inadequate.

The study provides a foundation for more targeted and effective water management policies in the region. However, future research incorporating longer data, seasonal patterns, and climate change impacts could further refine these models and offer valuable insights for regional planning and climate adaptation strategies. As global climate patterns evolve, such detailed, location-specific analyses will become increasingly crucial for sustainable urban development and resilience planning in the Niger Delta and similar regions worldwide.

Recommendations

To effectively manage flood risks and water resources in the Niger Delta, it is imperative to employ region-specific probability distributions for modeling rainfall patterns. Coastal cities such as Calabar and Port Harcourt, characterized by frequent extreme rainfall events, should prioritize GEV or Gumbel distributions. Conversely, inland cities like Akure, Benin City, Owerri, and Umuahia are better represented by Log-Pearson Type III or Pearson Type III distributions. A robust flood management strategy necessitates a combination of structural and non-structural measures. Regular model updates and calibration are crucial to account for the dynamic nature of rainfall patterns, particularly in the context of climate change. Furthermore, location-specific risk assessments and infrastructure designs are essential for building resilience in vulnerable coastal areas.

Limitations and Future Research

While this analysis provides valuable insights, it's important to note some limitations. The study relies on historical data and assumes stationarity in rainfall patterns, which may not hold true in the face of climate change. Future research could benefit from incorporating climate change projections to provide more accurate long-term estimates. Additionally, the analysis could be enhanced by considering other factors that influence flood risk, such as land use changes, urbanization, and local topography. A more comprehensive approach that combines rainfall analysis with hydrological modeling could provide a more complete picture of flood risks in these cities.

Disclaimer (Artificial intelligence)

The author hereby declares that generative AI technologies have been utilized during the writing and editing process of this manuscript. Specifically:

AI System: Claude
Version: 3.5 Sonnet
Developer: Anthropic
Purpose: Editing assistance and error correction

Input prompts provided to Claude were focused on reviewing the manuscript for clarity, coherence, and grammatical accuracy. The AI was used to suggest improvements in phrasing, identify potential errors, and enhance the overall readability of the text. All suggestions made by the AI were carefully reviewed and selectively implemented by the author to maintain the integrity and originality of the research content.
The core intellectual contributions, analysis, and conclusions presented in this manuscript remain the original work of the author. The use of AI was limited to language refinement and did not contribute to the generation of research ideas, data analysis, or scientific interpretations.

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