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Research Article

Development of a Predictive Model for Extreme Heat Wave Events in Gombe State, Nigeria

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ABSTRACT

Gombe State is experiencing escalating extreme heat waves that are profoundly affecting agriculture, public health, water resources, and broader socio-economic stability. The region's vulnerability is further intensified by pre-existing environmental challenges, such as desertification and climate change. These growing concerns highlight the urgent need for an in-depth analysis to understand the patterns of extreme heat events and to devise effective mitigation and adaptation strategies. In response to this need, this study focuses on developing a statistical model to investigate the dynamics and consequences of extreme heat waves in Gombe State using Extreme Value Theory (EVT). A dataset of monthly maximum temperatures covering the past decade was obtained from the Nigerian Meteorological Agency (NiMet). Before modeling, the stationarity of the data was confirmed using the Augmented Dickey-Fuller (ADF) test. Subsequently, the dataset was analyzed using both the Generalized Pareto Distribution (GPD) and the Generalized Extreme Value (GEV) distribution. To ensure a comprehensive assessment, two modeling approaches were employed: the Peaks-over-Threshold (POT) method for the GPD model and the Block Maxima method for the GEV model. The robustness and adequacy of the fitted models were evaluated using several diagnostic tools, including return level plots, probability-probability (P-P) plots, parameter stability plots, mean residual life plots, and quantile-quantile (Q-Q) plots. Furthermore, a comparative analysis based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) revealed that the GPD model derived from the POT approach provided a better fit than the GEV model based on the Block Maxima approach. Building on the selected model, return levels were estimated for 2, 5, 10, 20, 50, and 100-year return periods. The findings reveal an alarming upward trend in extreme temperatures in Gombe State, suggesting that heat conditions may soon reach intolerable levels. Notably, for the return periods, the temperature is projected to increase from 35.16 °C to 38.33 °C, and up to 43.66 °C for a 100-year return period. This indicates that both the frequency and intensity of extreme heat waves are likely to increase significantly in the near future.

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1 Introduction

Climate change has emerged as a paramount global issue, significantly influencing weather patterns around the world with a variety of severe phenomena. Among these, the rise in the frequency, intensity, and duration of extreme heat waves stands out as particularly alarming. These extreme events pose grave risks not only to public health but also to agricultural systems and the overall socio-economic fabric of regions already burdened with environmental vulnerabilities. Northeastern Nigeria exemplifies such a region, where the harsh, arid climate and complex socio-political circumstances exacerbate the detrimental effects of extreme heat waves (Galambos et al., 1994; Wilhelmi & Harden, 2010).

Traditional time series analysis often relies on examining the probability distribution of variables over all available observations. Such conventional methodologies typically deliver a better fit for the bulk of the dataset, where most observations cluster (Abiodun et al., 2013; Guedes-Soares & Sotto, 2004). However, these approaches fall short when the focus shifts to significant extreme observations, which, despite their lower frequency, carry greater importance and implications. In this context, Extreme Value Theory (EVT) emerges as a robust framework for modeling extreme events that hold considerable statistical significance. The Generalized Extreme Value (GEV) distribution emphasizes extreme data points by deliberately sidelining central observations when estimating the parameters of theoretical distributions. This method has gained traction across environmental sciences and numerous other fields for its effectiveness in modeling phenomena characterized by extremes (Reiss & Thomas, 2007).

Research into climatic extreme observations is a vibrant area of scientific inquiry. Weather and climate extremes—including maximum temperatures, intense rainfall, cold waves, and various drought types (such as atmospheric, hydrological, soil, and agricultural)—are frequently modeled through EVT (Razi et al., 2025; Alexander, 2016). Heat waves and elevated temperatures represent some of the most thoroughly researched

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extreme events due to their profound implications for agriculture, human society, water resource management, energy demand, and overall mortality rates (Allen et al., 2010). These phenomena also disrupt ecosystems; for instance, various animal species face habitat loss, leading to decreases in biodiversity, especially in tropical regions (Bailey, 2016).

Numerous models have effectively utilized the GEV distribution to analyze extreme heat waves and temperatures in diverse geographical settings. For example, researchers have applied this distribution to model extreme air temperatures in countries such as Cameroon (Ayuketang & Joseph, 2014), Kenya (Morris et al., 2020; Wambua et al., 2020), Ghana (Sampson & Kwadwo, 2019), and Penang (Hasan et al., 2012). A notable study by Meehl and Tebaldi (2004) developed a heat wave model for cities like Chicago and Paris, revealing distinct geographical patterns in the anticipated changes to heat wave occurrences. Lyon (2009) employed EVT to evaluate summer droughts and heat waves in southern Africa, while Nemukula and Sigauke (2018) utilized the "r-largest" approach to analyze South Africa's average maximum daily temperatures. Another notable investigation by Wang et al. (2013) assessed historical trends in Australian temperature extremes using EVT methodologies.

In Sub-Saharan Africa, the challenges posed by extreme heat waves are markedly pronounced, primarily due to limited adaptive capacities and an economy heavily reliant on climate-sensitive sectors, particularly agriculture (Niang et al., 2014). Research conducted by Diffenbaugh and Giorgi (2012) and Sylla et al. (2016) has anticipated an increase in the frequency of heat wave events in northeastern Nigeria, notably in Gombe State, underscoring significant future risks for this vulnerable region. Nonetheless, there remains a scarcity of focused research specific to the Sahel region—including Gombe State—with insufficient data regarding local climatic trends and the socio-economic ramifications of these extreme phenomena.

Globally, the investigation into extreme heat waves has progressed considerably in recent years, with numerous studies documenting the escalating frequency, intensity, and duration linked to climate change (IPCC, 2021). These extreme heat events have been associated with a myriad of adverse outcomes, including increased mortality rates (Gasparrini et al., 2015), diminished agricultural yields (Lobell, 2012), and a deepening of socio-economic inequalities (Hsiang et al., 2017). Additionally, a noteworthy study by Mínguez et al. (2025) improved methodologies for threshold selection, contributing to standard frequentist/POT fitting approaches while evaluating performance across multiple datasets. This work quantifies the improvements in fit and stability, focusing specifically on the threshold decision rather than introducing a new inference engine. Furthermore, Meng et al. (2024) employed likelihood-based non-stationary GEV fitting to generate trend and return-level estimates, interpreting underlying mechanisms through climatological diagnostics, with uncertainty quantified through confidence intervals and significance tests for trends.

Predictive models have significantly advanced the comprehension of heat wave dynamics, as evidenced by the work of Perkins-Kirkpatrick et al. (2017). However, these models often fall short in providing the essential region-specific granularity necessary for localized analysis. A more comprehensive exploration is presented by Dey and Patwary (2025), who delve into non-stationary Generalized Extreme Value (GEV) modeling specifically tailored to two major urban centers in Bangladesh. Their research yields precise return levels and exceedance probabilities, meticulously addressing uncertainty in a structured and quantifiable manner.

Research conducted by Adebayo and Oruonye (2013) and Adedayo et al. (2013) has highlighted the region's climatic trends, indicating a troubling trajectory towards increasing average temperatures alongside a rise in the frequency of heat waves. Furthermore, the region's environmental challenges—exacerbated by factors such as rampant deforestation, escalating desertification, and unsustainable agricultural practices—compound the difficulties faced by the local population.

In Gombe State, whose economy predominantly relies on agriculture, rising temperatures associated with climate change pose a considerable challenge. Thus, modeling monthly extreme temperatures is crucial not only for understanding current climatic conditions but also for forecasting future scenarios. It is essential for a diverse group of stakeholders, including farmers, climatologists, economists, meteorologists, and policymakers, to grasp the patterns and implications of extreme temperature events. This understanding will enable them to make informed decisions regarding planning, policymaking, and adaptive strategies.

This research aims to develop a suitable model for the extreme heat waves in Gombe State. By understanding the underlying mechanisms and potential impacts of heat waves, we can better predict their occurrence and devise effective mitigation and adaptation strategies. By constructing a model, this research seeks to provide valuable insights into the dynamics of extreme heat waves in Gombe State. This model will serve as a foundational tool for policymakers, researchers, and stakeholders in developing targeted interventions to enhance resilience and reduce the adverse effects of extreme heat on this fragile region (Hasan et al., 2012).

2 Materials and Methods

This research focused on constructing a predictive model to assess extreme heat waves, specifically in Gombe State, Nigeria. The modeling utilized the Generalized Extreme Value (GEV) distribution framework. The dataset employed for this analysis comprised monthly maximum temperature records gathered from the Nigerian Meteorological Agency's Gombe Station, spanning from January 2015 through to April 2025. To effectively analyze these temperature extremes, we applied the principles of Extreme Value Theory (EVT). This study incorporated two distinct EVT methodologies: the Block Maxima approach and the Peaks-over-Threshold (POT) approach. As a result of this rigorous analysis, two models were generated: the Generalized Extreme Value Distribution (GEVD) model and the Generalized Pareto Distribution (GPD) model. To evaluate the adequacy and performance of the fitted models, various graphical assessments were conducted, including probability-probability (P–P) plots, quantile-quantile (Q–Q) plots, return level plots, and mean residual life plots.

2.1 Study Area

Gombe State is situated in northeastern Nigeria and occupies a land area of approximately 18,768 square kilometers, ranking it 21st in size among Nigeria's 36 states. The geographical coordinates of Gombe State are approximately 10°15′N latitude and 11°10′E longitude (Figure 1). The state is bordered to the east and north by Borno and Yobe States, respectively, while it shares its southern boundary with Adamawa and Taraba States, and its western edge with Bauchi State. The climate of Gombe State is characterized by a distinct wet season, which typically lasts from April to October, and a dry season from November to March. According to the 2006 national census data, Gombe State had a population of 2,365,040, which is projected to have risen to approximately 3,960,100 by 2022, reflecting significant demographic growth (Wikipedia, 2026). In terms of population, Gombe ranks 33rd among Nigeria's states and comprises 11 Local Government Areas (LGAs): Akko, Balanga, Billiri, Dukku, Funakaye, Gombe, Kaltungo, Kwami, Nafada, Shongom, and Yamaltu/Deba.

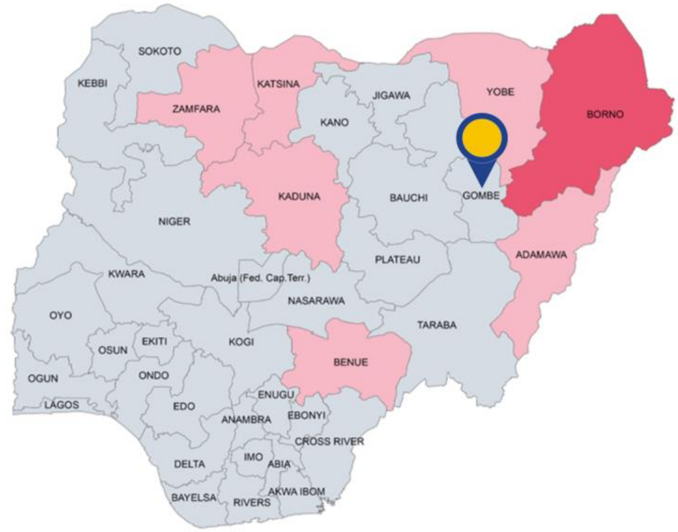

Figure 1: Gombe State of Nigeria
Source: EASO, 'Gombe' in Country Guidance Nigeria, October 2021.

2.2 Research Design

The primary objective of this research was to develop a robust and suitable predictive model for analyzing extreme heat waves within Gombe State. The study comprehensively covered the entire state area. To obtain the requisite data, secondary records detailing monthly maximum temperatures for Gombe State were sourced from the Nigerian Meteorological Agency (NiMet). The analysis was facilitated using the R software package, where the Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) models were meticulously fitted to the temperature dataset.

2.3 Extreme Value Theory

Extreme Value Theory (EVT) is a specialized branch of statistics dedicated to modeling and analyzing extreme events, deviating from the traditional focus on average or typical values. EVT emphasizes understanding the behavior of the tails of probability distributions, which capture rare and significant occurrences. In this context, we consider a sample of independent random variables $X_1, X_2, \cdots, X_n$ that share a common cumulative distribution function, denoted as F(x). Each X_i variable corresponds to a specific value observed at sequential time intervals, such as hourly or daily temperatures. EVT is particularly concerned with the characteristics of the sample maximum, denoted as M_n, which represents the highest value recorded over defined time periods.

$$\mathrm{M_n} = \max(X_1, X_2, \cdots, X_n)$$

For instance, if (n) observations of temperature are collected within a month, M_n reflects the monthly maximum temperature. Assuming (u) represents the upper limit of the distribution function F, the distribution of M_n can be derived using intricate mathematical formulations.

$$p(M_n \le u) = p(X_1 \le u, X_2 \le u, \cdots, X_n \le u)$$
$$= p(X_1 \le u) \times p(X_2 \le u) \times \cdots \times p(X_n \le u)$$
$$= [p(X_i \le u)]^n$$
$$P(M_n \le u) = [F(u)]^n \quad (1)$$

2.4 Extremal Types Theorem

Equation (1) shows that the finite maxima converge to th e upper endpoint of $[F(u)]^n$. We now consider the behavi or of F^n as the sample size n→∞. A distribution F^n is sai d to be *sum-stable* if there exist normalizing constants $a_n > 0$ and b_n , such that: $P\left(\frac{M_n - b_n}{a_n} \le u\right) = P(X \le u)$ [9]. If G is a non-degenerate distribution function and X_i foll ows a distribution that is max-stable with respect to G, th en: $P(M_n \le u) = G^n(u)$, A distribution is *max-stable* if:

$$G^n(a_n z + b_n) = G(u) \quad (2)$$

Now, for a normalized maximum M_n of a continuous di stribution F that converges to G as → ∞ , then

$$P\left(\frac{M_n - b_n}{a_n} \le u\right) = F^n(a_n z + b_n) \to G(u) \quad (3)$$

Thus, if equation (3) holds for the chosen normalizing se quences a_n and b_n, then the distribution of the maximum M_n of the random variables $X_1, X_2, \cdots, X_n$ (for sufficiently large n) converges to a max-stable distribution $G(u)$. The non-degenerate distribution function $G(u)$ belongs to on e of three families:

Gumbel: $G(u) = \exp\left\{-\exp\left[-\left(\frac{u-b}{a}\right)\right]\right\}, -\infty < u < \infty,\ u \le b;$

$$\text{Frechet: } G(u) = \begin{cases} 0 \\ \exp\left[-\left(\frac{u-b}{a}\right)\right]^{\xi}, u > b; \end{cases}$$

$$\text{Weibull: } G(u) = \begin{cases} \exp\left\{-\left[-\left(\frac{u-b}{a}\right)\right]^{\xi}\right\} \\ 0, \quad u < b; \end{cases}$$

where $a > 0$ and $a, b,$ and ξ represent the scale, location, and shape parameters, respectively. These three distributions collectively form Extreme Value Distributions (Coles, 2001).

2.5 Generalized Extreme Value Distribution

The concept of Extreme Value Theory originates from the Extremal Types Theorem. This theorem states that the limiting distribution of maxima belongs to one of three families: Gumbel, Fréchet, or Weibull. Hence, the Generalized Extreme Value (GEV) distribution is a generalization of these three distributions. The cumulative distribution functions (CDFs) of the three families—Gumbel, Fréchet, and Weibull—are given by:

$F(u) = \exp -\left[1 + \xi\left(\frac{u-\mu}{\sigma}\right)\right]^{-1/\xi}$, defined for $\left\{z: 1 + \left(\frac{u-\mu}{\sigma}\right) > 0\right\}$, $-\infty < \mu < \infty$, $-\infty < \xi < \infty$, and $\sigma > 0$.

The parameter μ represents the location parameter, σ denotes the scale parameter, and ξ denotes the shape parameter. Basically, there are two approaches to extreme value theory (EVT): block maxima and peaks-over-threshold approaches.

2.5.1 Block Maxima Approach

The maximum temperature dataset was divided into non-overlapping blocks (e.g., monthly, annual, or seasonal ma ximum) to identify extreme events. The maximum tempe rature value from each block was then selected to form a series of block maxima (Bako et al., 2020). In this approach, the generalized extreme value distributi on (GEVD) was applied. Given $X_1, X_2, \ldots, X_n$, a sequence of i.i.d. random variables with a common distribution G, let $M_n = \max(X_1, X_2, \ldots, X_n)$. The exact distribution of M_n is d enoted by H_n. Suppose there exist sequences of constants $\{a_n > 0\}$ and $\{b_n\}$ such that

$$P\left(\frac{M - b_n}{a_n} \le u\right) = H_n(b_n + a_n) \to G(u) \text{ as } n \to \infty$$

The cumulative distribution functions (CDFs) of the three extreme value distributions can be summarized by the Generalized Extreme Value Distribution (GEVD) as follows:

$$\text{GEV}(u; \xi, \mu, \sigma) = \exp -\left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}, \xi \ne 0$$
$$\text{GEV}(u; \xi, \mu, \sigma) = \exp\left[-\exp\left(\frac{z-\mu}{\sigma}\right)\right], \xi = 0$$

Where u represents the set of extreme values from the blocks, $\sigma > 0$, $-\infty < \mu < \infty$, and $-\infty < \xi < \infty$. The parameters μ, ξ, and σ are the location, shape, and scale parameters, respectively (Coles, 2001; Bako et al., 2020). The conditions for identifying the type of extreme value distribution are:

a) $\xi > 0$, Fréchet distribution

b) $\xi < 0$, Weibull distribution
c) $\xi = 0$, Gumbel distribution (Coles, 2001).

2.6 Generalized Pareto Distribution

A notable limitation of the Generalized Extreme Value (GEV) method is that it focuses exclusively on selecting a single extreme observation from each defined block of data. This approach tends to overlook additional extreme values that are close to the chosen maximum, which significantly decreases the sample size available for subsequent analysis. In contrast, a more comprehensive technique known as the Peak-Over-Threshold (POT) method allows for the consideration of multiple extreme values from each block.

In the POT method, researchers begin by establishing a specific threshold that is deemed significant for the analysis. Observations that surpass this predetermined high threshold are collected and analyzed. These exceedances are then modeled using the Generalized Pareto Distribution (GPD), a distribution specifically tailored for modeling the tails of distributions. According to Coles (2001), the exceedances—which are the values that go beyond the threshold—are treated as being independently and identically distributed random variables.

In this context, the variable x acts as the measure indicating the difference between each observed value that overtakes the threshold and the threshold itself. This approach not only utilizes a broader set of data points, thereby enhancing the reliability and robustness of the statistical analysis, but also provides greater insight into the behavior of extreme values in the dataset. By modeling these exceedances, researchers can gain a more nuanced understanding of extreme events and their implications in various fields of study.

The cdf of the GPD, defined for $x > 0$ and $\left(1+\frac{\xi x}{\tilde{\sigma}}\right) > 0$ is given by:

$$H(x) = 1 - \left(1+\frac{\xi x}{\tilde{\sigma}}\right)^{-1/\xi}$$

The GPD has two parameters: ξ and $\tilde{\sigma}$, where $\tilde{\sigma}$ is the scale parameter and ξ is the shape param eter. The scale parameter can also be expressed as

$$\tilde{\sigma} = \sigma + \xi(v - \mu)$$

The constant v is the suitably chosen threshold value. The parameter ξ determines the behavior of the GPD, as in the GEV distribution:

- When ξ<0, the distribution of exceedances has an upper bound of $-\frac{\tilde{\sigma}}{\xi}$.
- When ξ=0, the distribution has no upper limit and reduces to an exponential distribution with parameter $\frac{1}{\tilde{\sigma}}$.

2.6.1 Peaks over the Threshold (POT) Approach

The Generalized Extreme Value (GEV) model is particularly well-suited for analyzing block maxima derived from a stationary time series, where the focus is on the extreme values within specified intervals. In contrast, the Generalized Pareto Distribution (GPD) is the preferred choice for investigating instances where data points exceed a predetermined threshold. When we assume the series maintains stationarity—that is, its statistical properties do not change over time—standard asymptotic theory provides strong support for the notion that the distribution of these exceedances adheres to a GPD (Coles, 2001).

In practical terms, this means that the values that surpass the set threshold can be effectively modeled using the GPD framework. The cumulative distribution function (CDF), which serves to describe the probability that a random variable takes a value less than or equal to a specified value, for the GPD is expressed as follows:

$$\mathrm{GPD}(z;\xi,\mu,\sigma) = 1 - \left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}, \xi \neq 0$$
$$\mathrm{GPD}(z;\mu,\sigma) = \left[1 - \exp\left(\frac{z-\mu}{\sigma}\right)\right], \qquad \xi = 0$$

2.7 Return Level Estimation

A return level is the high threshold value expected to be e xceeded, on average, once every t time periods with an as sociated probability of return p. The time t is called the re turn period. In this study, return levels for different retur n periods (2-year, 10-year, 20-year, 50-year, and 100-year e vents) were computed to quantify the future severity and frequency of extreme heat waves in Gombe State. The sen sitivity of the return levels to variations in the GEV param eters was also analyzed to assess the uncertainty in the pr edictions (Coles, 2001; Bako et al., 2020).

3 Results

The research focused on creating a predictive model specifically targeting extreme heat waves in Gombe. To achieve this, a thorough data analysis was conducted utilizing the extRemes package within the R programming environment. The study employed two distinct methodologies for extreme value analysis: the block maxima method, which aggregates data into blocks to analyze the maximum values within each block, and the peak-over-threshold (POT) approach, which examines data points that exceed a predefined threshold for extreme temperatures.

In Figure 2, a time series plot illustrates the fluctuations in maximum temperature recorded in Gombe over the years. This plot reveals that the maximum temperature series maintains a relatively stable pattern, with an almost flat trend overall. However, a noticeable upward trajectory in maximum temperatures has emerged from the year 2020 onward, indicating a significant shift in climate patterns. Additionally, the data displays clear seasonal variations, showing that the peak maximum temperatures tend to occur during the months of March through May each year, highlighting the distinct seasonal heat dynamics in the region.

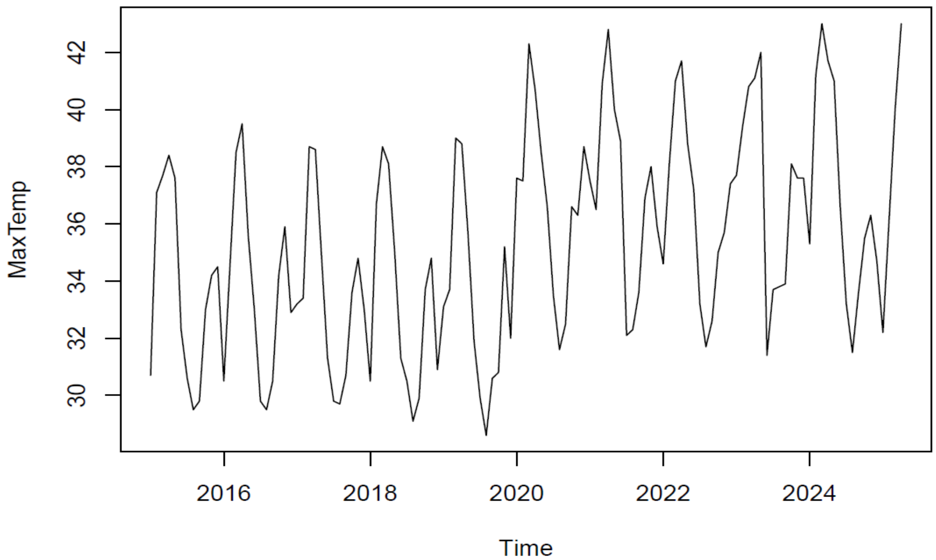

Figure 2: Time Plot of the Maximum Temperature in Gombe State

3.1 Unit Root Test

To ensure compliance with the requirements of the generalized extreme value (GEV) family of distributions concerning the stationarity of time series data, the Augmented Dickey–Fuller (ADF) test was employed. In statistical terms, the null hypothesis (H_0) of the ADF test posits that the series under investigation is non-stationary, implying that its statistical properties, such as mean and variance, change over time. The results of the ADF test, summarized in Table 1, demonstrate compelling evidence that the original series exhibits stationarity, marked by a p-value of less than 0.05. This signifies a strong rejection of the null hypothesis and confirms that the time series data can be reliably used for further analysis.

Table 1: ADF Test Result for the Gombe Maximum Temperature Data

Test Statistic	Lag Order	P-value
-5.4382	4	< 0.01

3.2 Generalized Extreme Value Modeling

Upon confirming the stationarity of the data, the maximum temperature series was modeled using the generalized extreme value (GEV) distribution, which is instrumental for analyzing extreme values. The parameter estimation was conducted using the maximum likelihood method, and the findings are detailed in Table 2. Notably, the shape parameter was found to be negative ($\xi < 0$), indicating that the Weibull distribution provides the most appropriate fit for the dataset. This finding is further supported by the confidence intervals for the population parameters presented in Table 3, all of which lie within their respective confidence bounds, thereby confirming the robustness of the estimates.

Table 2: Parameter Estimation

Location (s.e)	Scale (s.e)	Shape (s.e)	AIC	BIC
33.9317 (0.3646)	3.4939 (0.2733)	-0.2400 (0.8450)	676.1854	684.6462

Table 3: Confidence Interval of the Estimated Parameters

Parameter	95% lower CI	Parameter Estimate	95% upper CI
Location	33.2171	33.9317	34.6463
Scale	2.9582	3.4939	4.0296
Shape	-0.4066	-0.2400	-0.0734

To evaluate the adequacy of the fitted GEV model, a series of diagnostic plots was generated, which are shown in Figure 3: (1), (2), (3), and (4). These visual assessments suggest a commendable fit of the monthly maximum temperature data from Gombe to the GEV model. The QQ-plot reveals that the data points closely adhere to a linear pattern along the diagonal, indicative of a reliable fit. Moreover, both the quantile and probability plots reflect a reasonable alignment, particularly as the probability plot approaches a near-linear configuration. Additionally, the empirical density plot serves to reinforce the effectiveness of the GEV model in characterizing the temperature data accurately.

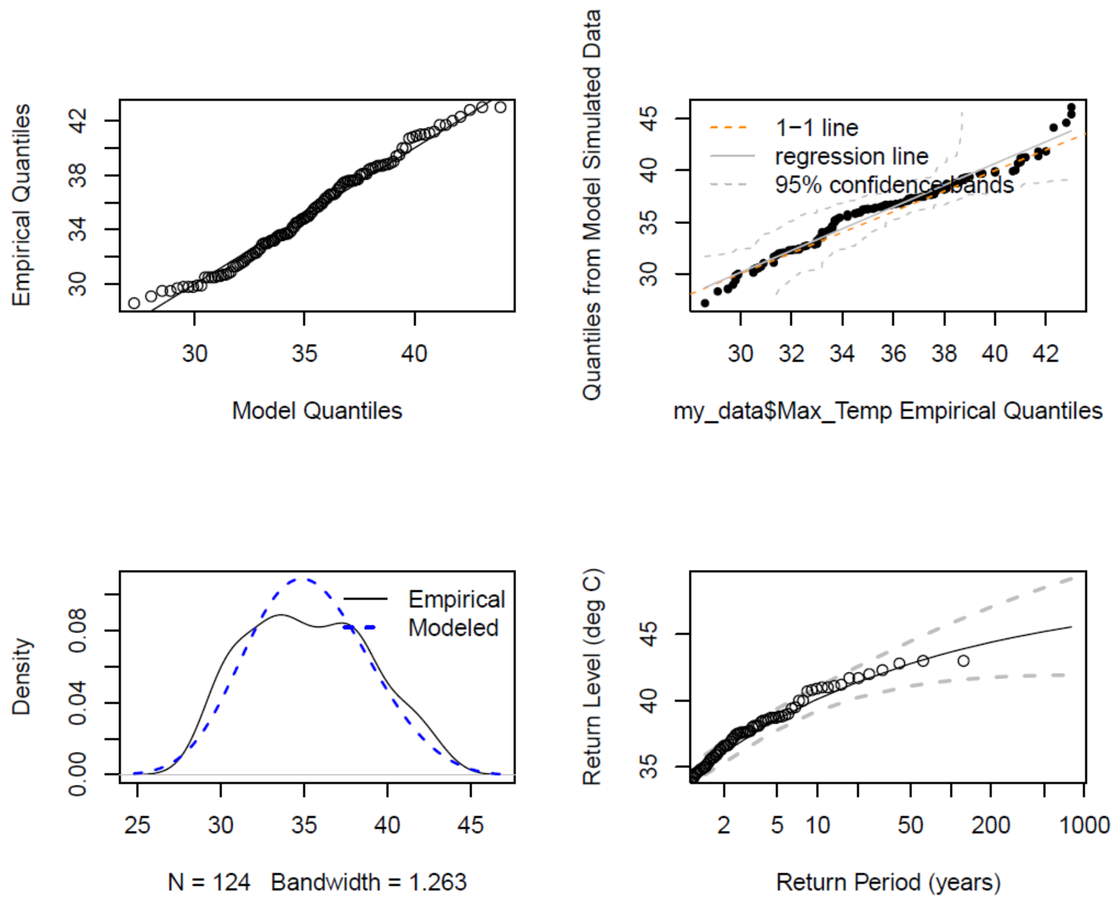

Figure 3: Diagnostic Plots of the fitted GEV Model to Monthly Maximum Temperature: (1) Probability Plot. (2) Quantile plot. (3) Density plot (4) Return period plot.

With the optimal model established and its adequacy affirmed, the subsequent task entails estimating the return levels of maximum temperature corresponding to the fitted GEV model. As depicted in Figure 3(4), all three parameters suggest a relationship where higher maximum temperatures are associated with longer return periods. For return periods ranging from 2 to 100 years, the expected monthly maximum temperature fluctuates between 35.1576 °C and 43.6628 °C, which is detailed in Table 4. The analysis further indicates that the highest monthly maximum temperature is likely to be equaled or surpassed in the future, with a predictive model showing that the maximum temperature will escalate as the return period lengthens. Remarkably, the extreme monthly maximum temperature of 43.6628°C is anticipated to occur only once every century. In comparison, a related study by Cherif (2025) reported a maximum monthly mean temperature of 30.2°C, with estimated return levels corresponding to periods of 300–350 years, highlighting differences in return periods and temperature characteristics across regions and datasets.

Table 4: Return Level for Maximum Temperature

Return Period (Years)	Return Level (°C)	95% Lower CI (°C)	95% Upper CI (°C)
2	35.16	34.4	35.91
5	38.33	37.54	39.13
10	40.01	39.12	40.9
20	41.35	40.2	42.5
50	42.78	41.1	44.46
100	43.66	41.51	45.82

3.3 Generalized Pareto Distribution Modeling

3.3.1 Mean Residual Life Plot

The peak-over-threshold (POT) method for extreme value analysis utilizes the mean residual life (MRL) plot, also known as the mean excess plot, as a critical tool for identifying a suitable threshold for modeling data with a generalized Pareto distribution (GPD) or for examining the tail behavior of a distribution, particularly in the context of rare or extreme events. The primary objective of the MRL plot is to ascertain the lowest threshold at which the relationship becomes linear or reasonably close to linear, factoring in the 95% confidence bounds. The mean residual life plot displayed in Figure 4 indicates that a threshold of 37 is advisable for effective modeling. The observed downward trend in the plot suggests a light-tailed distribution, further informing the choice of threshold for subsequent analysis.

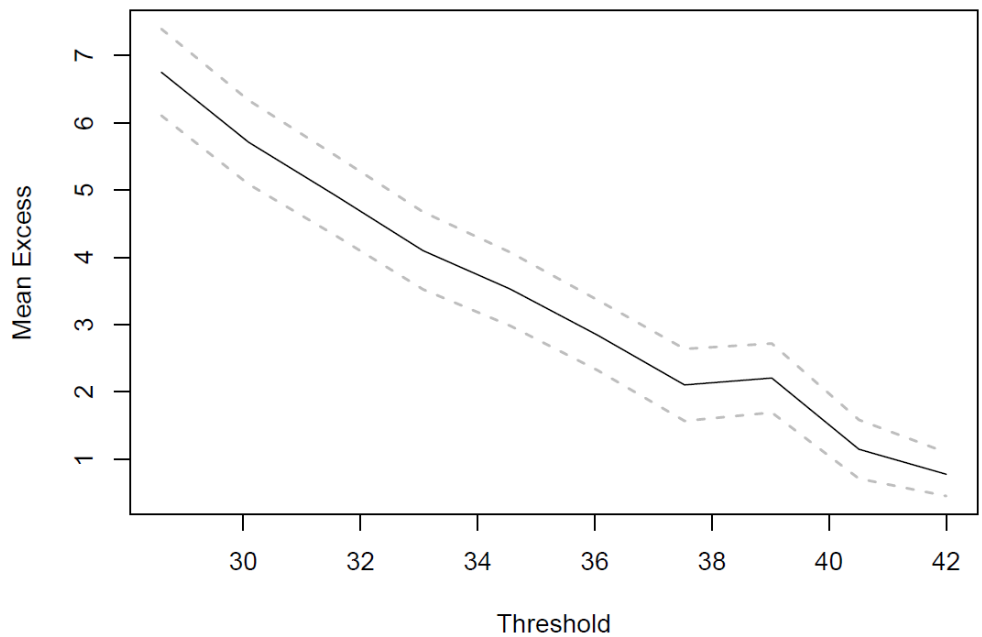

Figure 4: The Mean Residual Life (MRL) Plot or Mean Excess Plot of the Monthly Maximum Temperature

3.3.2 Parameters Stability

The parameter stability plot is an essential tool employed in the Peaks-over-Threshold (POT) methodology in conjunction with the Generalized Pareto Distribution (GPD). Its primary purpose is to evaluate the stability of the estimated parameters derived from the model when subjected to various threshold values. In this context, the objective is to pinpoint a specific range of thresholds where the parameter estimates exhibit minimal variation, ideally forming a "flat" or nearly horizontal section of the stability plot.

In the stability plots illustrated in Figure 5, a detailed examination reveals that setting a threshold minimum of 37 yields the most robust and stable parameter estimates. This indicates that within this threshold range, the model's parameters do not fluctuate significantly, providing a reliable foundation for further statistical analysis and ensuring the accuracy of the results derived from the GPD approach.

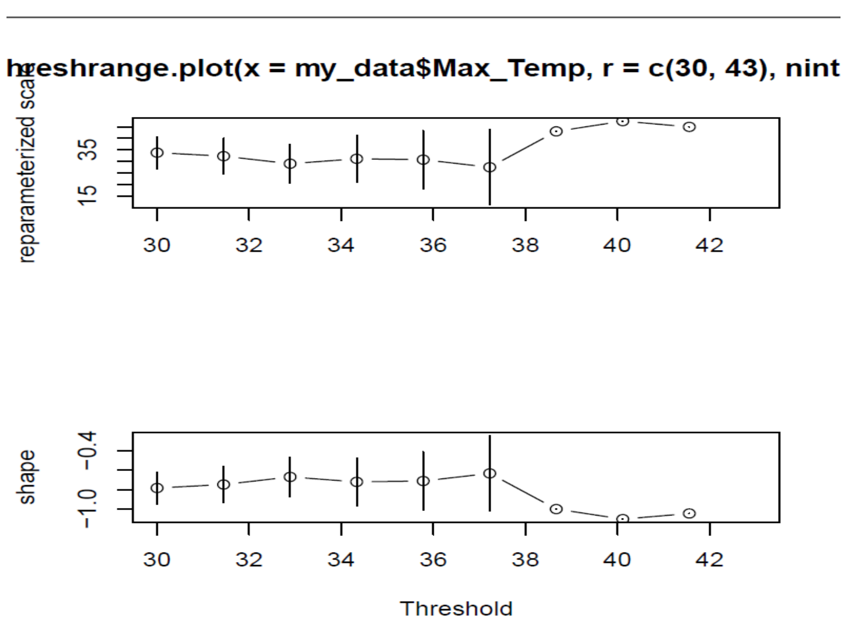

Figure 5: Parameter Stability Plots

3.3.3 Parameter Estimation

In the estimation of the parameters for the Generalized Pareto Distribution (GPD), we utilized the maximum likelihood estimation (MLE) method. This process involved analyzing parameter stability plots alongside the mean residual life plot to determine an appropriate threshold. After thorough examination, a threshold value of 37°C was deemed suitable for our analysis. The estimated parameters for the GPD model are detailed in Table 5. Notably, the shape parameter was found to be negative at -0.6523, a critical value that provides insight into the distribution's characteristics. A negative shape parameter suggests that the excess distribution is bounded above, signifying a potential upper limit or endpoint, which indicates a short-tailed distribution. This finding is consistent with results previously obtained through the Generalized Extreme Value Distribution (GEV) analysis, where the negative shape value implies that within the generalized Pareto family, the distribution resembles a Weibull distribution.

Table 5: Parameter Estimates of the GPD Model

Scale (s.e)	Shape (s.e)	AIC	BIC
4.1294 (0.9035)	-0.6523 (0.1866)	159.3919	162.9603

To quantify extreme events, we evaluated the exceedance probability, which measures the likelihood of a random variable surpassing a specified threshold. In our investigation, the probability of exceeding pertains to the likelihood that the maximum monthly temperature will exceed the established threshold of 37°C. The exceedance probabilities for selected maximum temperature values are summarized in Table 5. Analysis shows that the probability of the temperature reaching or exceeding 38°C is approximately 0.7583, indicating a significant chance of such occurrences, while the probability drops significantly to 0.0108 for temperatures reaching 43°C. This low probability suggests that it is highly unlikely for the monthly maximum temperature to surpass 43°C.

Table 6: Exceedance Probability Estimates for the Maximum Temperature

Temp.	38	39	40	41	42	43
Prob.	0.7583	0.5588	0.3737	0.2162	0.0915	0.0108

3.3.4 Fitted GPD Model Adequacy Check

In addition to employing the block maxima technique, which utilizes the GEVD, we also applied the peak-over-threshold (POT) method to model exceedances that occur above a predetermined threshold, utilizing the GPD. To ensure the model's appropriateness, we generated a series of diagnostic graphs based on our selected threshold of 37°C. The diagnostics presented in Figure 6 reveal that all necessary conditions for fitting the GPD to exceedances over this threshold have been met. Notably, the diagnostic plots for the GPD align well with those generated from the fitted GEVD model, reinforcing the reliability of our findings. The Quantile-Quantile (QQ) plot depicted in Figure 6 illustrates that the data points closely follow a straight line along the diagonal, evidence of a strong fit of the GPD model to our maximum monthly temperature dataset. This observation is further corroborated by the QQ-plot showcasing random samples drawn from the GPD compared against empirical quantiles (see Figure 6 (2)). Additionally, the empirical density plot in Figure 6 (1) substantiates the adequacy of the GPD for modeling the time series data, demonstrating well-defined exceedances within our chosen threshold, which totaled 44 in number. The return level plot, displayed in Figure 6 (4), exhibits a convex shape, further confirming consistency with the patterns observed in the GEVD model.

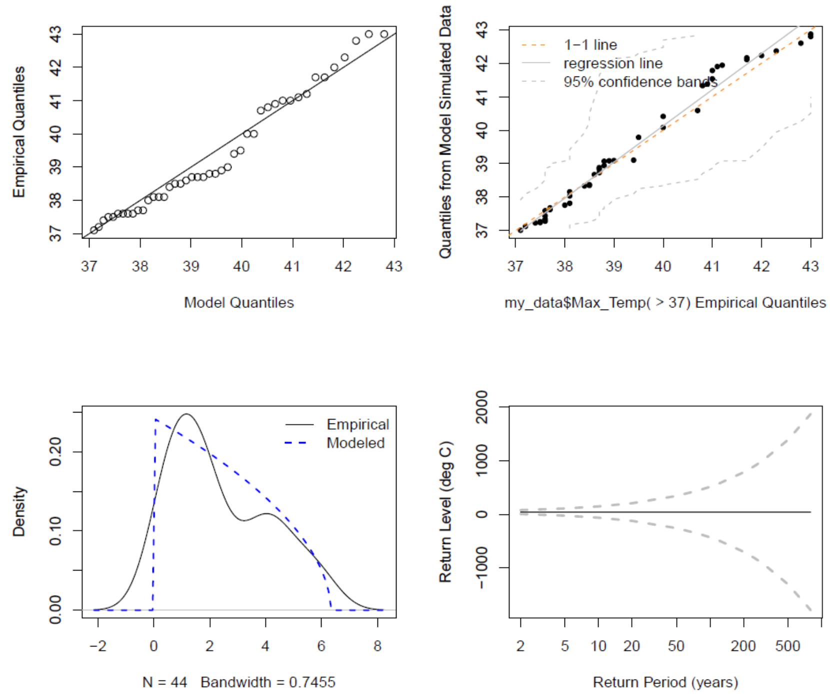

Figure 6: Diagnostic Plots of the fitted GPD Model to Monthly Maximum Temperature: (1) Probability Plot. (2) Quantile plot. (3) Density plot (4) Return period plot.

Table 7: Return Level Estimates

Period	2-Yr	5-Yr	10-Yr	20-Yr	50-Yr	100-Yr
Estimate	43.16	43.24	43.27	43.29	43.31	43.32

3.4 Selecting the Best Model

The comparative analysis of model effectiveness through the adequacy plots indicates that both the GEV and GPD models have a commendable fit to the observed maximum temperature data. However, a closer examination of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values, as illustrated in Tables 2 and 5, reveals that the GPD model holds a superior position in terms of fitting the maximum temperature data, characterized by lower AIC and BIC values. This statistical evidence suggests a more accurate representation of the underlying data trends by the GPD model compared to the GEV model. In contrast, Morris et al. (2020) found that the Generalized Extreme Value (GEV) model provided a better fit to maximum temperature data than the Generalized Pareto Distribution (GPD) model.

4 Conclusion

In this comprehensive research study, we analyzed the monthly maximum temperature data for Gombe State, covering the period from January 2015 to April 2025. To gain insights into the extreme temperature trends, we employed two distinct statistical modeling approaches: the block maxima method and the peaks-over-threshold method. By utilizing the block maxima approach, we fitted the Generalized Extreme Value (GEV) distribution to the data, while the peaks-over-threshold method allowed us to fit the Generalized Pareto Distribution (GPD).

When examining the GEV distribution, we explored three families: Gumbel, Fréchet, and Weibull. Notably, our findings indicated that the temperature data conformed to the Weibull distribution, characterized by a shape parameter (ξ) less than zero, signifying a right-skewed distribution of extreme values. Both fitted models demonstrated a satisfactory fit to the maximum temperature data, as determined by various diagnostic plots and the stability of their parameters over time. Similar results have been reported in previous studies. For instance, Morris et al. (2020) and Cherif (2025) obtained comparable Weibull distribution fits in their analyses of maximum temperature data for the Mediterranean city of Tunis and Northern Kenya, respectively. Likewise, Nemukula and Sigauke (2015) reported Weibull distribution fits under varying threshold levels, reinforcing the consistency of this distribution in modeling extreme temperature data.

However, the analysis highlighted that the GPD model exhibited a superior fit compared to the GEV model. This was evidenced by its significantly lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. Utilizing these fitted models, we derived return levels for specified return periods of 2, 5, 10, 20, 50, and 100 years, revealing a concerning trend: extreme temperatures in Gombe State are on the rise and are projected to reach dangerously high levels soon. Specifically, for the return periods, the temperature is projected to increase from 35.16 °C to 38.33 °C, and up to 43.66 °C for a 100-year return period. This indicates that the frequency and intensity of extreme heatwaves are likely to escalate in the near future.

These findings underscore the urgent need for strategic action from policymakers and decision-makers in Gombe State to address the impending risks linked to extreme temperature phenomena over the defined return periods. Such data-driven insights can empower the state government to craft informed policies and execute timely interventions. Given the persistent threat of global warming, it is essential to pursue ongoing adaptation and preparedness initiatives to bolster the resilience of communities in Gombe.

To mitigate the potential negative impacts of rising temperatures, we recommend the following targeted adaptation and mitigation strategies:

- Afforestation and Reforestation Initiatives: Both governmental authorities and local communities must take decisive steps against deforestation. Large-scale tree planting projects should be embarked upon, particularly along urban roads, within educational institutions, and in residential neighborhoods, to provide natural shade and cooling benefits. Moreover, efforts must be made to restore degraded land and increase forest cover to enhance local biodiversity and climate resilience.
- Promotion of Renewable Energy Resources: The government should actively promote the adoption of renewable energy solutions, particularly solar power. By decreasing reliance on diesel and petrol generators, major contributors to urban heat and greenhouse gas emissions, such initiatives can significantly alleviate the local heat burden and contribute to cleaner air.
- Enhanced Waste Management Practices: Establishing effective waste management and recycling systems is vital to minimizing methane emissions from landfills, which are potent contributors to climate change. Community involvement in waste segregation and recycling can foster a culture of sustainability.
- Community Sensitization and Awareness Campaigns: Engaging local communities through education campaigns about the health risks associated with extreme heat and viable protective measures is essential. Information dissemination can empower residents to adopt preventive behaviors and seek assistance during heat waves.
- Development of Climate-Resilient Infrastructure: There is a pressing need to advocate for the use of heat-resistant building materials and architectural designs that promote efficient ventilation, particularly in low-income areas. This will ensure that new developments are better equipped to withstand extreme temperature fluctuations.
- Ensuring Access to Clean Water: During periods of extreme heat, equitable access to safe drinking water must be prioritized to protect public health and well-being. The government should implement strategies to ensure that all communities have reliable water supply systems.
- Support and Resources for Farmers: Agriculture is highly susceptible to climatic changes, and therefore, farmers must receive support in the form of drought-resistant crop varieties and modern irrigation technologies. These resources can enhance agricultural productivity and resilience against the challenges posed by increasing temperatures.

Through the implementation of these strategies, Gombe State can foster a proactive approach to managing extreme heat events and protect its vulnerable populations and ecosystems from the adverse effects of climate change.

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