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Generalized Extreme Value (GEV) Distribution Analysis of Maximum Temperature: A Case Study of Gombe State Nigeria

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ABSTRACT

Data ranging for the period of ten years were used to study the problem of modelling extreme temperature. The Generalized Extreme Value distribution is fitted to the maximums of six distinct time periods: daily, weekly, biweekly, monthly, quarterly, and half-yearly. These selection periods are based on the findings, which indicate that only the daily, weekly, and biweekly maximums are substantial enough to suit the GEV model. In agreement with the Mann-Kendall (MK) test, which indicates that there is no significant trend for any of the three selection periods, neither the Augmented Dickey Fuller (ADF) nor the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) stationarity tests found any stochastic trends for maximum temperatures. After evaluating the three models, the model with a location parameter that increases over time was concluded to be the most effective for every selection period. All three selection period maximums converge to the GEV distribution, according to the Anderson-Darling and Kolmogorov-Smirnov goodness of fit tests, with the daily maximums exhibiting the best convergence to the GEV distribution. According to return level estimates, the return temperature that surpasses the observation period's maximum temperature (43.3) begins to show up in the return period of T = 10, 20, 50, and 100 for weekly and biweekly maximums, while it was anticipated to be higher than T = 20, 50, and 100 for daily maximum.

Keywords: Extreme, Maximum Temperature, Generalized Extreme Value, Return Level

INTRODUCTION

Nigeria's mean annual temperatures have increased significantly over the past 50 years, while the frequency of cold and hot extremes has decreased and increased nationwide, respectively (Chukwudum and Nadarajah, 2022). Given that climate change appears to be one of the most significant challenges of the last few decades, temperature is one of the primary climatic factors that can signal climate change (Moser, 2010). Globally, there are serious social, economic, and environmental dangers and challenges due to climate change, which is a demonstrable reality (Etkin and Ho, 2007). Natural systems face significant challenges as a result of global warming and the rise in temperature extremes that it causes.

There are 36 states in Nigeria, including Gombe State. It is situated in the Gombe state. The state is one of the most sensitive to the effects of climate change and ranks among the lowest in terms of state gross domestic product per capita. Nonetheless, the state is among the most fertile agricultural areas in Nigeria (Abdulhamid and Bamusa, 2018). Due to high temperatures and erratic rainfall, the state's primary issues impacting the agricultural sector include drought and flooding (Mama

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and Osinem, 2007). By burning fossil fuels like carbon dioxide and methane, which produce global warming, human activity is thought to be the primary cause of climate change, according to Tarmizi, (2019). Following that, these gasses are discharged into the atmosphere. Carbon dioxide, which blankets the earth and absorbs heat, pollutes the atmosphere. Extreme temperatures result from the Earth warming due to the heat that is absorbed (Sadatshojaie and Rahimpour, 2020). Ochanda, (2016) asserts that climate change can have an impact on the environment and endanger people in a variety of spheres of life, including social and economic ones. It seems probable that the earth's climate will be permanently altered if global warming results in temperature increases. Temperature increases are projected to cause drought conditions to worsen globally, evapotranspiration to reduce water resources, and agricultural demand to rise (Nhamo et al., 2019, Ochanda, 2016). In a nation like Nigeria, where the population is expanding quickly, the state's agricultural output is impacted by the high temperatures and frequent flooding, resulting in a shortage of food and water resources (Abdulhamid and Bamusa, 2018). According to Abdulkadir et al., (2017), Nigeria is also worried about the public health implications of severe hot events as opposed to extreme cold ones, as well as how these events' effects might evolve over time. Floods elevated the risk of disease and caused massive damage to businesses, infrastructure, and property. In addition to being the most common natural disaster, floods have killed over 200,000 people in the last three decades and impacted over 2.8 billion people worldwide. . According to the World Health Organization, the flood in Nigeria in 2012 was the worst to strike the country in the previous fifty years. (Louw et al., 2019).

Heat waves and other severe temperature occurrences brought on by climate change have a significant impact on both the environment and human activity. Areas like Gombe State in Nigeria are experiencing issues as a result of these events becoming more frequent and strong (Rogelj et al., 2012). Understanding and forecasting the occurrence of such severe temperatures is essential for the effectiveness of adaptation and mitigation initiatives (Easterling et al., 2000).

The Generalized Extreme Value (GEV) distribution is a potent statistical tool for modeling and interpreting extreme values in a variety of domains, including climatology (Coles, 2001). The GEV distribution is ideally suited to describe a variety of extreme occurrences since it conveniently combines three distinct extreme value distribution types (e.g., Gumbel, Frechet, and Weibull) (Coles, 2001). The behavior and trends of extreme temperatures in Gombe State can be better understood by modeling them using the GEV distribution. Therefore, the purpose of this study is to estimate the probability and return periods of extreme temperature events by applying the GEV distribution to historical temperature data. This will assist policymakers in making decisions regarding public health, infrastructure development, and disaster preparedness (Rogelj et al., 2012). The study of extreme temperatures advances our knowledge of extreme phenomena. The behavior of extreme temperatures will be useful to decision-makers, risk managers, and climatology researchers because it will enable the development of suitable plans and policies to prepare the public for changes brought on by extreme temperatures. Quantifying and characterizing the behavior of severe temperatures in Gombe State, Nigeria, is the aim of this study. Using the Generalized Extreme Value (GEV) distribution, we specifically want to mimic the extreme temperatures. We check for stationarity during the modeling process over a variety of selection periods, including daily, weekly, biweekly, monthly, quarterly, and half-yearly.

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Description of Data

The Nigerian Meteorological Agency (NIMET) in Gombe graciously contributed the study's data, which includes the maximum daily temperatures (in Celsius) for Gombe state. The years 2014–2023 are taken into consideration.

MATERIALS AND METHODS

We examine Generalized Extreme value distributions with distribution functions of the form $G_{max}(x) = \exp\{-[1 + \zeta x]^{-\frac{1}{\zeta}}\}$; $1 + \zeta x > 0$, where $G_{max}(x) = P(X_n \leq x)$, $X_n = (M_n - \mu_n)/\sigma_n \rightarrow G_{max}(x)$ where M_n is the maximum chosen among n values, as $n \rightarrow \infty$, and is reduced with a location parameter, μ_n, a scale parameter, σ_n, and ζ is a shape parameter. According to Bali, (2003), the Gumbel distribution corresponds to $\zeta = 0$, the Weibull distribution to $\zeta < 0$, and the Frechet class of extreme value distribution to $\zeta > 0$. These distributions are all members of the GEV family.

Selection Period

The distribution of block maxima can be modeled using the GEV function. A data set is divided into equal-length blocks for its application, and the GEV distribution is fitted to the set of block maxima. The block size must be selected when putting this model into practice in order for the distribution of individual block maxima to be uniform. As time advances, the distribution of temperature data is probably the same. Results from inferences that do not account for this uniformity are likely to be erroneous. Blocks of one year are frequently adopted due to standard considerations. Since we are employing a 10-year data set, if a one-year block is employed, this study will only have 10 yearly maximum temperatures or 10 data points for modeling purposes, which is insufficient for any significant modeling. As a result, several selection periods—daily, weekly, biweekly, and monthly block lengths—are taken into account and contrasted.

Stationary Test

The data is subjected to the Augmented Dickey Fuller (ADF) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) stationarity tests in order to satisfy the stationarity assumption of the generalized extreme value family of distributions. These two experiments are being conducted in order to search for patterns across several selection periods. The alternative hypothesis for the ADF test asserts stationarity, while the null hypothesis asserts difference stationarity. According to the KPSS test, the distribution is stationary according to the null hypothesis and difference-stationary according to the alternative. The Mann-Kendall (MK) test is used to find the presence of a monotonic trend (either increasing or decreasing) in datasets that contain missing or tied data. It does not require normally distributed data (Gilbert, 1987). The alternative hypothesis asserts that a trend exists, whereas the null hypothesis asserts that no trend exists (Hamed, 2008).

Model Choices and Parameter Estimates

We search for the most straightforward model that can account for the greatest amount of data variation. Three models are taken into consideration. Model 1 is a simple model with constants μ, σ, and ζ denoting the location, scale, and form parameters, respectively. Model 2 is a four-parameter model in which the other parameters are constants and μ is permitted to change linearly over time. In Model 3, all other parameters are constants, and σ is an exponential function of time. The following are the models:

Model 1: μ, σ, and ζ constants

Model 2: $\mu(t) = \beta_o + \beta_1 t$, σ, ζ are constants

Model 3: $\sigma(t) = \exp(\beta_o + \beta_1 t)$, μ, ζ are constants

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The units of measurement are day units for the daily selection period, week units for the weekly selection period, two-week units for the biweekly selection period, month units for the monthly selection period, quarter units for the quarterly selection period, and half-year units for the half-yearly selection period. The form parameter, ζ, is always a constant for all models since it is hard to predict precisely and it is typically impractical to attempt modeling ζ as a smooth function of time.

For Model 1, the L-moments method (LMOM) is selected as the parameter estimation approach. The L-moments, a summary statistic for probability distributions and data samples, are expectations of specific linear combinations of order statistics. It is comparable to ordinary moments that give information about the location, dispersion, skewness, kurtosis, and other features of the shape of data samples or probability distributions. However, the MLE algorithm for Model 1 is initialized using this method, which is limited to estimating a stationary process. Because Models 2 and 3's parameters are time-dependent, this method is inappropriate for them; instead, Models 2 and 3 employ the maximum likelihood estimation (MLE) method.

Likelihood Ratio (LR) Test and Model Diagnostics

Model 1 and Model 2 are contrasted. For the three-parameter Model 1 and the four-parameter Model 2, let L_o and L_1 be the maximum likelihoods, respectively. A chi-square distribution with one degree of freedom (which corresponds to the difference in the number of parameters; in this case, 1) is used to distribute the LR test statistic, which is specified as

$$\tau = -2\log\left(\frac{L_o}{L_1}\right)$$

The three-parameter model is selected in the event that

$$\tau < \chi^2_{1,0.95} = 3.8415$$

if not, the four-parameter model is the one that is recommended. Since Models 2 and 3 have the same amount of parameters, a direct comparison between them is not possible. Since three models are taken into consideration in this study, the results of Model 1 vs Model 2 will be compared with Model 3. For diagnostic reasons, a variety of graphs are used, including the probability plot, quantile plot, return level plot, and density plot. The quantiles of a model are contrasted with the empirical quantiles of the data in a quantile diagram. The model assumptions may not hold true for the depicted data if the quantile plot significantly deviates from a straight line. With an estimated 95% confidence interval, the return period is plotted against the return level in the return level plot. According to Maronna et al., (2019), graphical tests are not as accurate as robust statistical tests, notwithstanding their usefulness. More often than not, graphical tests are employed to supplement statistical analysis.

Kolmogorov-Smirnov and Anderson-Darling Goodness of Fit Test

The quality of convergence of the GEV distribution is evaluated using the Anderson-Darling goodness of fit test and the Kolmogorov-Smirnov goodness of fit test. To determine whether a sample is representative of a hypothesized continuous distribution, the Kolmogorov-Smirnov test is utilized. It is based on the empirical cumulative distribution function and the biggest vertical difference between the theoretical and empirical cumulative distribution function. A general technique for evaluating how well an observed cumulative distribution function fits an expected cumulative distribution function is the Anderson-Darling approach. Compared to the Kolmogorov-Smirnov test, this test gives a distribution's tails more weight. Both tests' null hypotheses state that the data adhere to the given distribution.

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Return Level Estimate

The level that is anticipated to be surpassed on average once every t time periods is known as the return level. The maximum temperature amount is the return level in this study, and t is equivalent to the selection intervals of day, one week, two weeks, a month, a quarter year, and a half year. Stationary models can be used to estimate return levels, which are crucial for planning and forecasting.

RESULTS AND DISCUSSION

Descriptive Statistics

Ten years' worth of data, including daily maximum temperatures from 2014 to 2023, are used in the study. The descriptive statistics for the daily temperatures and the different selection intervals are displayed in Tables 1 and 2. 43.3 is the maximum value.

A varied daily maximum temperature is shown by the 3653 daily maximum temperatures, which have a standard deviation of 3.80 and a rather substantial coefficient of variation of 11.52, as seen in Tables 1 and 2. Following data partitioning into distinct selection periods, it is shown that the coefficient of variation declines and the difference between the lowest and maximum gets smaller as the selection period lengthens. This suggests that as the selection period lengthens, the highest temperature data becomes less scattered from the mean.

Table 1: Summary statistics of maximum temperature

	N	Min	Mean	S.Dev
Daily	3653	24.2	33.016	3.803
Weekly	522	27.6	34.864	3.690
Biweekly	261	28.7	35.455	3.766
Monthly	120	30.0	36.261	3.723
Quarterly	40	30.8	38.028	3.927
Half yearly	20	34.6	39.353	3.039

While it is negative for the quarterly and half-yearly maximum temperatures, the skewness is positive for all selection periods. This finding suggests a distribution where the right tail is comparatively longer than the left. A diminishing skewness means that as the selection period lengthens, the right tail gets smaller.

Table 2: Summary statistics of maximum temperature

	CV	SK	J.B(p-value)
Daily	11.52	0.22	2286.04(0.00)
Weekly	10.58	0.15	355.51(0.00)
Biweekly	10.62	0.10	184.58(0.00)
Monthly	10.27	0.02	84.53(0.00)
Quarterly	10.33	-0.40	31.43(0.00)
Half yearly	7.72	-0.27	18.76(0.00)

CV = Coefficient of Variation, SK = Skewness

The null hypothesis is rejected in favor of a non-normal distribution by the p-value of the Jarque-Bera (J.B.) normality test, which has a chi-squared distribution with two degrees of freedom, for the daily, weekly, biweekly, and monthly maxima. Because of their negative skewness value, the quarterly and half-yearly periods are therefore deemed inappropriate. Right-skewed distributions are supported by a comparison with the

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maximum temperature histogram for the three selection periods (daily, weekly, and bimonthly). Thus, we deduce that it makes sense for this study to model using the GEV distributions with daily, weekly, and biweekly selection periods.

Testing for Stationarity

Line graphs of the highest temperatures are drawn for each of the chosen intervals in order to verify the stationarity assumption. The graphs demonstrate that neither trends nor a change in the pattern of variance in maximum temperatures are strongly supported. The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) and Augmented Dickey Fuller (ADF) tests, which are displayed in Table 3, agree with this observation.

Table 3: Unit root test for maximum temperature

		Test critical value			Test Statistic
SP	Test	1%	5%	10%	
D	ADF	-3.960	-3.410	-3.130	-12.0723
	KPSS	0.216	0.146	0.119	0.1635
W	ADF	-3.980	-3.430	-3.130	-4.1966
	KPSS	0.216	0.146	0.119	0.0451
B	ADF	-3.990	-3.430	-3.140	-4.1142
	KPSS	0.216	0.146	0.119	0.0331

SP = Selection Period, D = daily, W = weekly, B = biweekly

At the 1%, 5%, and 10% significance levels, the ADF tests' p-value (0.00) is significant. With the exception of 5% and 10% for the daily selection period, all test statistics have values that are less than the critical values over various selection periods, demonstrating that the KPSS test indicates that all test statistics are unimportant at the 1%, 5%, and 10% levels. As a result, difference-stationarity is preferred and the null hypothesis cannot be rejected. Therefore, we conclude that, with the exception of the daily selection period at the 5% and 10% significance levels, there is stationarity in the maximum returns over the difference of selection periods at the 1%, 5%, and 10% significance levels. With the null hypothesis that there are no trends, we run the Mann-Kendall (MK) test and get the following result in Table 4.

Table 4: Mann-kendall test

Selection Period	Z	p-value no trend
Daily	0.002161	0.998276
Weekly	0.007284	0.994188
Biweekly	0.02554	0.979624

According to the results of the stationary test, there is no discernible pattern for any of the three selection periods. This finding implies that in this investigation, we should solely model for stationarity.

Parameter Estimates and Model Selections

Tables 5 through 7 display the parameter estimates for the three models taken into consideration in section II.C during various

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selection periods. The parameter estimates for Model 1, Model 2, and Model 3 are obtained by maximizing the log likelihood of the GEV for daily maximums. These results are displayed in Table V. The variances of the various parameters (μ, σ, ζ) are represented by the diagonal of the variance-covariance matrix of the parameter estimations, with the standard errors shown in brackets.

The maximum likelihood estimate is obtained by fitting the GEV distribution to the weekly and biweekly maximums, as indicated in Table 6 and 7, respectively. It is observed that as the selection intervals increase, so does the standard error (s.e) for every parameter.

Table 5: Parameter estimates for daily maximum

Parameters	Model 1 (s.e)	Model 2 (s.e)	Model 3 (s.e)
μ	31.5003 (0.0733)		31.5645 (0.0703)
σ	3.6549 (0.0419)	3.8033 (0.0715)	
ζ	0.1921 (0.0113)	0.1999 (0.0275)	-0.2201 (0.0174)
β_o		33.0168 (0.1221)	3.5888 (0.0328)
β_1		-0.0008 (0.0001)	-0.0000 (0.0000)
LLV	-6079.2712	-10435.2079	-10002.3900

LLV = Log Likelihood Value

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Table 6: Parameter estimates for weekly maximum

Parameters	Model 1 (s.e)	Model 2 (s.e)	Model 3 (s.e)
μ	33.424 (0.2011)		33.5309 (0.1829)
σ	3.609 (0.1003)	3.5572 (0.1395)	
ζ	0.214 (0.0312)	-0.2651 (0.0438)	-0.2638 (0.0449)
β_0		33.5798 (0.3275)	3.5146 (0.0701)
β_1		-0.0002 (0.0010)	0.0000 (0.0002)
LLV	-851.3958	-1413.3950	-1413.3818

Table 7: Parameter estimates for biweekly maximum

Parameters	Model 1 (s.e)	Model 2 (s.e)	Model 3 (s.e)
μ	34.0214 (0.2994)		34.1899 (0.2711)
σ	3.7417 (0.1364)	3.7282 (0.2111)	
ζ	0.2370 (0.0445)	-0.3174 (0.0638)	-0.3169 (0.0649)
β_0		34.2704 (0.4744)	3.7191 (0.0952)
β_1		-0.0006 (0.0029)	0.0000 (0.0005)
LLV	-429.3146	-711.4811	-711.5014

The likelihood-ratio test is used to compare the three models and the test statistic and P-values are listed in Table 8 and Table 9.

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Table 8: Model 1 vs Model 2

Model 1 vs Model 2	τ	p-value
Daily	8711.8734	0.0000
Weekly	1123.9984	0.0000
Biweekly	564.333	0.0000

Table 9: Model 1 vs Model 3

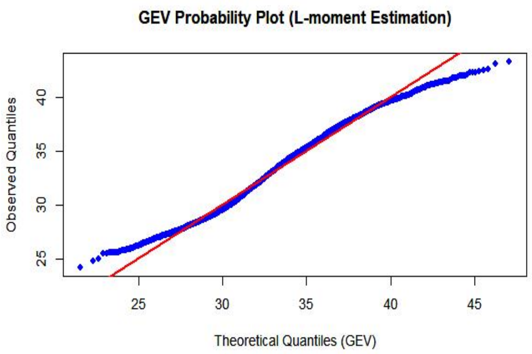
Model 1 vs Model 3	τ	p-value
Daily	7846.2376	0.0000
Weekly	1123.972	0.0000
Biweekly	564.3736	0.0000

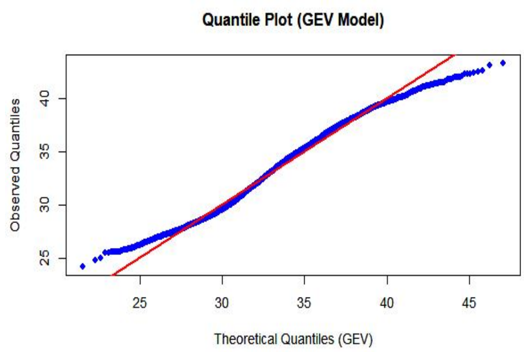
We found that Model 2 is a significant improvement over Model 1 throughout various selection periods when we compare the two models (Table 8). For every selection period, Model 3 is also favored above Model 1, according to Table 9.

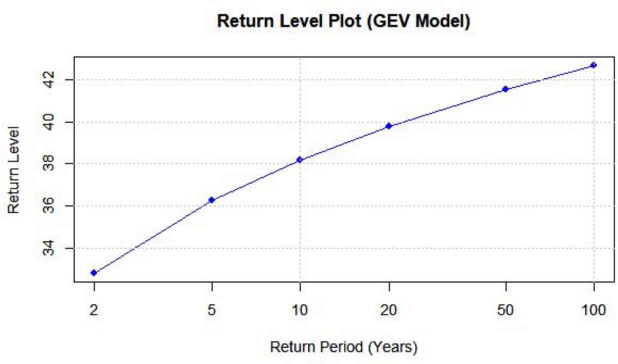
We can therefore conclude that Model 2, where μ is allowed to vary linearly with respect to time and other parameters are constants, is marginally better than Model 3, where σ is an exponential function of time and other parameters are constants over various selection periods, since Model 2 is superior to Model 1 and Model 3 is superior to Model 1.

Model Diagnostics

The model diagnostics for the daily maximum for Models 1, 2, and 3 are displayed in Figures 1(a) and 1(b), respectively. Since each set of displayed points seems to be linear, an examination of Model 1 diagnostics reveals that neither the probability plot nor the quantile plot cast doubt on the validity of the fitted model. Because ζ is near zero, the return level plot exhibits relative linearity.







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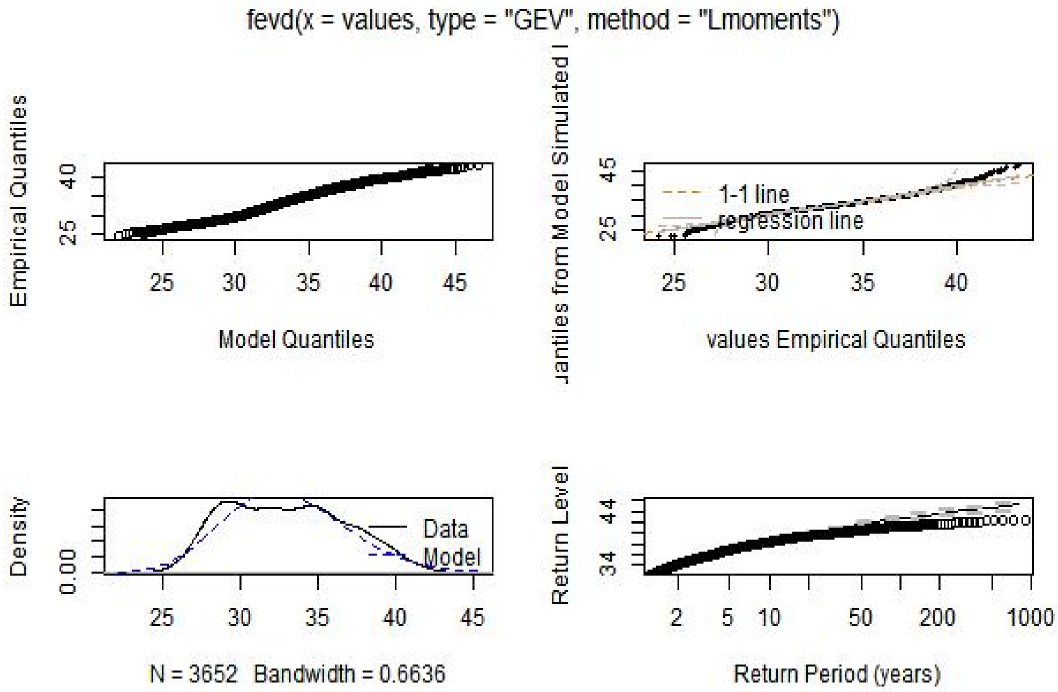

Figure 1(a): Model Diagnostic for Daily Maximum

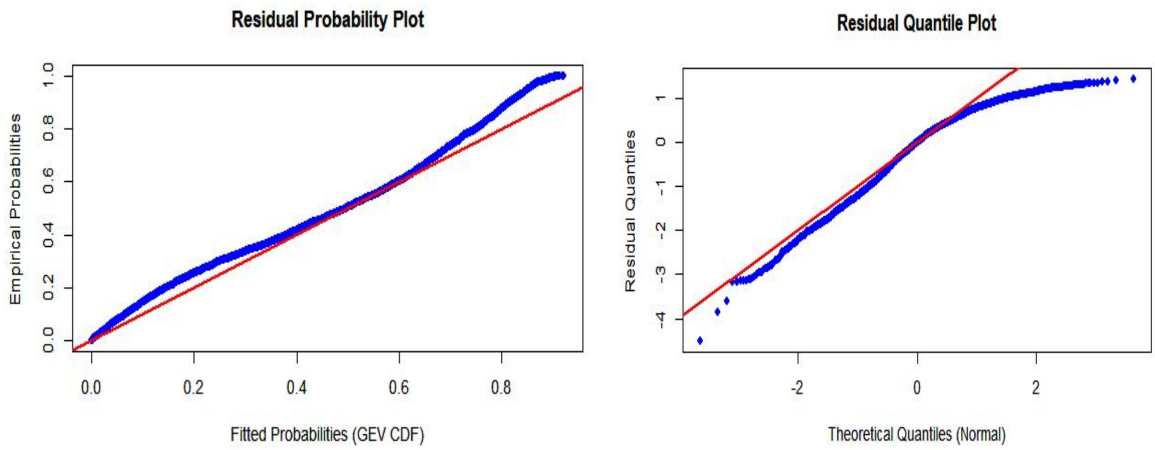

Figure 1(b): Model Diagnostic for Daily Maximum

Only the quantile plot on the Gumbel scale and the residual probability and quantile plots are shown for Models 2 and 3. Every plot indicates that every model fits well. Similar findings were obtained from inspections conducted at weekly and biweekly maximums (not shown here).

3.5 Kolmogorov-Smirnov and Anderson-Darling of Fit Test

The Anderson-Darling and Kolmogorov-Smirnov test results for various selection periods are displayed in Table 10. Fits from modeling with the various selection periods were nearly identical. The null hypotheses are not rejected over the various selection periods based on an examination of the p-values. Convergence to the GEV, however, is probably preferable for the weekly selection period as the selection period lengthens because its p-value is lower than the p-values for the other two selection periods.

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Table 10: Kolmogorov-Smirnov (KS) and Anderson-Darling (AD)

Sample size	Statistics	p-value
(daily = 3653)		
KS	0.10581	0.541
AD	72.982	0.526
(weekly = 522)		
KS	0.12434	0.543
AD	14.034	0.537
(biweekly = 261)		
KS	0.144	0.546
AD	8.7904	0.545

We then draw the additional conclusion that, for the daily, weekly, and biweekly selection periods, the data follow the given distribution. Daily maximums exhibit superior convergence to the GEV distribution compared to the other two selection periods, according to an examination of the p.d.f. graphs of a GEV distribution.

Return Level Estimate

During the 10-year monitoring period, 43.3 is the highest recorded daily temperature. Return values are used to forecast the likelihood that a daily maximum temperature of 43.3 will be reached over an extended period of time. Model 1 (stationary) of daily, weekly, and biweekly maximums is used to predict the return levels.

The return levels over various selection periods are displayed in Table 11 below, where a (*) denotes a return amount that is higher than the maximum temperature (43.3). The brackets indicate the 95% confidence intervals derived from profile likelihood. Examining the table reveals that as the return periods lengthen, so do the return level projections.

Table 11a: Return level estimate for T = 2, 5, 10

Selection period	T = 2	T = 5	T = 10
daily	32.8882 (32.7259, 33.0555)	37.8537 (37.5187, 38.1787)	41.7889 (41.2546, 42.3514)
weekly	34.8005 (34.3450, 35.2640)	39.8093 (38.8987, 40.7988)	43.8617 (42.4483, 45.5287)*
biweekly	35.4541 (34.7482, 36.1344)	40.7610 (39.3763, 42.2007)	45.1462 (42.8592, 47.6284)*

Table 11b: Return level estimate for T = 20, 50, 100

Selection period	T = 20	T = 50	T = 100
daily	46.1357 (45.2883, 47.0306)*	52.7328 (51.3169, 54.2752)*	58.5106 (56.5248, 60.7355)*
weekly	48.4115 (46.2487, 51.1263)*	55.4455 (51.7844, 60.3668)*	61.7176 (56.4954, 68.9962)*
biweekly	50.1527 (46.6272, 54.2125)*	58.0407 (52.0495, 65.3346)*	65.2049 (56.7495, 76.4052)*

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The table also demonstrates that, for weekly and biweekly maximums, the temperature that surpasses the observation period's maximum temperature (43.3) falls within the confidence interval T = 10, 20, 50, 100. For daily maximums, the temperature that is higher than the observation period's maximum temperature (43.3) falls within the T = 20, 50, and 100 confidence interval.

CONCLUSION

Maximum temperatures were studied and modelled using data from the Nigeria Metrological Agency weather station for the years 2014–2023 using the Generalized Extreme Value (GEV) distribution. While a trend test found no discernible trend, a stationarity test indicates that all of the selection periods are stationary. The model parameter were estimated and all selection periods were fitted to the GEV distribution. According to the likelihood ratio test, the optimal model has a location parameter that rises linearly with time and constant scale and shape parameters. A good fit was demonstrated by the model diagnostics, which include the probability plot, quantile plot, return level plot, and density plot. The modelling process, employed various selection periods produced nearly identical fits, according to the Kolmogorov-Smirnov and Aderson-Darling goodness of fit tests. The GEV distribution did, however, converge best when modeling with the daily maximum. At T = 2, 5, 10, 20, 50, and 100, the return level estimate—that is, the return level that is anticipated to be surpassed within a specific time frame—is projected. The findings showed that, for weekly and biweekly maximums, the temperature that surpasses the observation period's maximum temperature amount (43.3) begins to show up in the confidence interval T = 10, 20, 50, and 100. The temperature that surpasses the observation period's maximum temperature (43.3) is expected to occur within the confidence interval of T = 20, 50, and 100 for the daily maximum. Although data range for only ten years was used, estimating maximum temperatures using the GEV distribution is recommended based on the findings of this work. Also, the authors could have thought of possible extension of the work or their model to other fields as a future work focus for other researchers to consider.

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