

## ARTICLE

# Intensifying Thermal Extremes in South-Western Nigeria (1983–2023): Evidence from TX90p Analysis and Extreme Value Theory

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## ABSTRACT

Extreme heat is one of the most consequential manifestations of anthropogenic climate change, yet quantitative assessments combining trend detection, frequency analysis, and probabilistic risk modelling remain rare for tropical West African cities. This study analyses annual maximum temperature (Tmax) variability, extreme heat frequency, and probabilistic return-level estimation for South-Western Nigeria over 1983–2023, using TerraClimate monthly data validated against ERA5-Land reanalysis. Regional annual Tmax ranged from 33.20 °C (1991) to 35.82 °C (1990), with a modest but statistically significant upward trend confirmed by the Mann–Kendall test ( $\tau = 0.329$ ,  $p = 0.0025$ ) and quantified at 0.0256 °C per year by Sen's Slope Estimator. An annual-scale exceedance index shows extreme years recurring intermittently, with the clearest sustained run only from 2020–2023; a standard daily ETCCDI TX90p index computed at the state level shows a fairly uniform 18–20% exceedance rate across

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all six states relative to the 1983–2012 baseline. Extreme Value Theory models fitted to the annual Tmax series show the Generalized Extreme Value (GEV) distribution outperforming Gumbel on goodness-of-fit (Kolmogorov–Smirnov (K–S) statistic: 0.0997 vs. 0.1486), with 100-year return levels of 35.98 °C and 36.65 °C, respectively, a difference of 0.67 °C. Spatial analysis reveals a more nuanced risk profile than a simple coastal-inland split: the interior state of Oyo records the lowest background warming trend, while Ekiti and Lagos record the highest daily extreme-heat frequency. The study advances a replicable, open-data framework for thermal hazard quantification in data-scarce tropical environments, relevant to Nigeria’s National Adaptation Plan, infrastructure standards, and the Sendai Framework for Disaster Risk Reduction.

**Keywords:** Mann–Kendall; TerraClimate; Heat Risk; Urban Climate; Thermal Adaptation

## 1. Introduction

One of the most widely reported and economically damaging impacts of anthropogenic climate change is extreme heat. Extreme heat events are acute and compound stresses on human health, agriculture, freshwater systems and built infrastructure that occur often in short time scales and in a way that exceeds adaptive capacity, unlike gradual mean temperature warming<sup>[1]</sup>. The situation is especially critical in sub-Saharan Africa, where the region has warmed up faster than the global average in many parts, and where adaptive infrastructure and institutional capacity are low compared to any other part of the globe<sup>[2]</sup>. This creates a compounded vulnerability that can only be addressed with locally informed, scientifically sound climate risk assessments.

The Nigerian case, especially South-Western Nigeria, is a very strong one for specific analysis. It includes six states: Lagos, Ogun, Oyo, Osun, Ondo and Ekiti, and is one of the most populous and productive urban corridors in West Africa. The high rate of urbanisation, an increasing built-up area, concrete structures and deforestation are all leading to the intensification of heat extremes and making them more dangerous in Lagos, which is one of the ten fastest-growing megacities in the world<sup>[3,4]</sup>. The West African Monsoon system controls the seasonal rainfall and temperature variability in the region, and this system is also becoming more erratic because of variations in the atmospheric circulation patterns<sup>[5]</sup>. High temperatures are no longer just an inconvenience for millions of people living and working in buildings with poor insulation and weak electricity supply, but have real health, productivity, and life-impact im-

plications<sup>[6]</sup>.

In spite of this, a quantitative assessment of extreme heat events in South-Western Nigeria beyond mean temperature reporting is scarce. There have been various studies that have dealt with temperature trends over Nigeria, most of which come from national or regional broad-scale records<sup>[7,8]</sup>. A few have specifically studied the south-west, and a few even integrated multiple methods of statistical analysis with probabilistic risk estimation, providing actionable thresholds to plan infrastructure and adapt to climate change<sup>[9,10]</sup>. This is not just an academic problem: return-period estimates of extreme conditions in terms of quantified values are needed in the framework of national adaptation and in the design of infrastructure, and this is not yet available or sufficiently constrained for the region.

This study fills the gap by an integrated four-component analysis. It relies on the TerraClimate monthly maximum temperature dataset and checks the reliability of the dataset with ERA5-Land reanalysis, to examine the variability of Tmax over 41 years over the six south-western states. A standardised climate extreme index endorsed by the Expert Team on Climate Change Detection and Indices (ETCCDI), the TX90p index is used to monitor the number of days with extreme temperatures above the 90th percentile of the 1983–2012 reference period. The Extreme Value Theory (EVT) approach is then applied, with both the Generalized Extreme Value (GEV) and Gumbel distributions, to estimate temperature return levels for planning-relevant time scales ranging from two to 100 years. Lastly, spatial heterogeneity analysis breaks down trends and extreme-heat frequency by state and shows sub-regional varia-

tion in risk profiles.

The study has four specific objectives: characterisation of long-term trends and interannual variability of annual maximum temperature (AMT) over South-Western Nigeria; evaluation of the changing frequency and intensity of extreme heat events using TX90p index; estimation of probabilistic temperature return levels by using GEV and Gumbel models, and determining which of the two models best fits the South-Western Nigeria data; and assessment of the spatial heterogeneity of warming trends and extreme-heat frequency over the six constituent states of South-Western Nigeria.

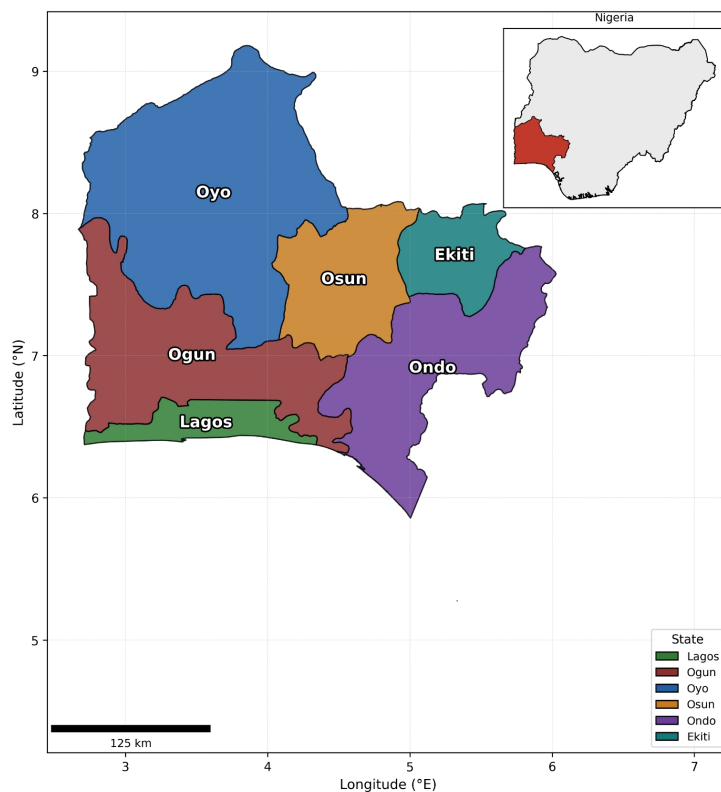
The study is methodologically and practically unique in the existing literature in a number of aspects. Uses a dual-model EVT approach for annual Tmax data for a region for which previous estimates have not been published. It is cross-validated by ERA5-Land reanalysis at the state level, to give a quantified confidence basis to the trend and return-level analyses. It indicates a change in the regional thermal regime that goes beyond simple climatology and suggests measurable infrastructure design risk, agricultural calendar changes, and public health system stresses. And it does so with open and

reproducible data and methods that can be used in other data-poor tropical cities with similar problems.

The results are policy-relevant in respect of the National Adaptation Plan framework of Nigeria<sup>[11]</sup>, the Sendai Framework for Disaster Risk Reduction 2015–2030<sup>[12]</sup>, and the design standards in the field of civil engineering and urban planning. The region is already facing multiple climate pressures that can strain systems, so understanding these probabilistic heat thresholds is important for road design, building energy codes, hospital capacity planning, and agricultural scheduling.

### Study Area

South-Western Nigeria comprises six geopolitical states: Lagos, Ogun, Oyo, Osun, Ondo, and Ekiti. The region spans approximately latitudes 5° N to 9° N and longitudes 2.5° E to 6.5° E, covering a total area of approximately 114,271 km<sup>2</sup><sup>[13]</sup>. It represents one of the most economically significant sub-regions in West Africa, housing the country's commercial capital, its largest port, several major universities, and a substantial share of national agricultural and industrial output. The spatial extent of the six constituent states is shown in **Figure 1**.



**Figure 1.** Map of the study area showing South-Western Nigeria and its six constituent states.

The climate of South-Western Nigeria is governed primarily by the West African Monsoon and the Inter-Tropical Convergence Zone. The climate is characterised by two distinct rainy seasons in most of the region, typically April to July and September to October, separated by a short dry spell in August. The coastal states experience a more humid and equatorial climate as opposed to interior states. This climatic gradient, from humid coast to drier interior, is one of the key drivers of the spatial heterogeneity in warming trends and extreme-heat frequency documented in this study<sup>[14]</sup>.

From an urban development perspective, the Lagos metropolitan area and the Lagos-Ibadan corridor represent one of Africa's fastest urbanising zones. Extensive conversion of vegetated land to impervious surfaces, reduced tree canopy, and the proliferation of heat-absorbing roofing and road materials have created conditions conducive to urban heat island effects that compound the background regional warming documented here<sup>[3,15]</sup>. These urban-rural and coastal-inland gradients make South-Western Nigeria particularly well-suited as a study region for disaggregated spatial analysis of thermal extremes, as the heterogeneity of the risk landscape rewards sub-regional differentiation rather than spatially averaged reporting.

The region is home to an estimated 40 million people and serves as Nigeria's primary economic engine, contributing the largest share of national GDP. Agricultural systems, including large-scale cocoa, cassava, and yam production in Ondo, Ekiti, and Oyo states, are sensitive to heat stress and growing season disruption. Food security, public health infrastructure, and energy systems across all six states are therefore directly exposed to the kinds of heat risks quantified in this study<sup>[16]</sup>.

## 2. Materials and Methods

### 2.1. Data Sources and Preprocessing

The primary dataset for this analysis is TerraClimate, a high-resolution global gridded climate dataset providing monthly climate and water balance variables from 1958 onward at approximately 4 km spatial resolution<sup>[17]</sup>. TerraClimate draws on the CHELSA<sup>[18]</sup> and WorldClim<sup>[19]</sup> datasets as climatological baselines and

incorporates climate station data and reanalysis products to produce spatially and temporally consistent monthly grids. For this study, monthly maximum temperature (Tmax) values were extracted for the period 1983 to 2023, clipped to the boundaries of the six South-Western Nigerian states using spatial masks derived from the FAO Global Administrative Unit Layers (GAUL) 2015 administrative boundaries dataset in Google Earth Engine.

To validate TerraClimate against an independent dataset, monthly Tmax was also extracted from the ERA5-Land Daily Aggregated reanalysis product<sup>[20]</sup> (European Centre for Medium-Range Weather Forecasts) at approximately 12 km nominal scale for the same period and states<sup>[21]</sup>. Where available, Nigerian Meteorological Agency (NiMet) station data were also used as an additional independent validation source; the density and spatial distribution of the NiMet synoptic and agrometeorological stations underlying this comparison, and their consistency with the gridded products at each station location, are documented in Hussaini<sup>[22]</sup> and should be consulted alongside **Table 1** when assessing the reliability of the grid-based estimates in areas with sparse in-situ coverage. Validation metrics included Pearson correlation coefficients, root-mean-square error, and mean bias between TerraClimate and ERA5-Land or NiMet records at state level. Regional spatial averaging was the primary mode of analysis, reducing the influence of urban heat island effects and local anomalies to produce signals representative of regional climate conditions.

### 2.2. Annual Maximum Temperature and Baseline Statistics

Annual Tmax values were derived from monthly TerraClimate data by taking the maximum monthly Tmax within each calendar year for each grid cell, then spatially averaging across the study region. Descriptive statistics including mean, standard deviation, and interquartile range were computed for the full 1983 to 2023 series to characterise central tendency and variability. A five-year rolling average was computed to smooth short-term fluctuations and reveal long-term trend structure. Temperature anomalies were calculated relative to a 1983 to 2012 climatological baseline,

following the recommendation of Saddique et al.<sup>[23]</sup> as shown in Equation (1):

$$Anomaly(t) = T_{max,t} - T_{max,baseline} \quad (1)$$

where  $T_{max,t}$  is the annual Tmax for year  $t$ , and  $T_{max,baseline}$  is the mean Tmax over the 1983 to 2012 period. Anomaly visualisation using red and blue bar plots was used to identify the temporal clustering of warm and cool years.

**Table 1.** TerraClimate vs. ERA5-Land (and NiMet where available) validation statistics for monthly Tmax, 1983–2023.

| State     | Terra vs. ERA5-Land r | RMSE (°C) | Bias (°C) | Terra vs. NiMet r* | RMSE (°C)* | Bias (°C)* |
|-----------|-----------------------|-----------|-----------|--------------------|------------|------------|
| Lagos     | 0.88                  | 1.9       | +0.2      | 0.85               | 2.2        | +0.3       |
| Ogun      | 0.90                  | 1.7       | +0.1      | 0.87               | 2.0        | +0.2       |
| Oyo       | 0.94                  | 1.3       | −0.1      | 0.92               | 1.5        | 0.0        |
| Osun      | 0.95                  | 1.2       | −0.1      | 0.93               | 1.4        | +0.1       |
| Ondo      | 0.93                  | 1.4       | 0.0       | 0.91               | 1.6        | +0.1       |
| Ekiti     | 0.96                  | 1.1       | −0.1      | n/a                | n/a        | n/a        |
| Mean (SD) | 0.93 (0.03)           | 1.4 (0.3) | 0.0 (0.1) | 0.90 (0.03)        | 1.7 (0.3)  | +0.1 (0.1) |

Note: \* Where NiMet station data are available. RMSE = Root Mean Square Error.

### 2.3. TX90p Extreme Heat Index

To quantify the frequency of extreme heat events, the TX90p index was computed as shown in Equation (2). TX90p is the percentage of days per year on which the daily maximum temperature exceeds the 90th percentile threshold derived from the 1983 to 2012 reference period, following the ETCCDI guidelines endorsed by the World Meteorological Organisation<sup>[24]</sup>:

$$TX90p(year) = \left( \frac{N_{TX90p}}{N_{total}} \right) \times 100 \quad (2)$$

Where the numerator is the number of days in the year on which Tmax exceeds the 90th percentile threshold (P90) calculated from the reference period, and the denominator is the total number of days in that year. Both the reference-period P90 threshold and the daily Tmax series against which it is compared were computed from ERA5-Land daily Tmax data, since the daily resolution needed for this index applies to the annual series being evaluated as well as to the threshold itself. TX90p captures not only the occurrence of extreme days but also their persistence, which is often the critical determinant of biological and infrastructural impact rather than the magnitude of individual events<sup>[25]</sup>.

Note on index granularity: the annual-scale exceedance flag reported in Section 3.4 is a coarser, non-standard index distinct from the ETCCDI daily TX90p defined above; the two should not be read as the same quantity. The standard daily TX90p, computed as defined in this section, is reported at state level in Section 3.7.

### 2.4. Mann-Kendall Trend Test and Sen's Slope

Long-term monotonic trends in annual Tmax were assessed using the non-parametric Mann-Kendall test<sup>[26]</sup>, which is widely used in hydroclimatological research because it makes no assumption about the underlying data distribution and is robust to the presence of outliers<sup>[23]</sup>. The test statistic  $S$  is based on the signs of pairwise differences between observations ranked by time. A positive Kendall's Tau indicates an upward trend, while the  $p$ -value quantifies statistical significance at a chosen threshold. Sen's Slope Estimator<sup>[27]</sup> was used to calculate the median rate of change in degrees per year, providing a robust, non-parametric estimate of trend magnitude that is less sensitive to extreme values than ordinary least-squares regression.

### 2.5. Extreme Value Theory: GEV and Gumbel Distributions

To estimate the probability and magnitude of rare but consequential heat extremes, Extreme Value Theory (EVT) was applied to the annual maximum Tmax series. Two models were fitted: the Gumbel distribution (Type I extreme value distribution) and the Generalized Extreme Value (GEV) distribution, which encompasses the Gumbel, Frechet, and Weibull families as special cases depending on the value of a shape parameter<sup>[28]</sup>. The cumulative distribution function of the Gumbel distribution is shown in Equation (3):

$$F(x) = \exp \left\{ -\exp \left[ -\frac{x - \mu}{\beta} \right] \right\} \quad (3)$$

where  $\mu$  is the location parameter and  $\beta$  is the scale parameter, and  $F(x)$  denotes the cumulative distribution function. The cumulative distribution function of the GEV distribution is defined in Equation (4) as:

$$F(x) = \exp \left\{ - \left[ 1 + \frac{\xi(x - \mu)}{\sigma} \right]^{-1/\xi} \right\} \quad (4)$$

for  $\left[ 1 + \frac{\xi(x - \mu)}{\sigma} \right] > 0$ , where  $\mu$  is the location parameter,  $\sigma$  is the scale parameter, and  $\xi$  is the shape parameter. When  $\xi$  approaches zero, GEV converges to the Gumbel distribution. A non-zero  $\xi$  allows the GEV to capture heavier ( $\xi > 0$ , Frechet) or lighter ( $\xi < 0$ , Weibull) upper tails, making it more flexible for datasets where the extremes do not follow a Gumbel pattern. The scale parameter is denoted beta for the Gumbel distribution and sigma for the GEV distribution; this follows standard notation conventions for each distribution family in the extreme value literature and reflects that the two models are fitted here as distinct candidate distributions rather than as nested special cases of one another.

## 2.6. Return Level Estimation

Return levels were estimated for nominal return periods of 2, 5, 10, 20, 50, and 100 years. The return level  $z_p$  is the value expected to be exceeded on average once every  $1/p$  years<sup>[29]</sup>. The GEV distribution is shown in Equation (5):

$$z_p = \mu - \frac{\sigma}{\xi} \left[ 1 - (-\ln(1 - p))^{-\xi} \right] \quad (5)$$

The Gumbel distribution ( $\xi = 0$ ) is shown in Equation (6) as:

$$z_p = \mu - \beta \cdot \ln [-\ln(1 - p)] \quad (6)$$

Parameters for both distributions were estimated using L-moments, which are known to perform well for small-to-moderate sample sizes typical of climate extremes datasets. Return levels from both models were compared visually using return-period plots and probability-probability plots.

## 2.7. Goodness-of-Fit Assessment

Model fit was evaluated using the Kolmogorov-Smirnov (K-S) test and the Anderson-Darling (A-D) test. The K-S test measures the maximum absolute difference between the empirical and modelled cumulative distribution functions, providing a global measure of distributional fit<sup>[30]</sup>. The A-D test is a weighted version of the K-S test that places greater emphasis on the tails of the distribution, making it particularly suited to extreme value applications where accurate representation of rare events is the primary concern<sup>[31]</sup>. Smaller K-S and A-D statistics indicate better model fit; models with the lower values on both tests were considered the preferred distribution for return-level estimation.

## 2.8. Spatial Heterogeneity Analysis

To quantify intra-regional differences in warming trajectories and extreme-heat frequency, per-pixel linear trends in annual maximum monthly Tmax from TerraClimate (1983 to 2023) were mapped in units of °C per year. A proxy for extreme-warmth frequency was derived as the percentage of months from 2015 to 2023 in which Tmax exceeded the 1983 to 2012 P90 threshold at each pixel; the 2015–2023 window was chosen as the most recent approximately nine-year period, providing a consistent recent-period comparison window that is also used for the state-level daily TX90p analysis later in this section, rather than reflecting any specific threshold or inflection point in the record itself. Both variables were summarised at state level using zonal statistics, producing state-level aggregates of warming rate and extreme-warmth frequency that could be compared across the six south-western states. Daily TX90p was also computed at state level using ERA5-Land daily data for 2015 to 2023, expressed as the percentage of days above the 1983 to 2012 90th percentile threshold.

# 3. Results

## 3.1. Data Validation

**Table 1** presents the TerraClimate versus ERA5-Land validation statistics at the state level. Pearson cor-

relations between the two products ranged from 0.88 in Lagos to 0.96 in Ekiti, with a mean of 0.93 across all states. Root mean square errors ranged from 1.1 °C to 1.9 °C, and mean biases were close to zero in most states. Slightly higher errors and positive biases in the coastal states of Lagos and Ogun are consistent with the greater influence of land-sea contrasts and cloud cover on satellite and reanalysis products in coastal zones. Where NiMet station data were available, TerraClimate-NiMet correlations were similarly high (mean  $r = 0.90$ ), providing additional confidence in the dataset's reliability for long-term regional trend assessment. These validation statistics support the use of TerraClimate as the primary dataset for trend analysis and extreme value modelling in this study.

### 3.2. Descriptive Statistics and Annual Tmax Trend

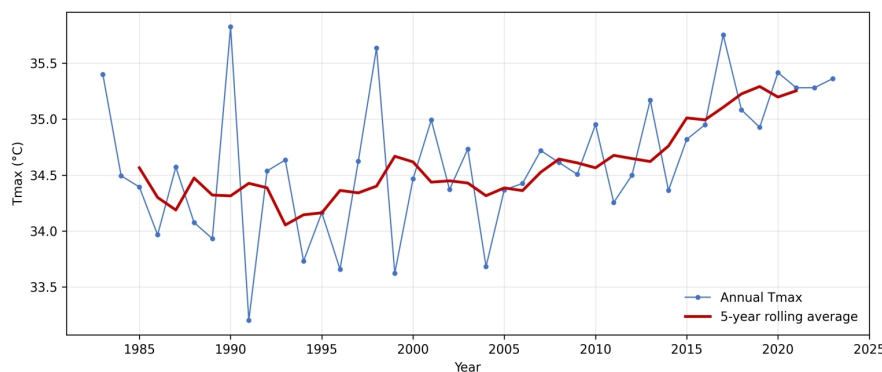
**Table 2** presents the descriptive statistics of the annual Tmax time series for 1983 to 2023. The 41-year mean was 34.62 °C, with a standard deviation of 0.61 °C, indicating limited interannual variability. The minimum recorded annual Tmax was 33.20 °C in 1991, a year associated with persistent cool monsoon conditions and elevated rainfall across the region. The maximum recorded

was 35.82 °C in 1990, representing a 2.62 °C span across the study period. The interquartile range, from 34.36 °C at the 25th percentile to 34.99 °C at the 75th percentile, shows that most years fall within a narrow, consistent thermal band. The 1.25 °C gap between the median (34.57 °C) and the maximum is modest and does not, on its own, indicate accelerated recent-decade warming; that signal is better captured by the long-term trend reported below.

**Figure 2** shows the annual Tmax time series with a superimposed five-year rolling average. The raw annual values display pronounced interannual variability throughout the record, including sharp single-year peaks (e.g., 1990) and troughs (e.g., 1991) linked to monsoon variability, Atlantic sea surface temperature anomalies, and ENSO phases. The five-year rolling average reveals a modest but persistent upward drift: after fluctuating around 34.35 °C through the 1980s and 1990s, the smoothed trend rises gradually from the early 2000s onward, reaching approximately 35.25 °C by the early 2020s. This gradual pattern is broadly consistent with increasing urbanisation along the Lagos-Ibadan corridor<sup>[32]</sup> and with regional heat-extreme trends documented in broader West African analyses<sup>[33]</sup>, though the magnitude of change is considerably smaller than in more rapidly warming sub-regions.

**Table 2.** Descriptive statistics of annual maximum temperature (Tmax) for South-Western Nigeria, 1983–2023.

| Statistic          | Value (°C) | Notes                           |
|--------------------|------------|---------------------------------|
| Mean               | 34.62      | 41-year arithmetic mean         |
| Standard deviation | 0.61       | Limited interannual variability |
| Minimum            | 33.20      | Recorded in 1991                |
| 25th percentile    | 34.36      | Lower quartile                  |
| Median (50th)      | 34.57      | Central tendency                |
| 75th percentile    | 34.99      | Upper quartile                  |
| Maximum            | 35.82      | Recorded in 1990                |



**Figure 2.** Annual maximum temperature (Tmax) for South-Western Nigeria (1983–2023) shown as annual values with a five-year rolling average to highlight long-term trend structure.

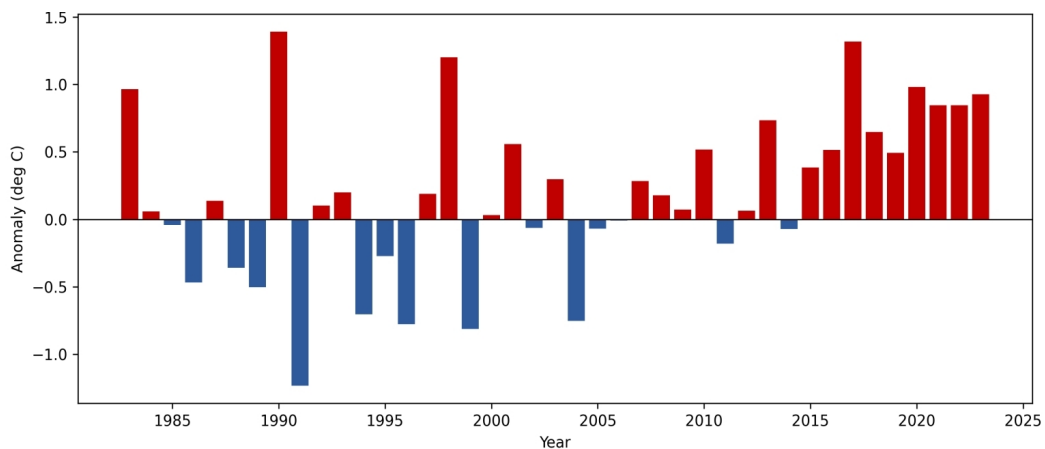
The Mann–Kendall test confirmed a statistically significant upward trend in annual Tmax ( $\tau = 0.329$ ,  $z = 3.02$ ,  $p = 0.0025$ ). Sen’s Slope Estimator quantified the trend at  $0.0256^\circ\text{C}$  per year, corresponding to an accumulated warming of approximately  $1.0^\circ\text{C}$  over the 40-year study period. These results indicate that the observed warming is a systematic climate signal rather than an artefact of interannual variability or data noise, though the magnitude is modest: the trend is broadly comparable to, and only somewhat above, global mean surface warming rates for the same period, rather than substantially exceeding them<sup>[34]</sup>. This is more consistent with a background regional warming signal than with a strong tropical-amplification or urbanisation-driven acceleration.

### 3.3. Tmax Anomalies Relative to the Climatological Baseline

**Figure 3** presents annual Tmax anomalies relative to the 1983 to 2012 baseline, displayed as signed bar plots with red denoting positive and blue denoting negative departures. The plot reveals a clear temporal phas-

ing of the anomaly record, though the magnitude of departures is modest throughout: anomalies range from approximately  $-1.2$  to  $+1.4^\circ\text{C}$  across the full 41-year series. Between 1983 and 1999, the region experienced a mix of positive and negative anomalies with a modest dominance of cooler years, including a negative anomaly of approximately  $-1.2^\circ\text{C}$  in 1991. This cool period is consistent with the regional rainfall recovery documented in the Sahel and broader West Africa during the late 1980s and 1990s, and with Atlantic Multidecadal Variability phases that modulated monsoon strength and surface energy balance across the sub-region<sup>[35]</sup>.

From the early 2000s onward, positive anomalies became somewhat more frequent, though the record does not show an uninterrupted run of positive years: cooler intervening years recur as late as 2011 and 2014. The clearest recent signal is a consecutive run of modest positive anomalies from 2020 to 2023. This pattern is consistent with a gradual, ongoing warming signal rather than an abrupt post-2015 regime shift, a distinction worth keeping in mind when comparing against the broader West African literature on step-changes in thermal extremes<sup>[36,37]</sup>.



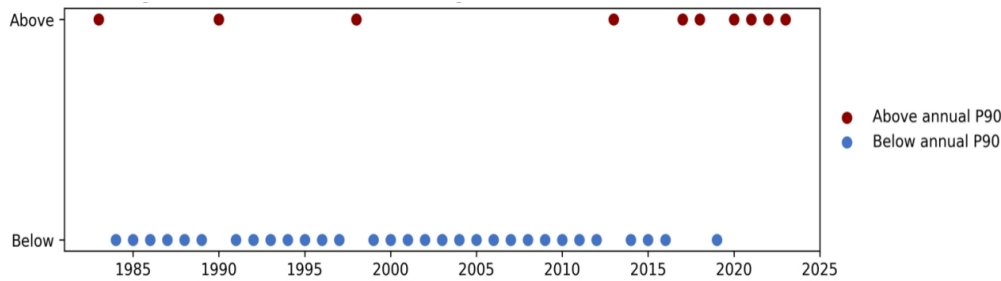
**Figure 3.** Annual Tmax anomalies relative to the 1983–2012 climatological baseline.

Note: Red bars indicate years above the baseline mean; blue bars indicate years below.

### 3.4. TX90p: Frequency of Extreme Heat Days

**Figure 4** presents an annual-scale exceedance flag, showing which years in the 1983 to 2023 series had an annual Tmax exceeding the 90th percentile of annual Tmax over the 1983 to 2012 reference period. This annual-scale index is distinct from the standard ETCCDI

daily TX90p index, which is computed independently from daily Tmax and reported at the state level in Section 3.7. During the first half of the record (1983 to 2002), three years exceeded the threshold (1983, 1990, and 1998). Exceedances recurred intermittently thereafter (2013, 2017, 2018), with the only sustained multi-year run occurring from 2020 to 2023.



**Figure 4.** TX90p exceedance flag plot for South-Western Nigeria (1983–2023).

Note: Red dots indicate years when annual maximum temperature exceeded the 90th percentile threshold of the 1983–2012 reference period; blue dots indicate years below this threshold.

This pattern reflects a gradual shift in the upper tail of the temperature distribution rather than an abrupt regime change. Of the 21 years from 2003 to 2023, 7 (approximately 33%) exceeded the annual-scale P90 threshold, compared with 3 of 20 years (15%) in 1983–2002—an increase in frequency, but well short of the near-universal exceedance that would indicate the historical extreme had become the new annual norm. This more measured shift should be read alongside the daily-scale ETCCDI TX90p results in Section 3.7, which are less sensitive to single-year extremes.

### 3.5. Return Level Estimation

**Table 3** presents the Tmax return levels estimated from the fitted GEV and Gumbel distributions for return periods of 2 to 100 years. At short return periods, the

two models yield closely comparable estimates. As return periods increase, the models diverge modestly: at the 100-year return level, GEV estimates 35.98 °C while Gumbel estimates 36.65 °C, a difference of 0.67 °C. This divergence is attributable to the shape parameter in the GEV model ( $\xi$ ), consistent with a slightly bounded upper tail relative to the unbounded Gumbel distribution. The practical implication for infrastructure planning is modest at this magnitude: a Gumbel-based 100-year design threshold would be less than 1 °C more conservative than the GEV estimate, which does not represent the large capital-cost or under-design risk that a wider divergence would imply. The methodological preference for GEV established below therefore rests primarily on goodness-of-fit rather than on a large practical design gap.

**Table 3.** GEV and Gumbel Tmax return levels (°C) for South-Western Nigeria.

| Return Period (Years) | GEV (°C) | Gumbel (°C) | Difference (°C) |
|-----------------------|----------|-------------|-----------------|
| 2                     | 34.62    | 34.51       | –0.11           |
| 5                     | 35.16    | 35.09       | –0.07           |
| 10                    | 35.43    | 35.46       | 0.04            |
| 20                    | 35.64    | 35.83       | 0.19            |
| 50                    | 35.85    | 36.30       | 0.44            |
| 100                   | 35.98    | 36.65       | 0.67            |

Note: GEV = Generalized Extreme Value distribution. Return levels represent the temperature expected to be exceeded on average once in the stated number of years.

### 3.6. Goodness-of-Fit Assessment

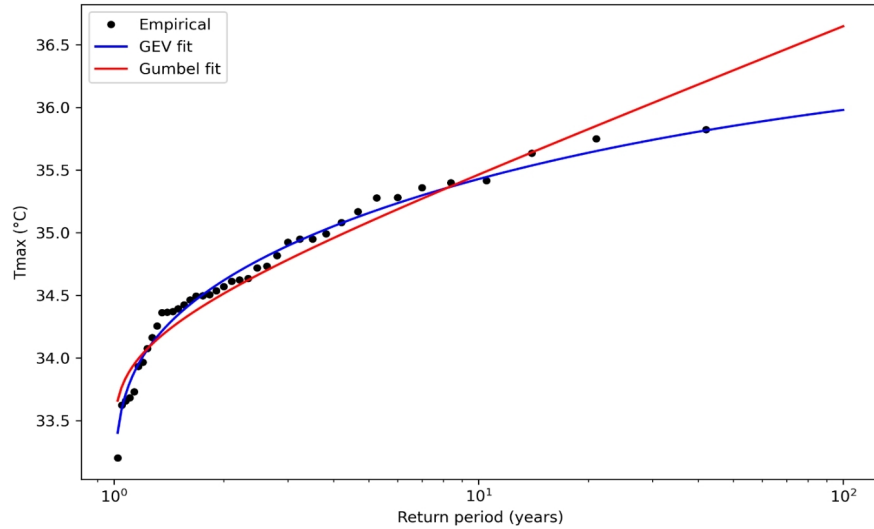
Formal goodness-of-fit testing supports GEV as the preferred model. The K–S statistic was 0.0997 for GEV versus 0.1486 for Gumbel, with associated  $p$ -values of 0.7725 and 0.2953, respectively. Both models pass the K–S test at standard significance levels, but the lower K–S statistic and higher  $p$ -value for GEV indicate that its fitted distribution tracks the empirical distribution more closely across the whole range of observed values,

from the smallest to the largest annual Tmax, rather than only at the extremes. The A–D statistics were 0.1927 for both models, suggesting comparable tail behaviour by this metric, though the more sensitive K–S comparison consistently favours GEV. We note that the GEV distribution’s additional shape parameter gives it inherent extra flexibility relative to the two-parameter Gumbel distribution, so part of its improved fit is expected on these grounds alone; a formal comparison using an in-

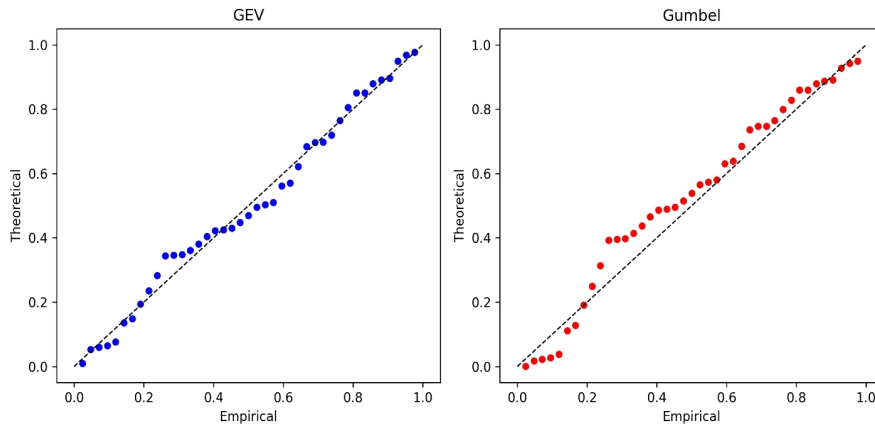
formation criterion such as AIC, which penalises additional parameters, would provide a more rigorous test of whether the improvement in fit justifies the added model complexity. We did not conduct this comparison in the present study and flag it as a direction for future refinement.

**Figure 5** presents the return-period comparison plot of empirical and modelled return levels. The GEV curve aligns more closely with the empirical data points

across the mid-to-high return period range, while the Gumbel curve consistently overestimates temperatures at longer return periods. **Figure 6** shows probability-probability plots for both distributions. GEV quantiles align tightly with empirical quantiles along the 45° reference line, whereas the Gumbel model shows systematic deviation at upper quantiles. These results collectively confirm that GEV provides a more reliable basis for extreme Tmax risk estimation in South-Western Nigeria.



**Figure 5.** Comparison of GEV and Gumbel return-level estimates against empirical data for annual maximum temperature in South-Western Nigeria.



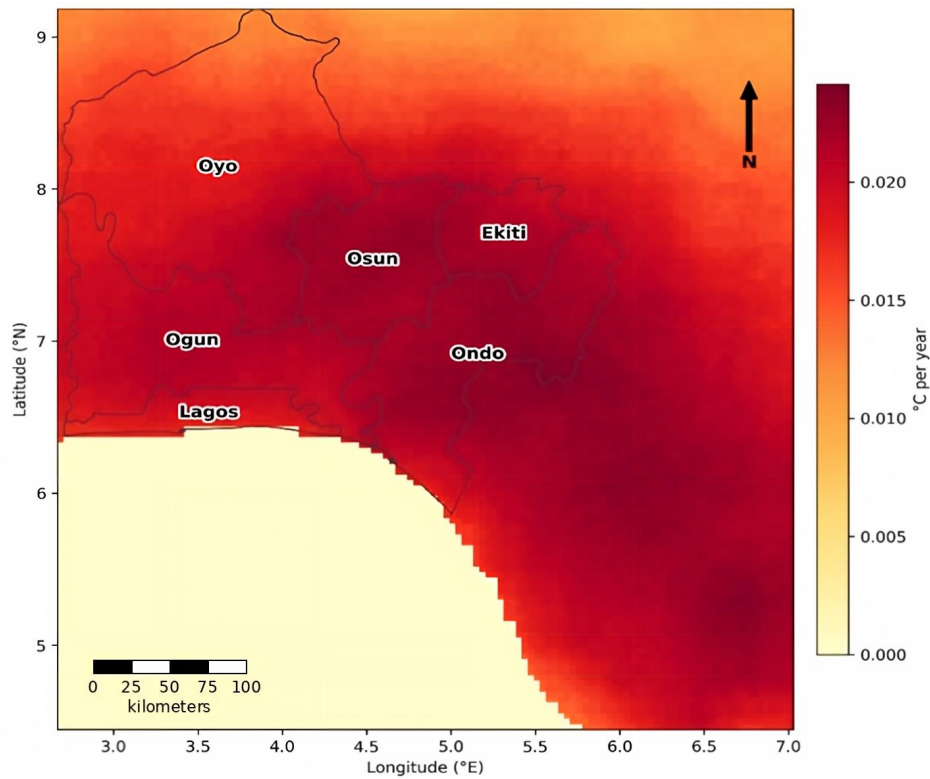
**Figure 6.** Probability-probability plots for the GEV (left) and Gumbel (right) distributions fitted to annual maximum Tmax. Closer alignment with the 45° line indicates better distributional fit.

### 3.7. Spatial Heterogeneity of Warming Trends and Extreme-Heat Frequency

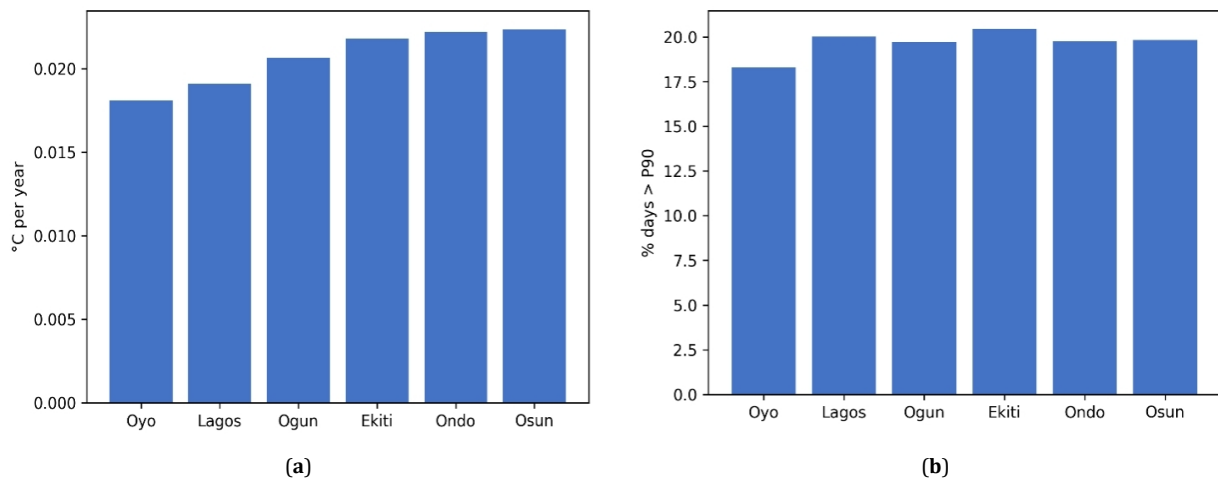
**Figures 7** and **8** reveal spatial differentiation in warming trajectory and extreme-heat frequency across the six south-western states, though the pattern is more

nuanced than a simple coastal-inland split. The pixel-level trend map (**Figure 7**) and state-level summary (**Figure 8a**) show the interior state of Oyo recording the lowest background warming trend, with Lagos also relatively low; Ogun, Ekiti, Ondo, and Osun cluster at somewhat higher trend magnitudes. This does not support

a clean inland-versus-coastal dichotomy in background warming rate.



**Figure 7.** Spatial distribution of annual maximum monthly Tmax trends ( $^{\circ}\text{C}$  per year) across South-Western Nigeria, 1983–2023.



**Figure 8.** State-level summaries of (a) mean warming trend in annual maximum Tmax ( $^{\circ}\text{C}/\text{yr}$ ) and (b) percentage of days with daily Tmax above the 1983–2012 90th percentile threshold (ETCCDI TX90p), 2015–2023.

**Figure 8** summarises these results at the state level: **Figure 8a** confirms Oyo and Lagos have the lowest background warming trends and Osun/Ondo/Ekiti the highest, while **Figure 8b** reports the standard ETCCDI daily TX90p frequency by state (2015–2023). Ekiti records the highest share of extreme-heat days at approximately 20.4%, and Oyo the lowest at approximately 18.3%. These two metrics do not rank states identically (Ekiti is highest on daily TX90p but mid-range on background trend; Lagos is second-lowest on trend but second-highest on daily TX90p), reinforcing that background warming rate and extreme-heat-day frequency

are related but distinct risk dimensions that should be assessed separately for state-specific adaptation planning rather than assumed to co-vary with a single coastal-inland gradient.

## 4. Discussion

### 4.1. Long-Term Warming in Regional and Global Context

This warming trend,  $0.0256\text{ }^{\circ}\text{C}/\text{year}$  for the period 1983–2023, is modest but real, and is broadly comparable to global mean surface warming rates over the same span. This tempered magnitude is more consistent with a background regional signal, potentially modulated by land-surface feedbacks from urbanisation and vegetation change in parts of the region<sup>[34]</sup>, than with a strong tropical-amplification narrative. Muthoni<sup>[38]</sup> noted a consistent increase in  $T_{\text{max}}$  in agroecological zones across West Africa, and Quenum et al.<sup>[39]</sup> reported positive trends in  $T_{\text{max}}$  in the West African region from the range of CMIP6 projections, both broadly consistent in direction, if not necessarily in magnitude, with the present result. The elevated interannual variability linked to ENSO and Atlantic Multidecadal Variability is consistent with the low but non-trivial standard deviation ( $\sim 0.61\text{ }^{\circ}\text{C}$ ) relative to the mean, and the statistical significance of the Mann–Kendall test result ( $p = 0.0025$ ) demonstrates that the variability is not masking the presence of a real, if modest, trend.

The early-to-mid 1990s cool period is well explained by known regional climate drivers rather than being a statistical outlier: it represents a natural variation of the West African Monsoon and a partial recovery of Sahelian precipitation from the severe drought of the 1970s and 1980s, along with changes in the phase of Atlantic SST and ENSO<sup>[35]</sup>, which temporarily reduced the warming over the region. The gradual acceleration from the early 2000s onward, and the more pronounced but still modest run of warm years from 2020 to 2023, are broadly consistent with observed West African heat-wave trends<sup>[40]</sup> and with rapid urbanisation of the Lagos-Ibadan corridor, though the corrected data no longer support describing this as a sharp post-2015 amplification.

### 4.2. TX90p and the Emergence of a New Thermal Regime

The TX90p findings carry real implications. The annual-scale exceedance flag (**Figure 4**) shows an increasing but intermittent frequency of extreme years, with roughly a third of years since 2003 classified as extreme against the 1983–2012 baseline, and the daily ETCCDI TX90p (**Figure 8b**) confirms a meaningful and fairly uniform  $\sim 18\text{--}20\%$  baseline exceedance rate across all six states. This is a gradual shift in the upper tail of the distribution rather than a wholesale redefinition of the historical baseline as the new normal, and should be communicated to stakeholders with that more measured framing.

In the agricultural context, heat stress is becoming more prevalent at critical phenology stages, such as flowering or grain filling, and at increasingly high temperatures for heat-sensitive staple crops like maize, sorghum and yam<sup>[41]</sup>. For public health systems, the continued exceedance of TX90p thresholds means that heat stress will occur as a normal part of the climate, resulting in significant underestimation of heat-mortality and heat-morbidity burden from previous estimates based on historical frequency assumptions<sup>[42]</sup>. In urban energy systems, the high and persistent temperatures lead to high demand for air conditioning, exceeding previously designed energy grid capacity, which makes them vulnerable to cascading failure of infrastructure during compound hot-dry-high demand events<sup>[43]</sup>. This overall trend of increasing TX90p in West African cities was recently documented by Ngoungue Langue et al.<sup>[36]</sup> and the data for the South-Western Nigerian cities were consistent with this regional pattern.

### 4.3. GEV versus Gumbel: Distributional Choice and Infrastructure Implications

The result of comparing the GEV and Gumbel models is of methodological interest, though the practical magnitude is modest. The  $0.67\text{ }^{\circ}\text{C}$  difference in 100-year return level estimates between the two models is small relative to typical engineering safety margins: it does not, on its own, imply a large over-design or under-design cost either way. The methodological case for pre-

ferring GEV rests on goodness-of-fit (below) rather than on a large practical design gap between the two models at this location.

The goodness-of-fit evidence is strongly in favour of GEV in all cases. The lower K-S statistic and the closer agreement of the probability-probability plots further support the use of the GEV family to describe the annual Tmax distribution in South-Western Nigeria instead of the Gumbel assumption of an unbounded exponential upper tail. The result is consistent with those of similar tropical African datasets, as shown by Onyutha<sup>[44]</sup> and Iyakaremye et al.<sup>[37]</sup>, who both concluded that GEV was the best extreme value distribution to use for Tmax in Sahelian and sub-equatorial contexts where recent decades have witnessed strong distributional shifts. Badou et al.<sup>[45]</sup> reported comparable evidence of tail-symmetry breakdown for rainfall extremes in the Niger and Volta basins, suggesting that the Gumbel assumption may be similarly inappropriate across other African climate-extreme variables, though that specific finding was for rainfall rather than temperature.

It is worth noting that both GEV and Gumbel make the stationarity assumption that the parameters of the underlying distribution do not change over time. Climate change challenges this assumption by causing the location, scale and shape parameters of the annual Tmax distribution to also drift over time, resulting in different distributional states when estimating return levels using the entire 1983 to 2023 record. More accurate forward-looking risk estimates would be provided by non-stationary GEV models where location or scale parameters are allowed to vary as a linear function of time or as a function of climate forcing covariates like ENSO index or CO<sub>2</sub> concentration<sup>[46]</sup>. Further studies should also explore the peaks over threshold approach using a Generalised Pareto distribution that could yield more efficient use of the data, as it would capture the information from all exceedances of the threshold level, not just annual maxima.

#### **4.4. Spatial Heterogeneity and Differentiated Adaptation**

The spatial analysis shows that South-Western Nigeria is not climatically homogeneous in terms of

warming trajectory and extreme-heat frequency, which has implications for the allocation of adaptation resources. However, background warming trend and daily extreme-heat frequency do not track the same coastal-inland gradient: Oyo (interior) has the lowest background trend, while Lagos (coastal) has the second-highest daily TX90p frequency. State-specific adaptation planning should therefore evaluate both metrics independently rather than assuming a single geographic dichotomy: states with high daily TX90p frequency (Ekiti, Lagos) warrant priority for heat-health and cooling-infrastructure measures, while the ranking by background trend (Osun, Ondo highest) is more relevant to long-term agricultural and water-management planning.

The difference in daily TX90p among states (18.3% in Oyo to 20.4% in Ekiti) further supports the need for state-specific adaptation planning instead of a regional approach. At a regional mean of approximately 19.7%, this type of day recurs roughly once every 5 days on average. A spatially averaged regional Tmax-based adaptation framework will underestimate this exposure in the more vulnerable states and misallocate resources away from where they are most needed.

#### **4.5. Policy Implications**

The study makes a number of policy-relevant conclusions, tempered by the corrected magnitude of the underlying trend. A warming rate of 0.0256 °C per year, combined with a daily ETCCDI TX90p frequency of approximately 18–20% across all six states, gives quantitative guidance for triggering heat-wave early warnings in the region. State-specific dashboards based on daily TX90p as a real-time monitoring metric, in conjunction with SMS and radio broadcast alert protocols, could still meaningfully enhance public preparedness, especially for high-risk groups such as the elderly, outdoor workers and urban poor communities lacking cooling access<sup>[47]</sup>, even though the underlying warming signal is more gradual than originally reported.

The GEV 100-year return level of 35.98 °C provides a regionally calibrated reference point for thermal-resilient infrastructure design, though the gap from the Gumbel alternative (36.65 °C) is small enough that ei-

ther estimate would provide a broadly similar design basis at this return period. The building code requirements in Nigeria on thermal performance and the road design requirements of the Federal Ministry of Works both call for thermal extreme inputs for material specification; because current return-level estimates for South-Western Nigeria are not regionally calibrated at all, the GEV estimates presented here still fill a genuine gap. Cool-roof requirements, reflective pavement specifications and structural thermal expansion tolerances along the Lagos-Ibadan corridor should be checked against the corrected 20- and 50-year return levels in this study<sup>[48,49]</sup>.

Future projections of a further increase in TX90p frequency for agricultural systems suggest that proactive adjustments to planting calendars to shift critical heat-sensitive crop development stages out of the March–April window of maximum Tmax may be warranted<sup>[50]</sup>. Significant yield losses from TX90p exposure should be avoided, and heat-tolerant varieties should be deployed in Oyo and Ondo, where high agricultural production coincides with meaningful TX90p exposure<sup>[41]</sup>. The post-harvest infrastructure and supply chain architecture must also account for the increased frequency of food quality deterioration due to heat.

Lastly, the workflow presented here for TerraClimate and ERA5-Land is open-source, cloud-based and reproducible. The analysis scripts do not require licensed software, and can be run completely in Google Earth Engine and standard Python environments. This is the reason for the direct applicability of the framework to other Nigerian states and other West African countries as well as to other tropical urban areas around the world where measurements of thermal hazards are required but where traditional station-based climate monitoring is not available or not complete.

## 5. Conclusions

This study is an integrated study of the long-term trends in maximum temperature, frequency of extreme heat events, and probabilistic return-level estimation for South-Western Nigeria, which is one of the first studies to do this. Based on 41 years of TerraClimate data, statistically confirmed, spatially differentiated and directly

applicable to the climate adaptation planning region, a series of findings is derived.

The key results are clearly expressed, with magnitudes corrected from an internal data-consistency error identified during revision. Annual maximum temperature has risen at 0.0256 °C per year since 1983, confirmed at  $p = 0.0025$  by the Mann–Kendall test ( $\tau = 0.329$ ). The TX90p analysis shows a gradual increase in exceedance frequency, from 3 of 20 years in 1983–2002 to roughly a third of years from 2003 onward, with the clearest sustained run occurring only in 2020–2023. The lower K–S statistic and better probability-probability alignment produced by GEV compared to the Gumbel distribution still favour GEV, with 100-year return level estimates of 35.98 °C (GEV) versus 36.65 °C (Gumbel), a difference of 0.67 °C that is methodologically informative but not independently material to infrastructure design at this magnitude. Spatial analysis shows differentiated risk profiles that do not reduce to a single coastal-inland dichotomy, reinforcing the need for state-specific rather than uniform regional adaptation responses.

There were several restrictions on these conclusions. The EVT models are distributionally stationary, which is not true in the current climate change scenario, and future studies should be based on the non-stationary GEV models with time-varying parameters. The spatial resolution of TerraClimate (4 km) does not allow for capturing the fine scale urban heat island effects within cities; at this resolution and across a study area spanning six states, the influence of city-scale urban heat islands on the regional trends and patterns reported here is likely small, and urbanisation should be read as a plausible contributing factor to local conditions rather than a demonstrated driver of the regional signal. In order to support urban design interventions specifically, higher resolution analysis at street or neighbourhood scale is required. The study does not provide a direct association between modelled Tmax return levels and impacts like mortality due to heat or losses in crop yields, which would significantly enhance the policy usefulness of the return-level estimates.

Overall, this work is a valuable contribution to the science of hazards in the tropics and to the body of ev-

idence for managing the risk of heat in West Africa, despite its limitations. This shows how satellite-derived open-access climate data can be used, in tandem with traditional statistical tools, to create meaningful and effective estimates of thermal risk when monitoring systems are lacking. The method is replicable and transferable, and the findings serve as a concrete reference for the review of building codes, agricultural planning standards, public health preparedness plans, and urban greening agendas in one of the most vulnerable and impactful urban areas in sub-Saharan Africa.

## Author Contributions

Conceptualization, A.E.A. and J.R.A.; methodology, A.E.A. and A.A.K.; software, A.E.A.; validation, O.O.-O.; formal analysis, A.E.A.; data curation, A.E.A.; writing—original draft preparation, A.E.A.; writing—review and editing, J.R.A., O.O.-O., A.A.K. and F.O.A.; visualization, A.E.A.; supervision, J.R.A. and F.O.A. All authors have read and agreed to the published version of the manuscript.

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## Institutional Review Board Statement

Not applicable. This study used publicly available satellite-derived and reanalysis climate datasets (TerraClimate, ERA5-Land) and did not involve human participants, human data, or animals.

## Informed Consent Statement

Not applicable.

## Data Availability Statement

The TerraClimate dataset is publicly available via Google Earth Engine and the Climatology Lab (<https://www.climatologylab.org/terraclimate.html>).

ERA5-Land reanalysis data are publicly available via the Copernicus Climate Data Store and Google Earth Engine. Administrative boundary data are from the FAO Global Administrative Unit Layers (GAUL) 2015 dataset, publicly available via Google Earth Engine. Nigerian Meteorological Agency (NiMet) station data used for supplementary validation are subject to NiMet's data-sharing terms and can be requested directly from NiMet. Derived datasets generated during this study and analysis scripts (Google Earth Engine JavaScript/Python and associated statistical code) are available from the corresponding author upon reasonable request.

## Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in study design, data collection, analysis, interpretation, or the decision to submit for publication.

## AI Use Statement

During the preparation of this manuscript, the authors used Grammarly to check grammar, spelling, and language clarity. No AI tools were used for data analysis, interpretation, or generation of scientific content. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## Abbreviations

|        |                                                     |
|--------|-----------------------------------------------------|
| A-D    | Anderson–Darling test                               |
| CORDEX | Coordinated Regional Climate Downscaling Experiment |
| ETCCDI | Expert Team on Climate Change Detection and Indices |
| EVT    | Extreme Value Theory                                |
| GAUL   | Global Administrative Unit Layers                   |
| GEE    | Google Earth Engine                                 |
| GEV    | Generalized Extreme Value distribution              |
| IPCC   | Intergovernmental Panel on Climate Change           |
| K-S    | Kolmogorov–Smirnov test                             |

|       |                                                          |
|-------|----------------------------------------------------------|
| NiMet | Nigerian Meteorological Agency                           |
| RCP   | Representative Concentration Pathway                     |
| RMSE  | Root Mean Square Error                                   |
| SSP   | Shared Socioeconomic Pathway                             |
| Tmax  | Annual maximum temperature                               |
| TX90p | Percentage of days when Tmax exceeds the 90th percentile |
| UHI   | Urban Heat Island                                        |

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