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CLIMATIC VARIABILITY OF RAINFALL AND TEMPERATURE OVER SELECTED STATIONS IN AFRICA SUB-REGIONS

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Abstract

Research has shown that Africa climate experience unpredictability presents serious obstacles to agriculture, environmental sustainability, and water resource management. For this research 26 years (2000–2025) dataset of MERRA-2 reanalysis data were used, to evaluate the spatial and temporal variability of temperature and rainfall throughout the following stations: Abuja, Cairo, Luanda, Nairobi, and Johannesburg. A one-way ANOVA, descriptive statistics, data quality control, and the Mann-Kendall test using Sen's slope estimator were all used for the analysis. The results showed significant environmental variety, with temperatures ranging from 289.6 to 299.2 K (16.5–26.1 °C) and annual rainfall from less than 50 mm in Cairo to more than 2,400 mm in Abuja. The temperature rose by 0.1–0.9 K while regional rainfall increased by 2–10%, with the biggest increases happening in the direction of Nairobi and Johannesburg. There were significant inter-station variances ($p < 0.001$), ranging from 243.34 to 1,694.54 mm in rainfall, 9.06 °C in maximum temperature differences, and 13.88 °C in minimum temperature differences. Highly substantial geographical variation in maximum ($F = 646.859$) and minimum ($F = 1371.112$) temperatures was verified by one-way ANOVA ($p < 0.001$). Sen's slopes ranged from –3.63 to 5.93, indicating significant natural climate variability, despite the Mann-Kendall test showing no statistically significant monthly rainfall trends. Growing climate variability is highlighted by rising temperature trends and more frequent rainfall extremes after 2010. This knowledge is vital for agricultural planning, water resource management, climate adaption, and catastrophe risk reduction throughout Africa.

Keywords: Atmospheric Variation, Datasets, Meteorology, Statistical Tools, Stations

1. INTRODUCTION

With substantial effects on ecosystems, agriculture, water resources, biodiversity, human health, and socioeconomic development, climate variability and climate change have become key worldwide environmental issues (Chu et al., 2010). Rising temperatures, protracted droughts, flooding incidents, uneven rainfall distribution, and an increase in the frequency of extreme

weather events are all signs of a changing climate throughout Africa (Serdeczny et al., 2017; Thornton et al., 2011). In areas where livelihoods primarily depend on climate-sensitive industries including agriculture, water resources, forestry, tourism, livestock production, and energy generation, these climatic disruptions continue to pose a danger to sustainable development (Cooper et al., 2008; Lobell, 2014).

Hydrological processes, crop production, environmental sustainability, and food security are all directly impacted by temperature and rainfall variations (Smit & Wandel, 2006). According to Moriasi et al. (2015) and Serdeczny et al. (2017), comprehending the spatiotemporal variability of climatic indicators has become crucial for catastrophe risk reduction, environmental management, and climate adaption.

Due to its heavy reliance on natural resources and the limited ability of many of its nations to adapt, Africa is widely acknowledged as one of the continent's most vulnerable to climate variability and climate change (Thornton et al., 2011). A number of African regions have already experienced decreased agricultural productivity, desertification, ecosystem degradation, water scarcity, and elevated health risks associated with climate change due to changes in rainfall and temperature patterns (Adhikari et al., 2015; Bessah et al., 2020; Githeko et al., 2000; Keller et al., 2022). According to earlier research, rising temperatures and erratic precipitation patterns are predicted to worsen environmental stress and decrease water availability in many African regions (Adhikari et al., 2015; Keller et al., 2011; Serdeczny et al., 2017). Urbanization, deforestation, unsustainable land-use practices, and rapid population expansion all exacerbate the effects of climate variability on human and environmental systems (Cooper et al., 2008; Ogunbode et al., 2025; Smit & Wandel, 2006). Thus, thorough research on temperature and rainfall variability is

required to promote sustainable development planning throughout the continent and enhance climate resilience (Bessah et al., 2021).

Since rain-fed agriculture is the primary source of income for most African nations, rainfall variability continues to be one of the continent's most pressing climate problems (Cooper et al., 2008; Thornton et al., 2011). Food security and economic stability can be threatened by variations in rainfall distribution, which can lead to droughts, floods, crop failure, soil erosion, and diminishing water resources (Donat et al., 2016; Lobell, 2014). Numerous studies have shown that rainfall patterns in many African regions are becoming more erratic, with longer dry spells, shorter wet seasons, and delayed rainfall onset (Adeola et al., 2026; Donat et al., 2016; Gebrechorkos et al., 2019). In numerous African climatic zones, rising temperatures linked to global warming have also been noted (Luhunga et al., 2018; Gebrechorkos et al., 2019; Samson and Aweda 2025). Greater evapotranspiration, decreased soil moisture, greater heat stress, decreased agricultural output, and more frequent drought conditions are all consequences of rising temperatures (Adhikari et al., 2015; Thornton et al., 2011). While Gebrechorkos et al. (2019) found long-term variations in temperature and rainfall across several climatic zones in East Africa, Luhunga et al. (2018) indicated notable warming trends throughout the continent.

According to Gebrechorkos et al. (2018) and Luhunga et al. (2018), the African continent is made up of various climatic regions, such as West Africa, East Africa, Central Africa, North Africa, and Southern Africa, each of which has unique rainfall regimes and temperature patterns. While East Africa has bimodal rainfall patterns connected to the migration of the Inter-Tropical Convergence Zone (ITCZ), West Africa experiences heavy seasonal rainfall linked to the West African Monsoon and Inter-Tropical Discontinuity (ITD) (Gebrechorkos et al., 2018). While North Africa is primarily arid with little precipitation, Southern Africa commonly experiences semi-arid

climates and numerous drought periods (Serdeczny et al., 2017). Due to differences in terrain, atmospheric circulation, vegetation cover, land-use patterns, and proximity to seas, climate variability thus shows significant spatial heterogeneity among African sub-regions (Luhunga et al., 2018; Gebrechorkos et al., 2019; Wilby & Dawson 2013).

Global Climate Models (GCMs), Regional Climate Models (RCMs), statistical downscaling methods, satellite observations, and reanalysis datasets have all been used in several African studies to examine climate variability and future climate forecasts (Mwabumba et al., 2022; Gulacha & Mulungu, 2017). Because general circulation models can mimic atmospheric, oceanic, and land-surface phenomena based on energy and mass balance equations, they have been widely used in climate studies (Chiew et al., 2009; Cooper et al., 2008). However, due to their inability to accurately depict local climatic variables, terrain, and convective processes, many GCMs' coarse spatial resolution restricts their applicability for local-scale climate studies (Donat et al., 2016; Keller et al., 2011). In order to produce higher-resolution climate data appropriate for regional and local climate assessments, statistical downscaling techniques like the Statistical DownScaling Model (SDSM) and Long Ashton Research Station Weather Generator (LARS-WG) have been used more frequently (Wilby et al., 2002; Semenov et al., 2002; Chen et al., 2013). SDSM and LARS-WG models have been effectively used in earlier research to downscale temperature and rainfall under future climate scenarios in several African locations (Amirabadizadeh et al., 2016; Gulacha & Mulungu, 2017).

Because of their enhanced spatial and temporal coverage across data-poor African regions, satellite and reanalysis climate datasets like CHIRPS, MERRA-2, NASA POWER, and CORDEX-Africa RCM outputs have also grown in importance as tools for climate variability studies (Funk et al., 2015; Gebrechorkos et al., 2018). Studies by Katsektor et al. (2024), and Mwabumba et al. (2022)

showed how satellite-derived temperature and rainfall datasets can be used for hydrological research and climate assessment in Africa. According to Kim et al. (2014) and Amekudzi et al. (2016), CORDEX regional climate simulations have demonstrated adequate performance in recreating rainfall and temperature characteristics across multiple African climatic zones.

Increasing temperature trends and significant changes in rainfall features under various climatic scenarios have been observed by recent climate studies carried out throughout Africa (Mwabumba et al., 2022; Bessah et al., 2021; Nkiaka et al., 2017). Through research on atmospheric processes, climate modeling, solar radiation variability, rain rate prediction, environmental physics, radio refractivity analysis, and machine learning applications throughout tropical African regions, Aweda et al., 2022 made a substantial contribution to our understanding of climatic variability and environmental dynamics in Africa. In order to comprehend climate variability and environmental sustainability throughout Africa, their studies highlighted the significance of long-term meteorological datasets, satellite observations, atmospheric modeling, and machine learning techniques (Aweda et al., 2022; Samson et al., 2024; Adebayo et al., 2022). Similarly, under RCP4.5 and RCP8.5 climate scenarios, Mwabumba et al. (2022) predicted rising rainfall and temperature trends across watersheds surrounding Tanzania's Ngorongoro Conservation Area, while Umar et al. (2019) used Mann-Kendall trend analysis to report rising rainfall and temperature variability in semi-arid regions of Nigeria. According to Bessah et al. (2021) and Serdeczny et al. (2017), other research conducted in sub-Saharan Africa has also shown rising climate variability, which has consequences for agriculture, biodiversity protection, water resource management, and socioeconomic stability.

Climate variability has continued to have an impact on animal management, ecosystem sustainability, and biodiversity conservation in East Africa, especially in protected areas like

Tanzania's Ngorongoro Conservation Area (Estes et al., 2006). Additionally, research by Göaba and Gaidzik (2011a, 2011b) demonstrated the significance of topographical and geological features in affecting environmental processes and climatic variability throughout East African Rift systems.

The geographical and temporal variability of temperature and rainfall among several chosen meteorological stations within African sub-regions is still poorly understood despite a large number of climate research conducted throughout Africa (Gebrechorkos et al., 2019; Mwabumba et al., 2022). A thorough understanding of climate variability patterns throughout several African climatic zones has been limited by numerous prior studies that concentrated on regional-scale analysis or specific climatic variables. Additionally, due to variations in terrain, vegetation cover, urbanization, atmospheric circulation, and land-surface interactions, climate variability frequently displays strong local characteristics (Luhunga et al., 2018; Gebrechorkos et al., 2019). For precise evaluation of climate trends and variability at local scales, station-based analyses are still necessary (Moriasi et al., 2015; Larbi et al., 2018; López-Moreno et al. 2010).

For sustainable environmental management, agricultural planning, climate adaption, disaster preparedness, and policy formation, it is essential to comprehend the climatic variability of temperature and rainfall across specific African stations (Smit & Wandel, 2006). Comprehensive climate assessments offer important scientific data for planning food security, infrastructure development, ecosystem protection, water resource management, and environmental sustainability (Moriasi et al., 2015; Thornton et al., 2011). Additionally, this knowledge is crucial for enhancing climate resilience and promoting socioeconomic development in all African nations (Bessah et al., 2021; Serdeczny et al., 2017; Omambia, and Gu 2010; Li & Babovic 2019). Furthermore, research on climate variability is crucial to comprehending future climate risks and vulnerabilities,

especially in areas where economic activity is heavily reliant on climate change (Lobell, 2014; Adhikari et al., 2015).

Thus, the climatic variability of temperature and rainfall among a few locations within African sub-regions is examined in this work. Examining rainfall and temperature fluctuations in space and time, identifying current climatic trends and anomalies, and assessing the effects of climate variability on environmental sustainability and socioeconomic activity throughout the chosen stations are the objectives of the study. Policymakers, environmental managers, academics, and stakeholders engaged in climate adaptation and sustainable development planning throughout Africa are anticipated to benefit from the study's findings.

2. MATERIALS AND METHODS

2.1 Examine the location, elevation, and study area.

The study's stations were situated in the Western, Northern, Eastern, and Southern sub-regions of Africa. These stations were selected geographically based on variables like proximity to the coast, the Sahara, the rainforest, and the significance of farming. Table 1 and Figure 1, respectively, display the coordinates, elevation data, and plotted positions for each station.

Table 1: The coordinates and elevation of the selected studied stations

Nation	Locations	Longitude	Latitude	Altitude(m)	Period
Angola	Luanda	8.8157°S	13.2302°E	6.0	2000-2025
Egypt	Cairo	30.0444°N	31.2357°E	23.0	2000-2025
Kenya	Nairobi	1.2921°S	36.8219°E	1795	2000-2025
Nigeria	Abuja	9.0563°N	7.4985°E	360	2000-2025
South Africa	Johannesburg	28.0416°N	-26.2044°E	1753	2000-2025

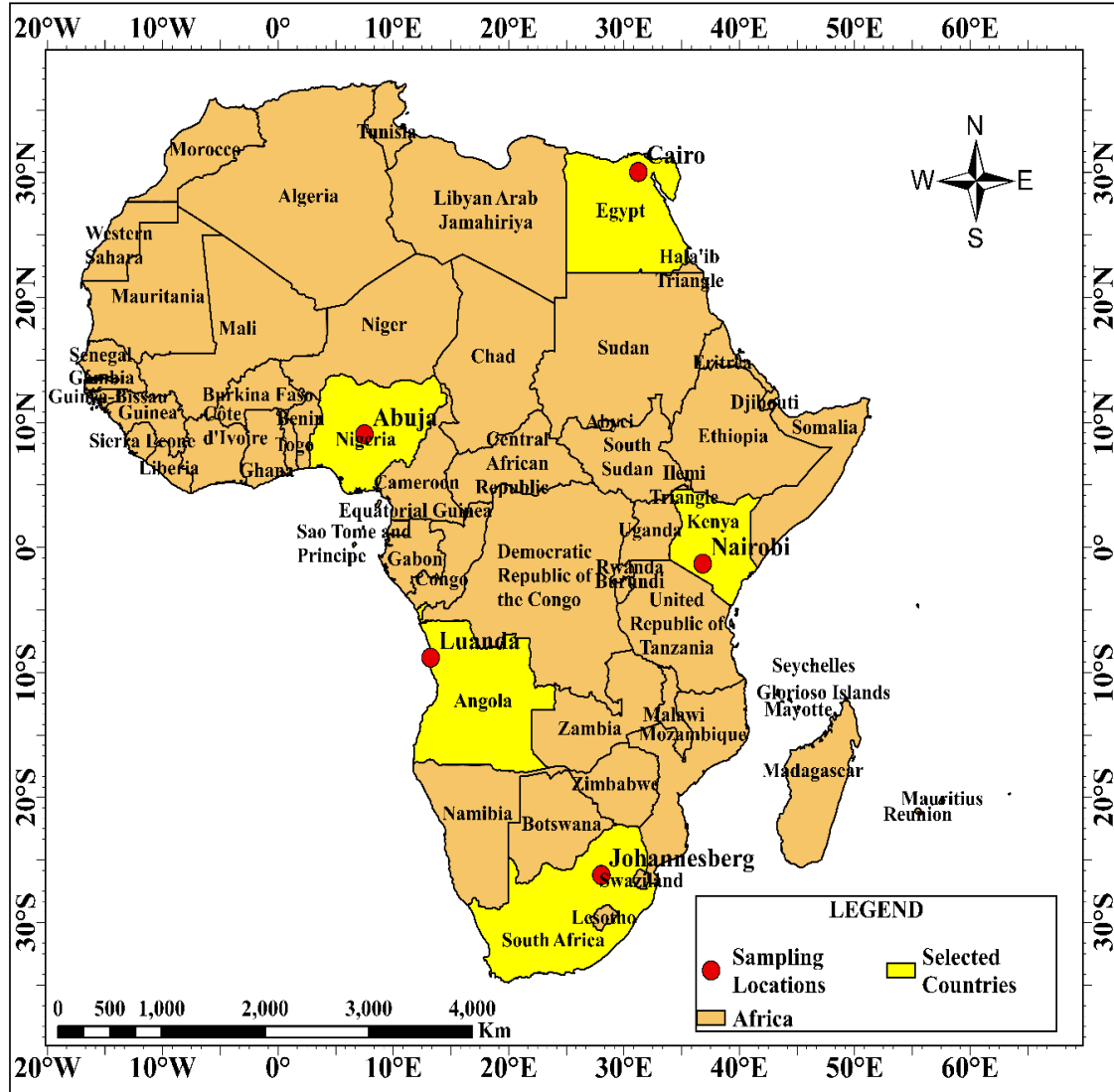


Figure 1: Map of the study area showing the selected stations

2.2 Data Acquisition, Validation and Control

The Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) reanalysis database provided the meteorological data used in this study, which spans 26 years from January 2000 to December 2025. Luanda, Cairo, Nairobi, Abuja, and Johannesburg. The monthly MERRA-2 surface flux diagnostics dataset (M2TMNXFLX), distributed through the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC), was used for the analysis (Global Modeling and Assimilation Office (2015)). The chosen stations offer a solid

foundation for regional comparison research since they reflect a variety of geographical, topographical, and climatic variables throughout Africa. The downloaded datasets were subjected to validation and quality control processes, such as screening for missing values, duplicate records, temporal inconsistencies, and outliers, in order to guarantee data dependability. Prior to statistical analysis, consistency checks were carried out to guarantee consistent measurement units, chronological continuity, and completeness of the time series.

2.3 Rainfall and Temperature Annual Mean

The rainfall and temperature annual mean was calculated using the following equation:

$$\bar{Y} = \frac{1}{m} \sum_{j=1}^m Y_j \quad (1)$$

Where $\bar{Y}$ represent the mean rainfall or temperature, Y_j represent the value observed, m represent the observed total number (26 years)

2.4 Standard Deviation

The rainfall and temperature were evaluated based on their variability using the following equation:

$$SD = \sqrt{\frac{\sum_{j=1}^m (Y_j - \bar{Y})^2}{m-1}} \quad (2)$$

Where SD represent the standard deviation.

2.5 The Percentage Bias (PB) of the Study

The study uses percentage bias model for the observed and generated dataset which was computed using the following equation.

$$PB = \frac{\sum_{j=1}^m (PR_j - OB_j)}{\sum_{j=1}^m OB_j} \times 100 \quad (3)$$

Where PR_j represent the predicted or generated value in the study and OB_j represent the observed value in the study.

2.6 Analysis of the one-way variance (ANOVA)

The study use statistical tools difference for different stations to evaluate the ANOVA based on the equation bellow:

$$F = \frac{NU_{between}}{NU_{within}} \quad (4)$$

Where

$$NU_{between} = \frac{UU_{between}}{L-1} \quad (5)$$

$$NU_{within} = \frac{UU_{within}}{Q-L} \quad (6)$$

$UU_{between}$ represent the between –group sum of the square, while UU_{within} represent within-group sum of the square, L represent number of the stations used within the study, M represent the total number of the observation. Therefore, a significant level of $P < 0.05$ was considered in the study.

2.7 The Honest Significant Different (HSD)

$$HSD = a_{\beta} \sqrt{\frac{NU_{within}}{m}} \quad (7)$$

Where a_{β} represent the student range statistics, NU_{within} represent the mean of the square within the group of study and m represent the observation according to each station considered.

2.8 The Test of the Mann-Kendall Trend

The study employed the use of Mann-Kendall Statistics to generate some result based on the datasets used. The equation used is as follow:

$$T = \sum_{l=1}^{m-1} \sum_{i=l+1}^m sgn(Y_i - Y_l) \quad (8)$$

Where

$$sgn(Y) = \begin{cases} 1, & y > 0 \\ 0, & y = 0 \\ -1, & y < 0 \end{cases} \quad (9)$$

The variance of T

$$Var(T) = \frac{m(m-1)(2m+5) - \sum_{j=1}^h v_j(v_j-1)(2v_j+5)}{18} \quad (10)$$

Where h represent the number of the tied group, v_j represent the number of the observation in the j^{th} tied group.

2.9 The test of the standardized statistics

$$W = \begin{cases} \frac{T-1}{\sqrt{var(T)}}, & T > 0 \\ 0, & T = 0 \\ \frac{T+1}{\sqrt{var(T)}}, & T < 0 \end{cases} \quad (11)$$

The trend considered significant in this study was $|W| > 1.96$ which was at the 95% in confidence level for the study

2.10 The Slope Estimation of Sen's

The two observations of the slope used are shown in the equation below:

$$R_j = \frac{Y_i - Y_l}{i - l} \quad \text{for } i > l \quad (12)$$

Therefore, the Sen's overall slope used is $R = \text{Median}(R_j)$

$R > 0$ This indicate increase in the trend of the analysis

$R < 0$ This indicate decrease in the trend of the analysis

2.11 Interpolation of Spatial Variation of the Inverse Distance Weight

The spatial interpolation of the inverse distance weight for the research was calculated using the equation shown below:

$$Q(y) = \frac{\sum_{j=1}^M \frac{Q_j}{e_j^q}}{\sum_{j=1}^M \frac{1}{e_j^q}} \quad (13)$$

Where $Q(y)$ represent the interpolated value of the data used, Q_j represent the observed value of each station at various j , e_j represent the distance from one station to the other at j , q represent the

power parameter which is commonly use as $q = 2$ and M represent the number of the station surrounding the selected ones used.

2.12 Trend Linear Model

$$Y = a + bX \quad (14)$$

Where Y represent the temperature or rainfall, X represent years used, a represent the intercept and b represent the slope of the linear equation, known as trend coefficient.

3. RESULTS AND DISCUSSION

The result in Figure 2(a) shows that there is model bias which is between -15.4% and $+12.1\%$. The positive bias (up to $\sim 12\%$) in the northern area surrounding Cairo and extending southeastward toward Nairobi, which suggests that the model overestimates this area. While the southernmost region, around Johannesburg, exhibits a considerable negative bias (down to -15%), suggesting significant underestimate, the bias lowers into slightly negative values (about -1.7%) as one moves toward central Africa (around Abuja and Luanda). This implies a shift from northeastern overestimation to southern underestimate. The bias, which ranges from roughly $+5.4\%$ to $+20.3\%$, is completely positive in Figure 2 (b). The northeastern region close to Cairo has the greatest values ($>20\%$), which progressively decline southwestward. While the southern region near Johannesburg still exhibits positive bias, albeit at lesser levels ($\sim 5\text{--}7\%$), the central regions surrounding Abuja have moderate positive bias ($\sim 10\text{--}13\%$). This shows that the model continuously overestimates throughout the entire domain, with a substantial gradient from northeast to southwest, in contrast to Figure 2 (a).

The bias in Figure 2 (c) is primarily negative, ranging from around -28.9% to -5.1% , making it the scenario with the biggest underestimate magnitude. The southern region around Johannesburg exhibits the highest negative bias (-29%), and the center portions surrounding Luanda also exhibit

significant underestimate (-20%). Although the negative bias in the northern region near Cairo is somewhat less (-5%), it is still below zero. Figure 2 (d), the bias alternates between negative and positive values once more, with a range of roughly -2.1% to $+14.5\%$. Strong positive bias ($14-15\%$) is seen in the northeastern area close to Cairo, which is comparable to Figure 2 (a) but marginally higher. The southernmost region, close to Johannesburg, moves to somewhat negative values (-2%), whereas the central regions (Abuja to Luanda) show a moderate positive bias ($6-10\%$).

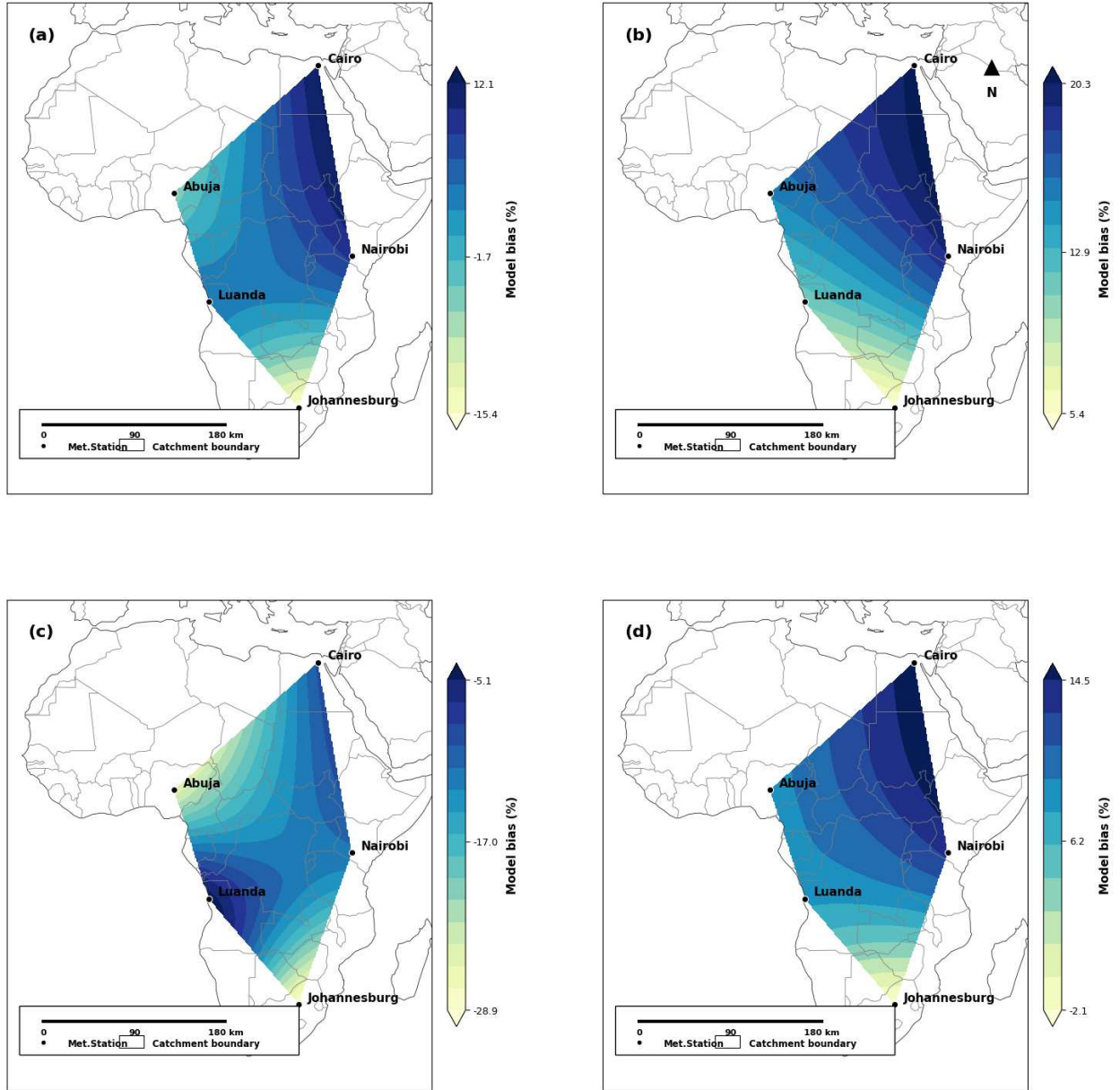


Figure 2: The Spatial Distribution of Rainfall over Selected Stations

The result in Figure 3(a) revealed the model bias of temperature spanning 0.12 K to 0.85 K which is the lowest magnitude of all the scenarios. The northeastern area close to Cairo has the biggest bias ($\sim 0.8\text{--}0.85$ K), which progressively decreases southward. The southernmost area close to Johannesburg has the lowest bias ($\sim 0.12\text{--}0.3$ K), whereas Abuja and Luanda have intermediate bias rates ($\sim 0.4\text{--}0.6$ K). This trend shows a distinct declining gradient from north to south, with

overall overestimation being somewhat minor. The highest positive bias is shown in Figure 3 (b), where the magnitude of bias increases dramatically, ranging from roughly 0.05 K to 1.98 K. The highest values ($\sim 1.5\text{--}2.0$ K) are found in the northeastern and eastern regions (Cairo toward Nairobi), suggesting significant overestimation. While the southern region near Johannesburg still exhibits substantial overestimation ($\sim 0.05\text{--}0.5$ K), albeit less than elsewhere, the central regions (around Abuja and Luanda) show moderate bias ($\sim 1.0\text{--}1.3$ K). The geographical gradient is more intense, particularly in the east, although it is still comparable to panel Figure 3 (a).

The bias has a noticeably different spatial structure and runs from roughly 0.88 K to 1.55 K in Figure 3 (c). In contrast to earlier panels where the maxima were in the northeast, the highest values ($\sim 1.4\text{--}1.55$ K) are centered in the western and central regions surrounding Abuja and extending toward Luanda. Johannesburg records the lowest bias ($\sim 0.88\text{--}1.0$ K), whereas the eastern side near Nairobi exhibits somewhat lower values ($\sim 1.1\text{--}1.3$ K). This shows a gradient that decreases from west to east, indicating that in this instance, the model overestimation is greatest over western and central Africa. The bias ranges from around 0.54 K to 1.82 K in Figure 3 (d). Once more, the northwest to central areas surrounding Abuja have the highest values ($\sim 1.6\text{--}1.8$ K), which progressively drop toward the east and south. The southernmost region near Johannesburg displays lower values ($\sim 0.5\text{--}0.8$ K), while the eastern region near Nairobi displays moderate bias ($\sim 1.1\text{--}1.3$ K). The spatial pattern is comparable to Figure 3 (c), but it has a slightly wider high bias that stretches from west to north.

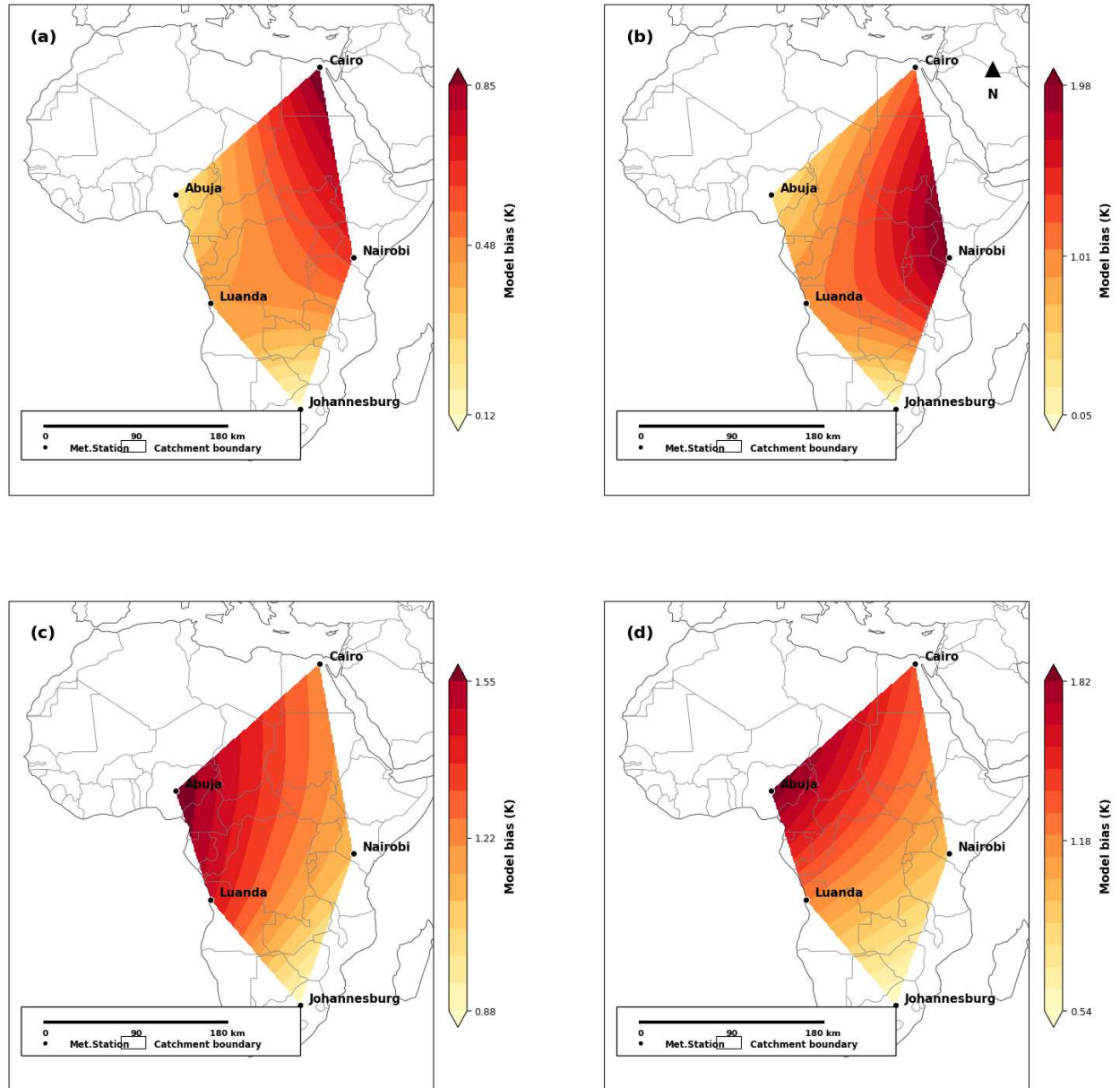
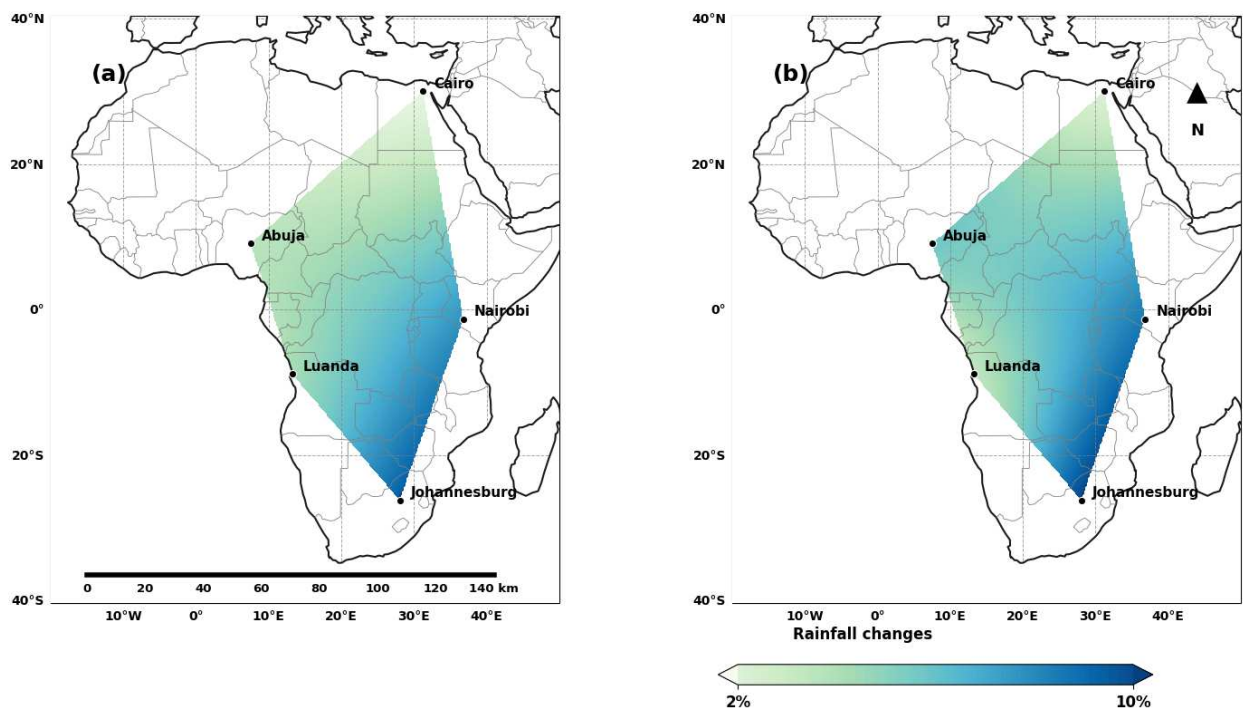


Figure 3: The Spatial Distribution of Temperature over Selected Stations

With values ranging from around 2% to 10%, Figure 4 (rainfall changes) clearly displays a regional pattern in the expected rainfall increase throughout the study region. The northern region of the domain, particularly in the vicinity of Cairo, shows the lowest rises (around 2-4%) in both panels Figure 4 (a) and (b). Rainfall progressively increases as one travels eastward and southward. There are moderate rises of between 4–7% in the central region, which includes the districts surrounding

Abuja and Luanda. The southeast of the region experiences the largest rainfall increases (about 8–10%), especially from Nairobi to Johannesburg. Compared to Figure 4 (a), Figure 4 (b) displays a marginally greater and more extensive growth, with regions surpassing 8% expanding farther inland. The northern area close to Cairo has the lowest temperature increases (about 0.1–0.3 K) in Figures 4 (a) and (b). With values of roughly 0.4–0.7 K, the warming intensifies as one moves into the center regions (near Abuja and Luanda). The southeast, particularly in the vicinity of Johannesburg and continuing toward Nairobi, has seen the largest temperature increases (around 0.8–0.9 K). Compared to Figure 4 (a), Figure 4 (b) once more displays somewhat higher values and a larger area of severe warming, with more locations surpassing 0.7 K.



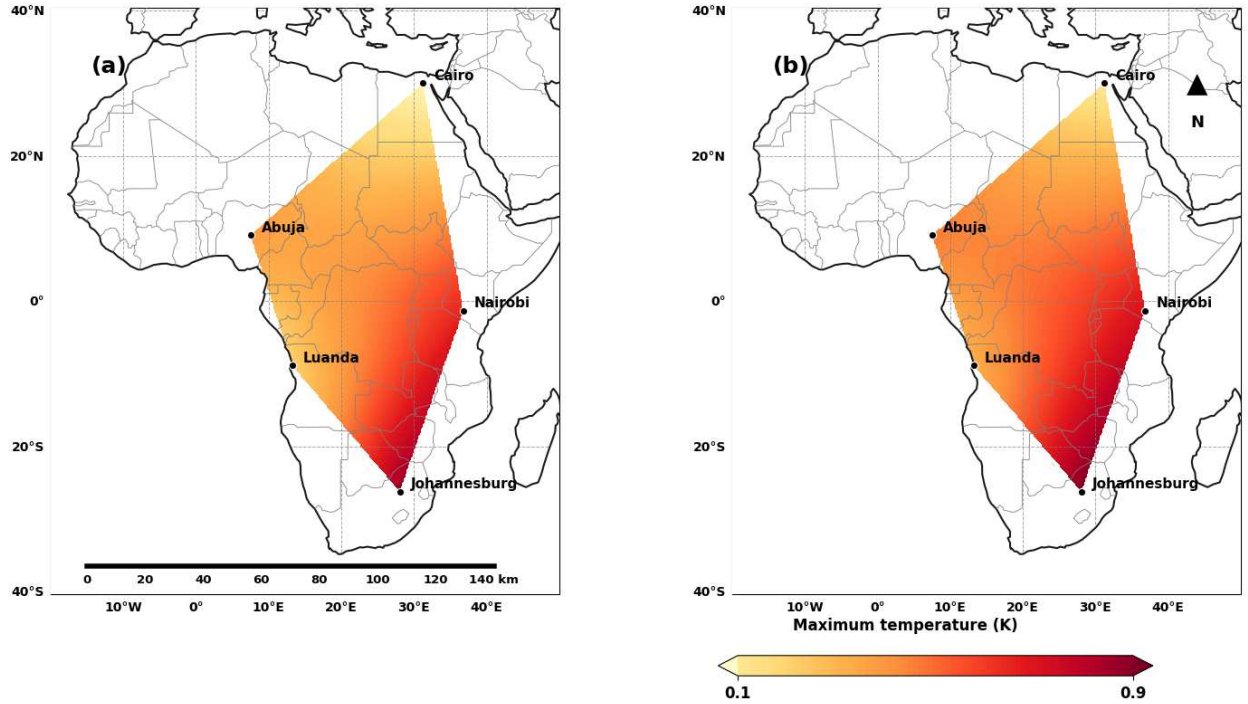


Figure 4: Regional Rainfall and Temperature Pattern for the studied Stations

As seen in Figures 5(a–c), the result shows the geographical distribution of rainfall across the chosen African stations (Cairo, Abuja, Luanda, Nairobi, and Johannesburg) shows a clear north–south and west–east gradient. The range of rainfall values is roughly 0–150 mm, with Abuja (9°N, 7°E) having the maximum concentration (>120 mm). The seasonal migration of the Inter-Tropical Discontinuity (ITD) and the impact of the West African monsoon are reflected in this region's rich green shading, which indicates annual mean rainfall values between 120 and 150 mm. The red to orange contours show a rapid drop in rainfall to less than 30 mm as one moves northeast into Cairo (30°N, 31°E), which is compatible with the hyper-arid conditions of the Sahara Desert. In a similar vein, Nairobi (1°S, 37°E) and Luanda (9°S, 13°E) display moderate rainfall levels of roughly 60–90 mm and 90–120 mm, respectively, whereas Johannesburg (26°S, 28°E), the southern station, shows comparatively low rainfall ranging from 30–60 mm. The interpolated outlines show how drier subtropical and desert climates in northern and southern Africa gradually replace humid

tropical conditions in West Africa. Large-scale atmospheric circulation processes, such as monsoon flow, subtropical high-pressure belts, and regional topography impacts, play a major role in regulating precipitation patterns throughout the continent, as this geographic variability demonstrates.

The temperature distribution in Figures 5(d–i) ranges from about 289.6 K to 299.2 K (16.5–26.1 °C) and shows an inverse association with rainfall. The central tropical region and the vicinity of Abuja have the greatest temperatures (298–299.2 K), with dark brown and dark green hues predominating due to strong land-surface heating and intense sun radiation. While Nairobi enjoys moderate temperatures of roughly 294–296 K, perhaps due to its higher elevation, Luanda likewise reports reasonably high temperatures between 296 and 298 K. Due to its higher altitude and southern latitude, Johannesburg has the lowest temperatures (289.6–292 K). It's interesting to note that Cairo's interpolated temperature field stays within the 294–296 K range despite its desert surroundings, suggesting the moderating effect of the wider continental gradient that the interpolation represents. The temperature trend is further supported by the climate index, variability, and anomaly maps (Figures g–i), which display maximum index values in tropical West Africa that are close to 299 K and gradually decline toward eastern and southern Africa.

The findings highlight the impact of latitude, atmospheric circulation, elevation, and regional climatic regimes on the spatial climate patterns of Africa, with rainfall varying by more than 120 mm and temperature varying by almost 10 K between the warmest and coolest regions.

Spatial Distribution of Rainfall and Temperature Over Africa

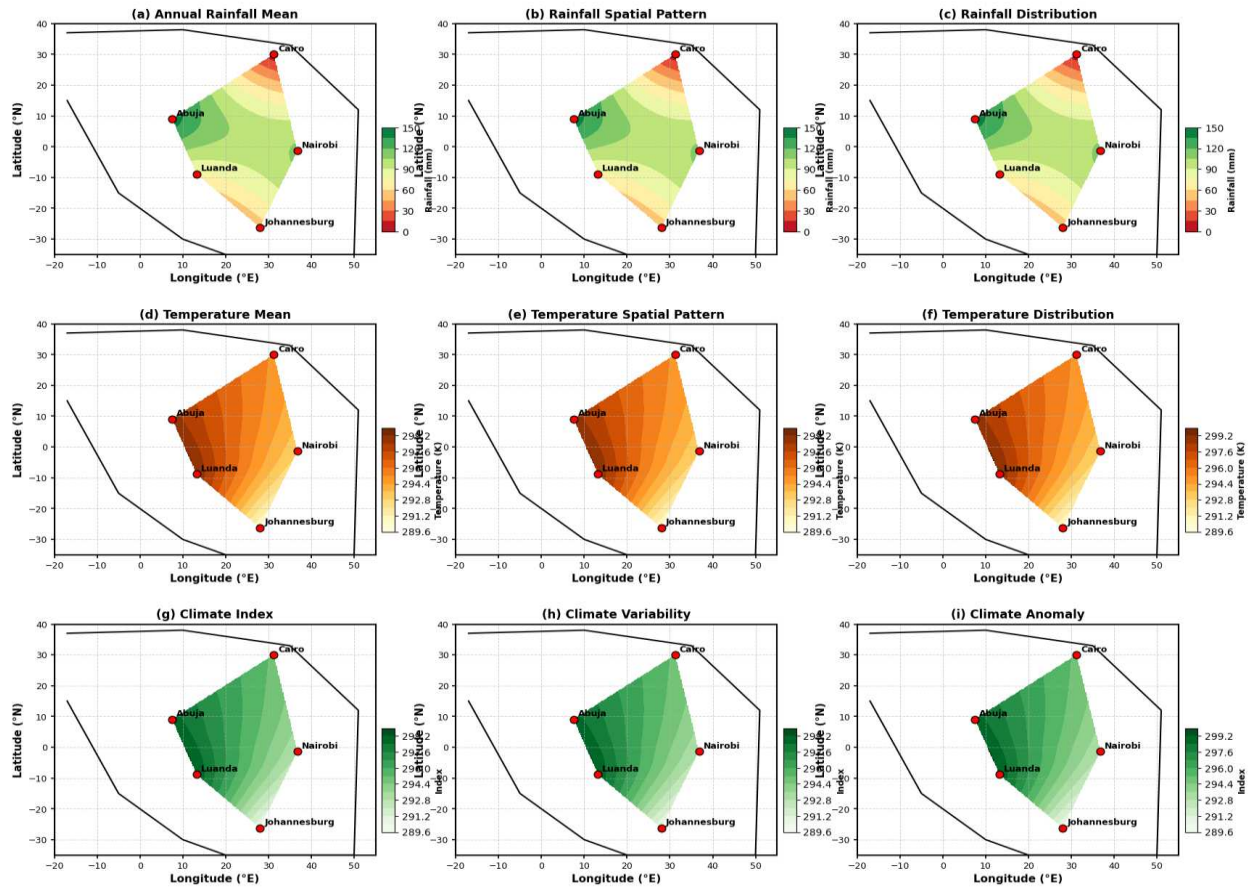


Figure 5: Geographical Distribution of Rainfall and Temperature over the selected Stations

The range, maximum, and minimum values for five major African cities are shown in Figure 6 (a), which is distinguished by noticeably high maximum values and insignificant low baselines. Abuja has the highest range and maximum value, both of which reach over 810,000 units. Its lowest value is nil. Nairobi comes next, with a minimum baseline of 10,000 units, a range of 530,000 units, and a maximum value of approximately 540,000 units. Luanda shows a range of 500,000 units, a minor minimum value of 5,000 units, and a high value of 505,000 units. Johannesburg has a zero minimum value and the same range and maximum value of 350,000 units. Cairo has the lowest metrics in this collection, with a minimum value of zero and a maximum and range that level off at 90,000 units.

Figure 6 (b) shows that Cairo had the greatest variation in this dataset, with a high value of 32,000 units and a minimum value of 10,500 units, at 21,500 units. With a minimum value of 21,200 units and a corresponding range of 10,300 units, Abuja has the second-highest maximum value at 31,500 units. A highest value of 29,000 units, a high lowest value of 21,000 units, and a smaller range of 8,000 units are all reported by Luanda. The maximum value for Johannesburg is 24,700 units, the minimum is 7,500 units, and the range is 17,200 units. With a range of 6,300 units, a maximum value of 23,000 units, and a minimum value of 16,700 units, Nairobi has the lowest numbers in this category.

The findings in Figure 6(c) show a modified metric distribution in which the maximum values for the majority of cities are either stabilized at nearly comparable levels or capped. The maximum value in Abuja, Cairo, Luanda, and Johannesburg is all the same, peaking at precisely 25,000 units. Despite having the same maximum, their internal distributions differ: Abuja has a minimum of 21,200 units and a range of 10,300 units, whilst Cairo has a minimum of 10,500 units and a range of 21,500 units. Johannesburg maintains a range of 17,200 units in addition to a minimum of 7,500 units, whereas Luanda exhibits a range of 8,000 units against a minimum of 21,000 units. With a lower maximum value of 23,000 units, a minimum value of 16,700 units, and a total range of 6,300 units, Nairobi departs somewhat from the other cities' shared maximum ceiling.

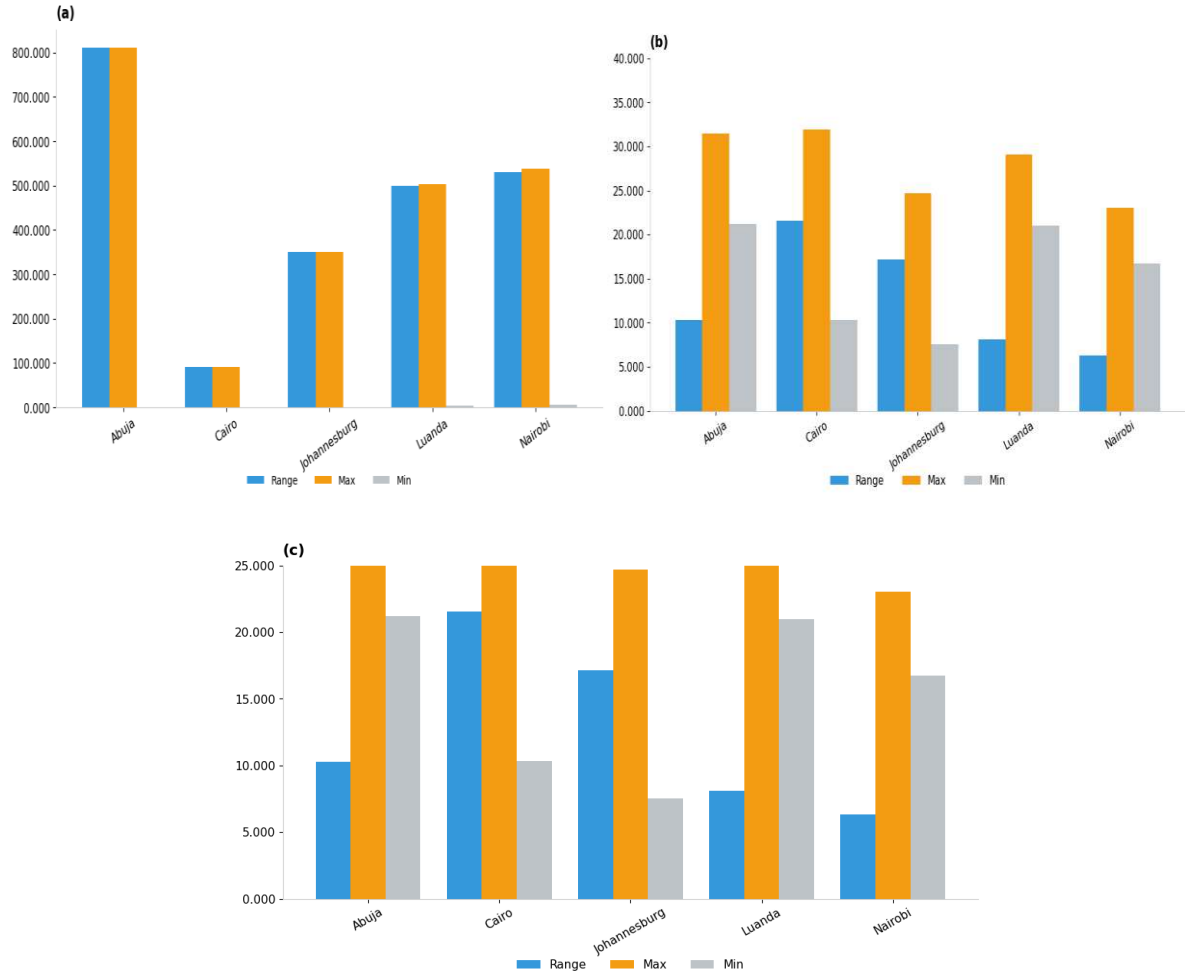


Figure 6: The histogram variation of rainfall and temperature over the selected stations

As revealed in Figure 7, the historical variance shows significant volatile jumps, while the baseline linear trend spans a move from about 28.3 K to 29.2 K over the course of 25 years. A significant warming phase propelled values up to 30.5 K in 2019, culminating in a historic time-series maximum of nearly 31.5 K by 2025, while the lowest recorded thermal decline occurred early in the sequence around 2001, plummeting to roughly 26.7 K. In order to represent actual warming volatility, AI climate models with feature engineering must substantially weight peak yearly departures above simple mean regressions. This high fluctuation pattern indicates an ecosystem that is extremely susceptible to climatic extreme events.

With the underlying regression vector shifting from a base of roughly 30.2K in 2000 to nearly 31.0K by 2025, Cairo's thermal dataset shows a structural rise in T_{max} . Recurrent, severe thermal crests, most notably an early spike to 31.7 K around 2002 and later big peaks near 31.6K in 2015 and 31.9K in 2024, define the city's temperature profile. On the other hand, the lowest localized cooling troughs were as low as 29.7 K in 2003 and a baseline low of 29.5 K in 2013. For neural networks predicting regional urban heat islands, this cyclic distribution, which alternates quickly between high crests and deep valleys, creates a classic high-amplitude wave pattern. This indicates strong autoregressive features where deep drops are regularly offset by sharp, multi-year thermal rebounds.

Johannesburg's data in download.png shows a very stable, lower-temperature climate regime, with a little linear increase scaling from around 22.3 K to 22.7 K, in contrast to the northern and equatorial zones. A notable outlier spike in 2015 that raised the maximum temperature to an absolute series peak of 24.7 K and a further surge to 24.5 K in 2024 punctuate this narrowly restricted structural variance. In 2000, 2017, and 2021, the minimal thresholds consistently bottom out around 21.2 K, demonstrating their remarkable uniformity. The low slope and recurring boundaries indicate a predictable, low-entropy system from the standpoint of algorithmic forecasting, where anomaly detection layers would identify the heat surges in 2015 and 2024 as notable statistical disruptions rather than systemic changes.

Luanda exhibits a consistent, long-lasting warming signal, with the trend line gradually rising from 28.0K from the year 2000 to roughly 28.6K in 2025. The historical data points reveal a strong, early baseline minimum of 27.2K in 2001, which swiftly recovered into a persistent oscillation between 27.8K and 28.5K that lasted for ten years. Warming intensifies in the second half of the time period, surpassing earlier thresholds to peak at 29.1K in 2019 and sustaining elevated

baselines around 29.0K by 2024. The declining frequency of deep cooling anomalies over the past ten years is a powerful signal of localized climate forcing when training predictive AI frameworks on this data, locking the model into a higher-confidence upward forecast vector for the following ten years.

Nairobi's average T_{max} predictions are expected to increase from a cool 21.0K in 2000 to 22.0K by 2025, according to research that shows a strong positive trend line. Deep, rhythmic decreases to about 20.4 K in 2001, 2007, and 2010 are indicative of the city's extreme inter-annual volatility. On the other hand, warming cycles rise to 22.6 K in 2016–2017 and a series maximum of 23.1 K in 2019, while cooling cycles fail to fall below 20.8K (2020). Standard linear models will probably underestimate future extremes due to the high degree of non-linear complexity introduced by this shift from deep historical valleys to elevated contemporary peaks; in this case, an advanced recurrent neural network (RNN) or LSTM would be needed to accurately capture the accelerating momentum of Nairobi's microclimate warming phases.

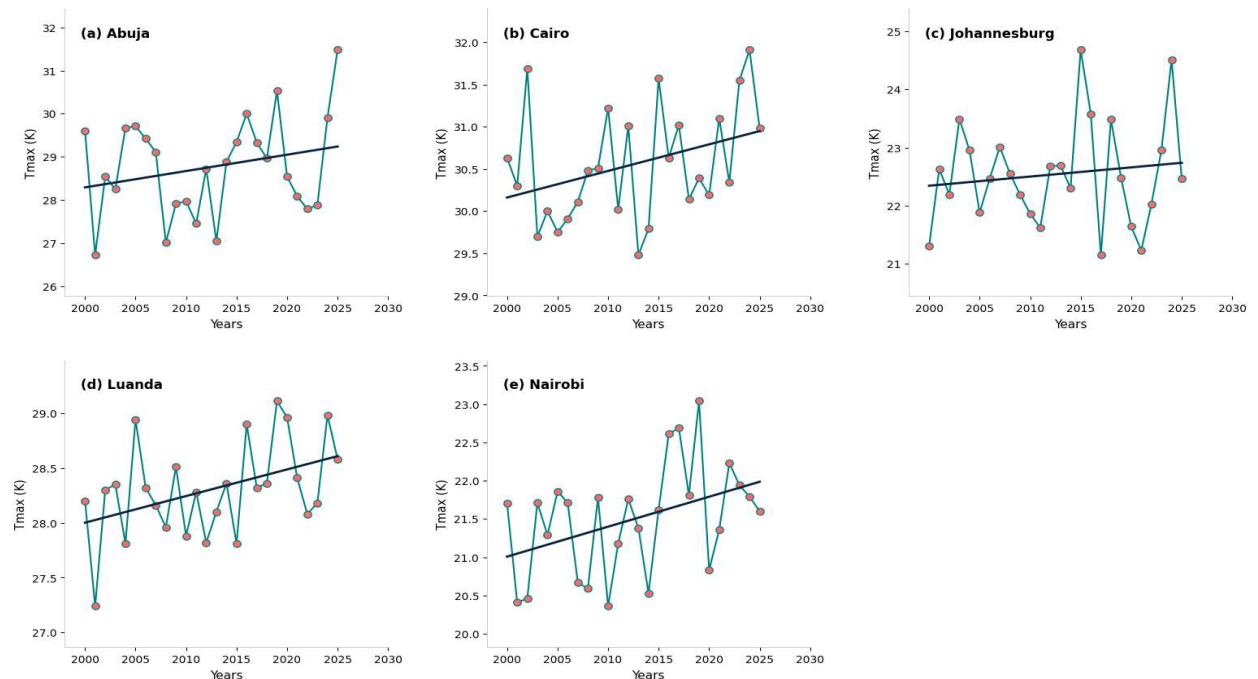


Figure 7: Variation of temperature over the selected stations

Figure 8 the precipitation patterns of the chosen African stations from 2000 to 2025 show notable climate variability and divergent regional trends. Despite significant inter annual changes, including a minimum of 990 mm yr⁻¹ in 2002 and high of 2,420 mm yr⁻¹ in 2012 and 2,300 mm yr⁻¹ in 2016, Abuja showed an increasing trend in rainfall, with the baseline growing from roughly 1,640 mm yr⁻¹ in 2000 to 1,830 mm yr⁻¹ in 2025. Although there was an unusual rainfall event of 121 mm yr⁻¹ in 2020, greatly exceeding its minimal values of 17 mm yr⁻¹ in 2009 and 20 mm yr⁻¹ in 2024, Cairo maintained a hyper-arid environment with a modest increase from 35 to 43 mm yr⁻¹.

With an extreme high of 1,230 mm yr⁻¹ in 2006 and severe drought minima of 320 mm yr⁻¹ in 2015 and 280 mm yr⁻¹ in 2024, Johannesburg showed a trend of diminishing rainfall from 660 to 590 mm yr⁻¹. Luanda likewise saw a decline from 940 to 790 mm yr⁻¹, peaking at 1,270 mm yr⁻¹ in 2007 until hitting a record low of 480 mm yr⁻¹ in 2025. On the other hand, rainfall in Nairobi increased from a minimum of 620 mm yr⁻¹ in 2000 to a maximum of 1,980 mm yr⁻¹ in 2018, showing the strongest positive trend from 1,030 to 1,540 mm yr⁻¹. These results show significant geographical variety in precipitation regimes, and the necessity for reliable prediction models and flexible water resource management techniques is highlighted by rising climate variability and extreme events.

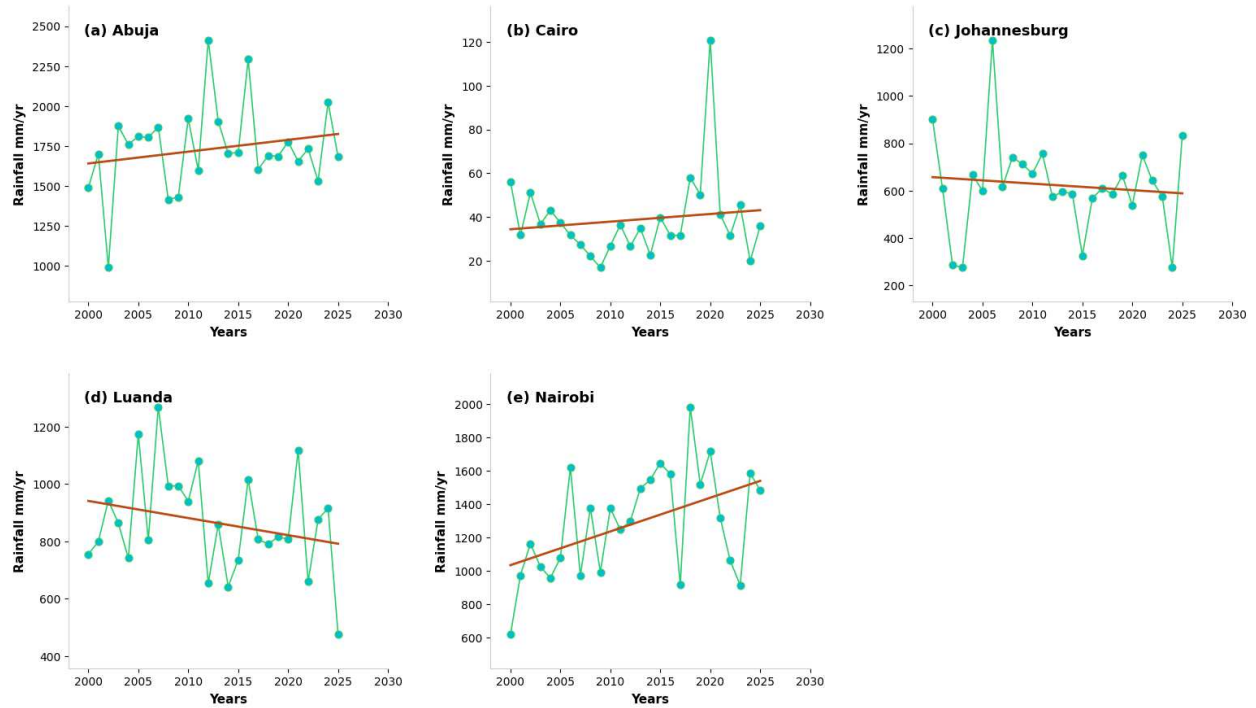


Figure 8: Variation of rainfall over the selected stations

Figure 9 show the monthly rainfall and temperature trends from 2000 to 2025 show significant temporal and geographical climate variability. With monthly precipitation varying from about 0 mm during the dry season to over 800 mm around 2016, Abuja had the most rainfall variability. Several years saw peaks above 700 mm, indicating the West African Monsoon's strong influence and an increased danger of floods. With monthly totals ranging from between 20 to 540 mm and many peaks surpassing 500 mm, Nairobi has the second-highest rainfall variability, which is consistent with its bimodal rainfall regime. While Johannesburg recorded lower rainfall quantities of 0–250 mm, Luanda experienced moderate–high rainfall variability, with monthly totals ranging from 0 to 500 mm.

Cairo continued to be parched, with monthly rainfall typically falling below 50 mm and only sometimes reaching 80 mm. Temperature patterns showed clear regional traits. The highest temperatures were reported in Cairo, with maxima often above 303 K and ranging from roughly

284 to 305 K. Due to its elevation, Nairobi showed the steadiest temperatures (290–296 K), whereas Abuja and Luanda sustained warm tropical conditions of 296–304 K and 296–302 K, respectively. With temperatures between 281 and 297 K and the greatest seasonal variance, Johannesburg has the coldest climate. Overall, rising temperatures and increasing rainfall extremes, especially after 2010, point to increased climatic variability and continued effects of climate change throughout Africa, highlighting the necessity of better water resource management and climate adaptation.

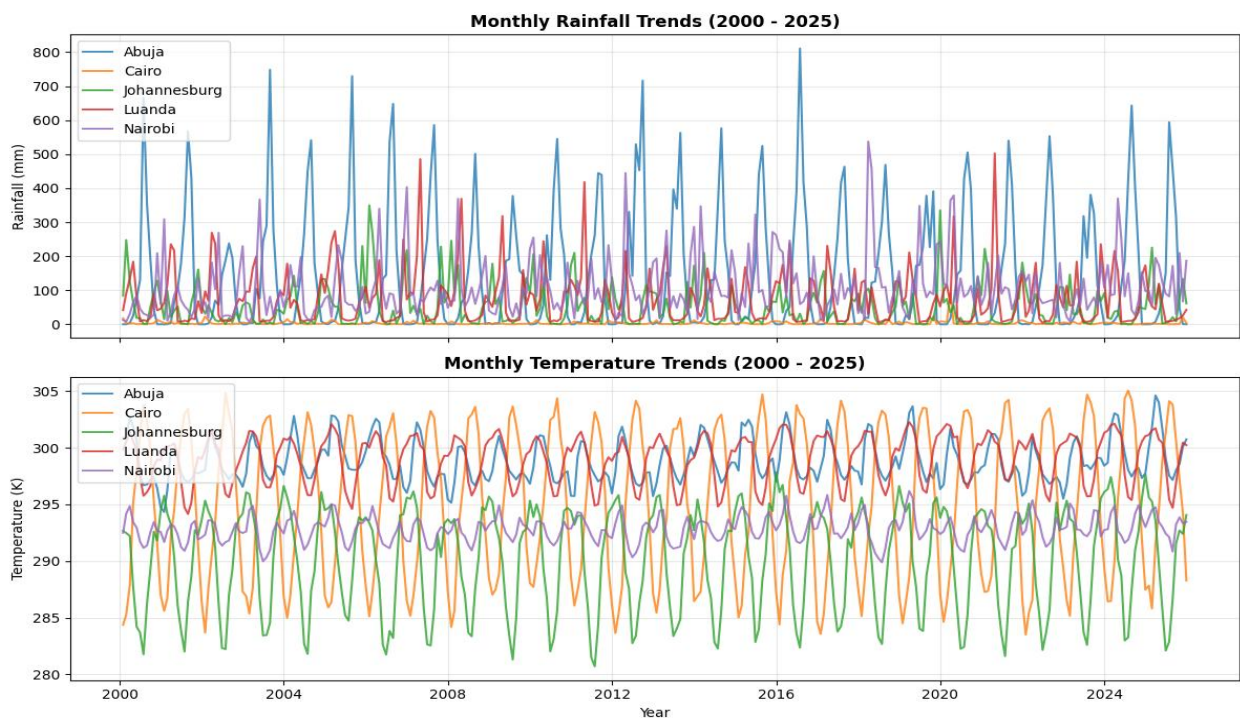


Figure 9: Seasonal Variation of Rainfall and Temperature over Selected Stations

As shown in Figure 10, the climatologists show that the generated dataset faithfully replicates seasonal hydro climatic trends across Abuja, Cairo, Johannesburg, Luanda, and Nairobi with just slight differences when comparing observed (OBS) and created (GEN) monthly rainfall and temperature. Rainfall in Abuja exhibited a unimodal trend, rising from almost 0 mm in January and February to 390 mm (OBS) and 380 mm (GEN) in July. It then peaked at 520 mm (OBS) and

500 mm (GEN) in August before falling to 110 mm in October and nearly 0 mm in December. While T_{max} ranged from 28.5–33.0°C and T_{min} from 20.0–24.5°C, with GEN deviating by <0.5°C, rainfall variability rose from less than 10 mm during the dry season to almost 150 mm in July–August. Cairo continued to be arid, with monthly rainfall of less than 8 mm, peaking in March at 7.6 mm (OBS) and 7.0 mm (GEN), with rainfall SD of 1–18 mm. T_{max} and T_{min} rose from 17–35°C and 8–27°C, respectively. In January, Johannesburg saw 105 mm of austral summer rainfall, which dropped to less than 10 mm in June and August before surpassing 100 mm in December. The rainfall SD ranged from 80 mm to less than 10 mm.

The range of temperatures was 26–14°C (T_{max}) and 18–5°C (T_{min}). Rainfall in Luanda increased from 75 mm in January to 225 mm in April, then decreased to less than 10 mm in June and August before rising to 110 mm in November. SD peaked at 115 mm, while T_{max} and T_{min} varied from 27 to 33°C and 18 to 24°C, respectively. With peaks of 185 mm in April and 160 mm in November, secondary maxima of 130 mm in March and 135 mm in May, and dry-season rainfall of 55–75 mm with SD between 35 and 130 mm, Nairobi exhibited a bimodal rainfall regime. T_{max} and T_{min} were constant at 22.5–25.8°C and 14–16.5°C, respectively. Overall, variations between OBS and GEN were typically within 5–10 mm for rainfall and 0.5–1.0°C for temperature, indicating that the generated dataset is a trustworthy representation of observed climatology appropriate for hydrological, climate variability, and future climate projection studies across various African climatic regions.

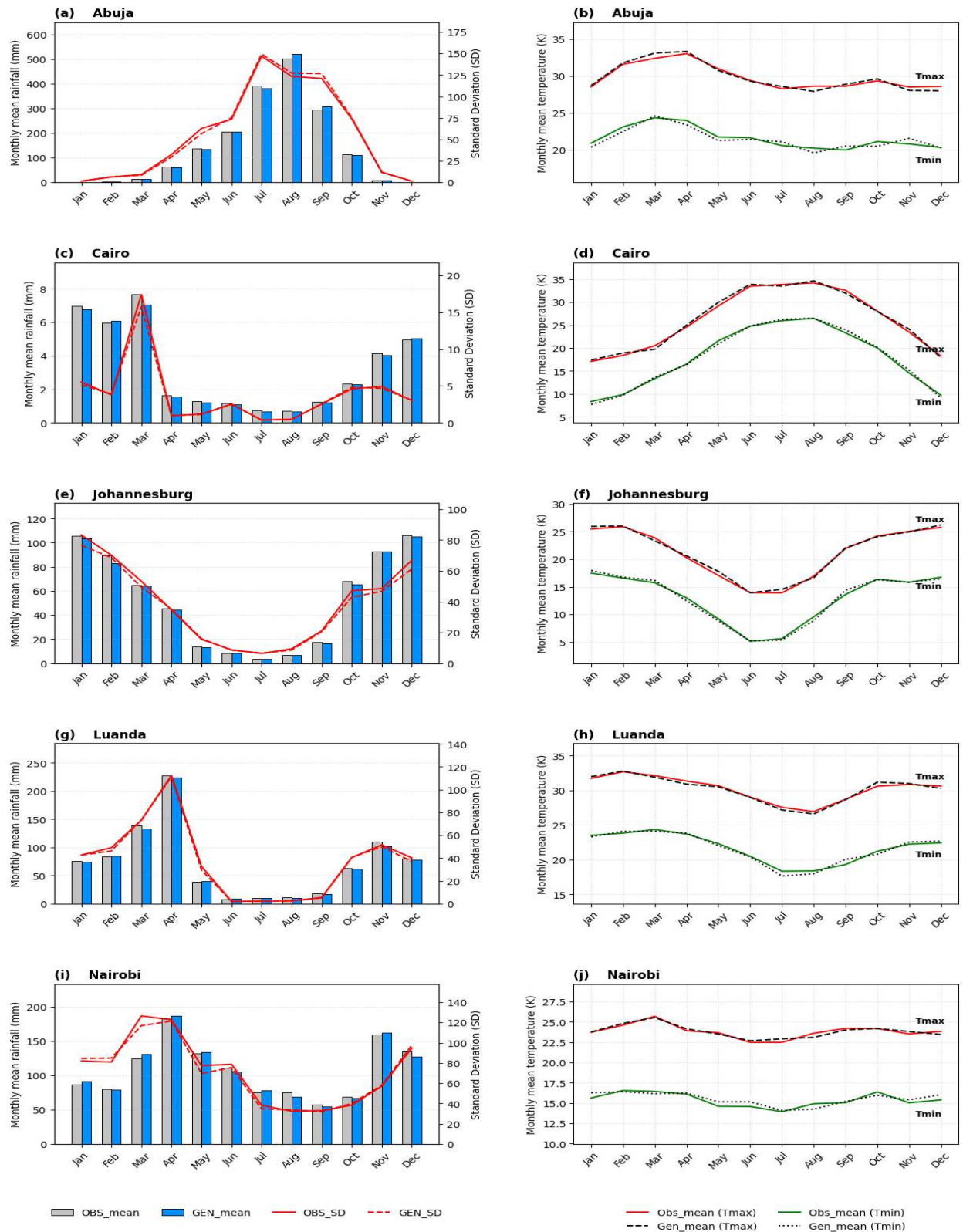


Figure 10: The variation of the Observed and Generated Mean for Both Rainfall and Temperature for the Selected Stations

The result in Table 1 revealed Abuja, Cairo, Johannesburg, Luanda, and Nairobi were found to have significantly different climates in terms of rainfall, maximum temperature (T_{max}), and minimum temperature (T_{min}). All comparisons were significant at $p < 0.001$, with the exception of T_{max} between Abuja and Luanda ($MD = 0.46^{\circ}\text{C}$, $p = 0.066$). Abuja had more rainfall than Cairo (1694.54 mm), Johannesburg (1110.19 mm), Luanda (866.85 mm), and Nairobi (445.27 mm). Cairo had the least amount of rainfall—584.35 mm less than Johannesburg, 827.68 mm less than Luanda, and 1249.27 mm less than Nairobi. Luanda received 421.59 mm less rainfall than Nairobi, while Johannesburg received 243.34 mm less and 664.92 mm less.

In terms of T_{max} , Abuja was warmer than Nairobi (7.27°C) and Johannesburg (6.22°C), but 1.79°C colder than Cairo. Cairo had the greatest (T_{max}), 8.02°C higher than Johannesburg, 2.25°C higher than Luanda, and 9.06°C higher than Nairobi. Luanda was 6.81°C hotter than Nairobi, while Johannesburg was 5.77°C colder but 1.04°C warmer. Cairo's T_{min} was 2.72°C higher than Johannesburg but 10.27°C and 5.96°C lower than Luanda and Nairobi, respectively. Abuja had the greatest (T_{min}), surpassing Cairo by 11.16°C , Johannesburg by 13.88°C , Luanda by 0.88°C , and Nairobi by 5.20°C . At 13.88°C , 2.72°C , 13.00°C , and 8.68°C below Abuja, Cairo, Luanda, and Nairobi, respectively, Johannesburg had the lowest (T_{min}). While Nairobi's T_{min} was 5.96°C and 8.68°C higher than Cairo and Johannesburg but 4.32°C and 5.20°C lower than Luanda and Abuja, Luanda's T_{min} was 10.27°C , 13.00°C , and 4.32°C higher than all three cities. Overall, the five African stations' rainfall variations varied from 243.34 to 1694.54 mm, T_{max} from 0.46 to 9.06°C , and T_{min} from 0.88 to 13.88°C , demonstrating significant climatic disparities influenced by latitude, altitude, location, and atmospheric circulation.

Table 1: Variation of Rainfall and Temperature Using Statistical Parameters

Station (I)	Station (J)	Rainfall		T_{max}		T_{min}	
		MD	Sig	MD	Sig	MD	Sig
Abuja	Cairo	1694.54	0.000*	-1.79	0.000*	11.16	0.000*
	Johannesburg	1110.19	0.000*	6.22	0.000*	13.88	0.000*
	Luanda	866.85	0.000*	0.46	0.066	0.88	0.000*
	Nairobi	445.27	0.000*	7.27	0.000*	5.20	0.000*
Cairo	Abuja	-1694.54	0.000*	1.79	0.000*	-11.16	0.000*
	Johannesburg	-584.35	0.000*	8.02	0.000*	2.72	0.000*
	Luanda	-827.68	0.000*	2.25	0.000*	-10.27	0.000*
	Nairobi	-1249.27	0.000*	9.06	0.000*	-5.96	0.000*
Johannesburg	Abuja	-1110.19	0.000*	-6.22	0.000*	-13.88	0.000*
	Cairo	584.35	0.000*	-8.02	0.000*	-2.72	0.000*
	Luanda	-243.34	0.000*	-5.77	0.000*	-13.00	0.000*
	Nairobi	-664.92	0.000*	1.04	0.000*	-8.68	0.000*
Luanda	Abuja	-866.85	0.000*	-0.46	0.066	-0.88	0.000*
	Cairo	827.68	0.000*	-2.25	0.000*	10.27	0.000*
	Johannesburg	243.34	0.000*	5.77	0.000*	13.00	0.000*
	Nairobi	-421.59	0.000*	6.81	0.000*	4.32	0.000*
Nairobi	Abuja	-445.27	0.000*	-7.27	0.000*	-5.20	0.000*
	Cairo	1249.27	0.000*	-9.06	0.000*	5.96	0.000*
	Johannesburg	664.92	0.000*	-1.04	0.000*	8.68	0.000*
	Luanda	421.59	0.000*	-6.81	0.000*	-4.32	0.000*

The results in Table 2 show highly significant regional variations in maximum temperature (T_{max}) and minimum temperature (T_{min}) between Abuja, Cairo, Johannesburg, Luanda, and Nairobi by one-way ANOVA findings. 26 observations were provided by each station ($n = 130$; error $df = 125$). The extremely high F-values (T_{max} : $F = 646.859$; (T_{min}): $F = 1371.112$; $p < 0.001$) verify that the temperature variations are not due to random variability but rather to different climatic regimes. The highest T_{max} was reported in Cairo ($30.55 \pm 0.67^{\circ}\text{C}$), followed by Abuja ($28.76 \pm 1.15^{\circ}\text{C}$) and Luanda ($28.30 \pm 0.43^{\circ}\text{C}$), with Luanda being 0.46°C colder than Abuja and Abuja being only 1.79°C colder than Cairo. The lowest daytime temperatures were reported in Johannesburg and Nairobi, at $22.54 \pm 0.90^{\circ}\text{C}$ and $21.50 \pm 0.72^{\circ}\text{C}$, respectively.

Compared to Luanda, Abuja, and Cairo, Johannesburg was 5.76°C, 6.22°C, and 8.01°C colder, whereas Nairobi was 1.04°C, 7.26°C, 6.80°C, and 9.05°C colder. Abuja had the greatest temperature ($23.24 \pm 0.90^{\circ}\text{C}$), followed by Luanda ($22.35 \pm 0.64^{\circ}\text{C}$), Nairobi ($18.04 \pm 0.58^{\circ}\text{C}$), Cairo ($12.08 \pm 1.12^{\circ}\text{C}$), and Johannesburg ($9.35 \pm 0.88^{\circ}\text{C}$). Abuja outperformed Luanda by 0.89°C, Nairobi by 5.20°C, Cairo by 11.16°C, and Johannesburg by 13.89°C, whereas Luanda outperformed Nairobi, Cairo, and Johannesburg by 4.31°C, 10.27°C, and 13.00°C, respectively. While Johannesburg recorded the lowest nightly temperatures, remaining 13.89°C, 13.00°C, 8.69°C, and 2.73°C below Abuja, Luanda, Nairobi, and Cairo, respectively, Cairo remained 5.96°C colder than Nairobi but 2.73°C warmer than Johannesburg. Abuja had the highest T_{max} SD (1.15°C), Luanda had the lowest T_{max} SD (0.43°C), Cairo had the highest T_{min} SD (1.12°C), and Nairobi had the lowest T_{min} SD (0.58°C), according to variability study. Strong climatic controls of latitude, altitude, and regional atmospheric circulation throughout Africa were confirmed by the fact that Cairo had the hottest daytime temperatures, Abuja the warmest nights, Luanda stable coastal temperatures, Nairobi cool equatorial highland conditions, and Johannesburg the coldest nights.

Table 2: ANOVA test of meteorological stations on mean annual maximum and minimum Temperature.

Variable	n	Mean $\pm$ SD	Df	F	P
Maximum Temp			4	646.859	0.000
Abuja	26	28.76 ± 1.15	125		
Cairo	26	30.55 ± 0.67			
Johannesburg	26	22.54 ± 0.90			
Luanda	26	28.30 ± 0.43			
Nairobi	26	21.50 ± 0.72			
Minimum Temp			4	1371.112	0.000
Abuja	26	23.24 ± 0.90	125		
Cairo	26	12.08 ± 1.12			
Johannesburg	26	9.35 ± 0.88			
Luanda	26	22.35 ± 0.64			
Nairobi	26	18.04 ± 0.58			

Table 3 shows that while substantial differences in Mann-Kendall Z-values and Sen's slopes (Q) were noted, no statistically significant monthly trends were found in Abuja, Cairo, Johannesburg, Luanda, and Nairobi. January ($Z = 0.38$, $Q = 0.00$), February ($Z = -0.22$, $Q = -0.01$), March ($Z = 1.45$, $Q = 0.26$), May ($Z = 0.04$, $Q = 0.05$), June ($Z = 0.31$, $Q = 0.40$), September ($Z = 2.42$, $Q = 5.93$), and October ($Z = 1.94$, $Q = 2.63$) showed the biggest decline. Only April ($Z = 0.71$, $Q = 0.02$), November ($Z = 1.15$, $Q = 0.06$), and December ($Z = 0.18$, $Q = 0.01$) showed positive tendencies, whereas January ($Z = -1.37$, $Q = -0.12$) and August ($Z = -2.91$, $Q = -0.02$) showed weak negative trends. Johannesburg experienced mild swings, with the biggest decrease in March ($Z = -0.84$, $Q = -0.97$) and the sharpest upward trend in April ($Z = 1.23$, $Q = 1.19$).

Prior to improving in October ($Q = 1.31$), November ($Z = 1.37$, $Q = 1.65$), and December ($Z = 0.79$, $Q = 0.72$), Luanda was marked by persistent unfavorable trends, notably March ($Z = -1.81$, $Q = -3.63$), which had the biggest negative Sen's slope among all stations. With positive trends in 11 out of 12 months—April ($Z = 1.85$, $Q = 3.16$), June ($Z = 2.29$, $Q = 2.95$), July ($Z = 2.64$, $Q = 2.50$), August ($Z = 2.91$), September ($Z = 2.20$, $Q = 1.93$), and December ($Z = 0.97$, $Q = 1.97$), with May ($Z = -0.97$, $Q = -1.70$). Overall, Luanda had the largest negative Sen's slope ($Q = -3.63$ in March) and Abuja had the largest positive Sen's slope ($Q = 5.93$ in September). Cairo, Johannesburg, and Luanda displayed weak or erratic trends, suggesting that the observed changes primarily reflect natural climatic variability rather than significant long-term change.

Table 3: Mann-Kendall test statistic for monthly precipitation by stations (2000–2025).

January				February			March		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	0.38	0.00	No Trend	-0.22	-0.01	No Trend	1.45	0.26	No Trend
Cairo	-1.37	-0.12	No Trend	-0.75	-0.04	No Trend	-0.44	-0.04	No Trend
Johannesburg	0.00	0.03	No Trend	-0.18	-0.32	No Trend	-0.84	-0.97	No Trend
Luanda	-1.06	-1.39	No Trend	-1.01	-1.31	No Trend	-1.81	-3.63	No Trend
Nairobi	0.40	0.70	No Trend	1.37	1.68	No Trend	0.31	0.39	No Trend
April				May			June		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	-1.41	-1.03	No Trend	0.04	0.05	No Trend	0.31	0.40	No Trend
Cairo	0.71	0.02	No Trend	-0.44	-0.01	No Trend	-0.13	-0.00	No Trend
Johannesburg	1.23	1.19	No Trend	-0.26	-0.04	No Trend	-0.97	-0.15	No Trend
Luanda	-1.06	-2.58	No Trend	1.23	0.78	No Trend	-1.50	-0.07	No Trend
Nairobi	1.85	3.16	No Trend	-0.97	-1.70	No Trend	2.29	2.95	No Trend
July				August			September		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	-0.13	-0.72	No Trend	-0.71	-2.91	No Trend	2.42	5.93	No Trend
Cairo	-1.41	-0.02	No Trend	-2.91	-0.02	No Trend	-1.10	-0.01	No Trend
Johannesburg	1.10	0.06	No Trend	-0.40	-0.02	No Trend	0.57	0.12	No Trend
Luanda	-2.34	-0.11	No Trend	-0.09	-0.01	No Trend	-1.45	-0.18	No Trend
Nairobi	2.64	2.50	No Trend	2.34	1.91	No Trend	2.20	1.93	No Trend
October				November			December		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	1.94	2.63	No Trend	-0.62	-0.05	No Trend	-0.93	-0.00	No Trend
Cairo	-0.09	-0.00	No Trend	1.15	0.06	No Trend	0.18	0.01	No Trend
Johannesburg	0.13	0.20	No Trend	-0.22	-0.55	No Trend	1.01	1.04	No Trend
Luanda	-0.88	1.31	No Trend	1.37	1.65	No Trend	0.79	0.72	No Trend
Nairobi	1.41	0.95	No Trend	0.40	0.42	No Trend	0.97	1.69	No Trend

Table 4 presented that none of the five stations (Abuja, Cairo, Johannesburg, Luanda, and Nairobi) showed statistically significant by the monthly trends. According to the Mann–Kendall trend analysis and Sen's slope estimates. All months were categorized as "No Trend," suggesting that observed fluctuations were more likely to be the result of natural variability than long-term, persistent change. Sen's slopes (Q) varied from −2.91 (August) to 5.93 (September), whereas monthly **Z-values in Abuja ranged from −1.41 (April) to 2.42 (September). January (Z = 0.38, Q = 0.00), March (1.45, 0.26), May (0.04, 0.05), June (0.31, 0.40), September (2.42, 5.93), and October (1.94, 2.63) had positive tendencies, while February (−0.22, −0.01), July (−0.13, −0.71), August (−0.71, −2.91), November (−0.62, −0.05), and December (−0.93, −0.00) had declining

tendencies. Weak negative trends predominated in Cairo, where Z-values ranged from -2.91 (August) to 1.15 (November) and Q-values from -0.12 (January) to 0.06 (November). January ($-1.37, -0.12$), February ($-0.75, -0.04$), March ($-0.44, -0.04$), May ($-0.44, -0.01$), June ($-0.13, -0.00$), July ($-1.41, -0.02$), August ($-2.91, -0.02$), September ($-1.10, -0.01$), and October ($-0.09, -0.00$) showed weakly positive tendencies. Z-values ranged from -0.97 (June) to 1.23 (April) in Johannesburg, whereas Q-values ranged from -0.97 (March) to 1.19 (April). January ($0.00, 0.03$), April ($1.23, 1.19$), July ($1.10, 0.06$), September ($0.57, 0.12$), October ($0.13, 0.20$), and December ($1.01, 1.04$) had positive trends, while February ($-0.18, -0.32$), March ($-0.84, -0.97$), May ($-0.26, -0.04$), June ($-0.97, -0.15$), August ($-0.40, -0.02$), and November ($-0.22, -0.55$) displayed negative tendencies.

Luanda's Z-values ranged from -2.34 (July) to 1.37 (November) and Q-values from -3.63 (March) to 1.65 (November), indicating a predominance of negative trends. January ($-1.06, -1.39$), February ($-1.01, -1.31$), March ($-1.81, -3.63$), April ($-1.06, -2.58$), June ($-1.50, -0.07$), July ($-2.34, -0.11$), August ($-0.09, -0.01$), and September ($-1.45, -0.18$) had positive Sen's slopes despite the lack of statistical significance. With Z-values ranging from -0.97 (May) to 2.64 (July) and Q-values from -1.70 (May) to 3.16 (April), Nairobi showed the most consistent positive tendencies. January ($0.40, 0.70$), February ($1.37, 1.68$), March ($0.31, 0.39$), April ($1.85, 3.16$), June ($2.29, 2.95$), July ($2.64, 2.50$), August ($2.20, 1.91$), September ($2.20, 1.93$), October ($1.41, 0.95$), November ($0.40, 0.42$), and December ($0.97, 1.97$) had positive trends. Overall, Nairobi recorded positive Z-values in 11 out of 12 months, Abuja had the largest positive Sen's slope ($Q = 5.93$) in September, Luanda had the strongest negative slope ($Q = -3.63$) in March, Cairo had mostly weak negative tendencies, and Johannesburg had only minor month-to-month oscillations. These results

confirmed that, despite temporal variability, the climatic variable remained statistically stable across all stations during the study period.

Table 4: Annual and monthly minimum temperature trends (M-K) by stations (2000–2025).

January				February			March		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	1.41	0.0350	No Trend	0.04	0.0027	No Trend	0.51	0.0180	No Trend
Cairo	0.13	0.0027	No Trend	-0.51	-0.0095	No Trend	-0.24	-0.0133	No Trend
Johannesburg	0.71	0.0176	No Trend	1.06	0.0475	No Trend	0.84	0.0353	No Trend
Luanda	0.42	0.0078	Increasing	2.25	0.0353	Increasing	1.57	0.0250	No Trend
Nairobi	1.41	0.0240	No Trend	1.68	0.0317	No Trend	1.61	0.0357	No Trend
April				May			June		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	1.65	0.0582	No Trend	1.61	0.0409	No Trend	1.96	0.0271	No Trend
Cairo	-0.35	-0.0100	No Trend	1.72	0.0378	No Trend	1.52	0.0431	No Trend
Johannesburg	0.13	0.0021	No Trend	0.55	0.0183	No Trend	-0.26	-0.0080	No Trend
Luanda	1.59	0.0236	No Trend	2.80	0.0550	Increasing	1.72	0.0300	No Trend
Nairobi	0.68	0.0109	No Trend	1.41	0.0214	No Trend	2.16	0.0400	Increasing
July				August			September		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	0.99	0.0150	No Trend	0.44	0.0054	No Trend	1.54	0.0162	No Trend
Cairo	1.79	0.0425	Increasing	2.62	0.0540	No Trend	2.71	0.0511	Increasing
Johannesburg	0.84	0.0250	No Trend	0.95	0.0424	No Trend	2.25	0.0747	Increasing
Luanda	0.68	0.0100	No Trend	-0.04	-0.0014	No Trend	1.59	0.0223	No Trend
Nairobi	2.29	0.0350	Increasing	1.57	0.0247	No Trend	1.81	0.0271	No Trend
October				November			December		
Station	Z	Q	Trend	Z	Q	Trend	Z	Q	Trend
Abuja	1.30	0.0185	No Trend	1.61	0.0379	No Trend	0.77	0.0388	No Trend
Cairo	1.83	0.0550	No Trend	1.65	0.0585	No Trend	1.76	0.0514	No Trend
Johannesburg	0.22	0.0067	No Trend	1.01	0.0357	No Trend	0.26	0.0075	No Trend
Luanda	3.99	0.0514	Increasing	3.02	0.0513	Increasing	2.12	0.0473	Increasing
Nairobi	2.87	0.0367	Increasing	1.74	0.0242	Increasing	1.30	0.0175	No Trend

4. CONCLUSION

This research provides a comprehensive assessment of the geographical and temporal variability of rainfall and temperature across five selected African stations (Abuja, Cairo, Johannesburg, Luanda, and Nairobi) using 26 years (2000–2025) of MERRA-2 reanalysis data. The results clearly demonstrate climatic variety driven by latitude, height, regional air circulation, and geographic position, with notable differences in temperature characteristics and rainfall distribution across the selected stations. Spatial studies showed a clear north-south rainfall gradient and opposing

temperature regimes, while seasonal assessments highlighted the influence of the West African Monsoon, the Inter-Tropical Convergence Zone (ITZ), and local topographic constraints on regional climatic variability.

The long-term records showed rising temperature tendencies, increased rainfall irregularity, and more frequent climate extremes, especially after 2010, indicating an intensification of climate variability across several African sub-regions, despite Mann-Kendall and Sen's slope analyses showing that monthly rainfall variations were generally not statistically significant. The robustness of the chosen methodology and its appropriateness for climate assessment and future forecasting applications are further confirmed by the remarkable agreement between the generated and observed datasets. These results offer vital scientific proof for enhancing climate adaption strategies, agricultural planning, water resource management, environmental sustainability, and disaster risk reduction throughout Africa.

In order to improve climate projections and enable well-informed policy decisions under changing climate conditions, future research should make use of satellite observations, high-resolution regional climate models, and cutting-edge artificial intelligence and machine learning approaches.

Data Availability Statement: The datasets generated during and/or analysed during the current study are available in the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) repository, <https://doi.org/10.5067/0JRLVL8YV2Y4>.

Clinical Trial

No clinical trial.

Consent to publish declaration

Not applicable.

Consent to participate declaration

Not applicable.

Ethics declaration

Not applicable

Funding Declaration

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