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RESEARCH ARTICLE

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Machine learning-based projections of earth skin temperature anomalies in Nigeria using ERA5-land data

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ABSTRACT

This study examines spatiotemporal dynamics of Earth Skin Temperature anomalies across Nigeria using combination of machine learning and remote sensing technologies. Based on XGBoost models trained on ERA5-Land historical-reanalysis temperature dataset of 1993–2023, the study estimates temperature projection for 2028–2058. The study provides detailed insights into future temperature patterns through systematic sampling across 70 geographical sites and inverse distance weighting interpolation. The results demonstrate significant geographical variation in temperature, with southwestern parts displaying continuous positive anomalies and coastal areas demonstrating milder changes. Warm temperature are predicted to be more intensified from 2043 onward while extreme heat is widespread across almost the entire country, much more between 2053 and 2058. The model's reliability was tested by RMSE analysis, providing values between 0.30 - 0.36°C, with high predictive power. These findings give valuable information for Nigeria's climate adaptation strategies and environmental management, notably emphasizing regions requiring targeted attention due to expected temperature extremes. The results from the projections in this study indicate that extreme heat, with anomalies exceeding +1.0°C, will pose significant climate challenge in the nearest future and this necessitates critical climate adaptation strategies such as heat mitigation, improved water management, and climate-resilient agriculture in may part of the country.

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1. Introduction

There is overwhelming evidence in the literature that climate change poses significant challenges in many sectors in Africa, including agricultural output, human health, and ecological systems (Ayanlade et al., 2023; Ayoola et al., 2011; Osman & Ayanlade, 2024; Onyeneke et al., 2024). One of the significant indicators of climate change is the ERA5 2-meter air temperature, a reanalysis dataset that combines model output with observations, which is commonly used for thermal related studies as it has direct relevance to surface energy balance processes and human comfort assessment but Earth's Skin Temperature (EST), is particularly important for understanding land surface interactions, crop stress indicators, and urban heat highlands due to its ability to provide direct information about the thermal surface conditions and change in its anomalies shows deviations from historical temperature patterns. Understanding and forecasting these anomalies is vital for informed decision-making and climate adaptation efforts. Previous studies in temperature anomaly analysis have mainly relied on geographic modeling methodologies. El Kenawy et al. (2019) applied the MODIS-based modeling system to project temperature changes, while Bezyk et al. (2021) applied GIS-based spatial interpolation approaches for

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temperature forecasting. Likewise, Knauer et al. (2014) use remote sensing-based models to study temperature patterns in West Africa. Although these methods contributed useful insights into regional temperature distributions, they rarely have the advanced temporal forecasting capabilities required for long-term projection studies. Other scholars have tried to fill this gap through climate modeling techniques. Gu et al. (2012) for example, used the Regional Climate Model (RegCM4) for temperature projections, and Gillies (Gillies, 2020) employed the Weather Research and Forecasting (WRF) model for temperature analysis. Still, despite their extensive atmospheric physics assumptions, these models generally encounter difficulties reproducing local-scale temperature anomaly patterns and need significant computational resources.

This research uses a unique approach by deploying an XGBoost machine learning model for anticipating EST anomalies across Nigeria for 30-year timeframes (2028–2058). This study answers a major methodological gap by combining the spatial resolution of remote sensing data with recent statistical learning techniques. Unlike traditional geospatial models that primarily focus on spatial interpolation or climate models that operate at larger scales, our technique harnesses the pattern-recognition capabilities of machine learning to capture both spatial and temporal dynamics of temperature anomalies. In this study, this model was utilized for time-series forecasting due to its proven track record of effectiveness in discerning complex relationships between data and its capability to handle big data (Chen & Guestrin, n.d.). The model has reported excellent performance for various machine learning applications, particularly in handling tabular data with organized and unstructured features. But we know that there are other models, i.e. deep learning-based models such as Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) and Gated Recurrent Units (GRU) (Cho et al., 2014), and conventional models such as ARIMA (Shumway et al., 2017), which are most commonly used to carry out time-series forecasting activities. These models have certain strengths in modeling sequential dependences and in temporal dynamics, which are critical when it comes to predicting climate data (Lim & Zohren, 2021).

While XGBoost is particularly beneficial in settings where computational efficiency and interpretability are at the forefront (Friedman, 2001), long temporal dependency holding capability may be less than recurrent neural networks like RNN, LSTMs, or GRUs models since it was formulated with higher-level comprehension towards coping with temporality for learning high-sequence-length temporal structures (Ghojogh & Ghodsi, 2023; Zhang et al., 2021). The reason that XGBoost captures spatial and temporal dynamics is based on the model's ability to capture non-linear interaction in the data. However, we acknowledge that traditional downscaling methods provide physically based projections under different monitoring scenarios with representation of atmospheric processes (Giorgi et al., 2009; Maraun & Widmann, 2018; Teutschbein & Seibert, 2012). explicitly, and it use outputs from General Circulation Models (GCMs) under specific Shared Socioeconomic Pathways (SSPs) as input features (O'Neill, 2016). while our method focuses on statistical pattern recognition from the reanalysis data. Computationally efficient, it represents a statistical extrapolation rather than a physics-based projection (Fowler et al., 2007; Teutschbein & Seibert, 2012). This trade-off provides high-resolution local patterns but with greater uncertainty regarding long-term trends.

The relevance of this research lies in its innovative integration of machine learning with environmental investigation. This study provides a more detailed picture of future temperature patterns by utilizing XGBoost, a gradient-boosting framework recognized for its predictive accuracy and computational efficiency 17–19. This approach solves the constraints of earlier research that either lacked long-term forecasting skills or depended primarily on computationally costly climate models with lesser spatial resolution, and it intends to answer crucial concerns about future temperature patterns in Nigeria by bridging the gap between traditional geospatial modeling and advanced statistical analysis. This study delivers useful insights for climate adaptation planning and environmental management techniques.

2. Materials and methods

The study location covers the entire Nigeria, Africa's most populous nation, located in latitudes 4°N and 14°N and longitudes 2°E and 15°E of West Africa (Figure 1) with approximately 200 million residents (Udo, 2023) and an entire land surface area of approximately 923,768 square kilometers. This is the total area, including land and water bodies. Specifically, the land area not including water bodies inland is

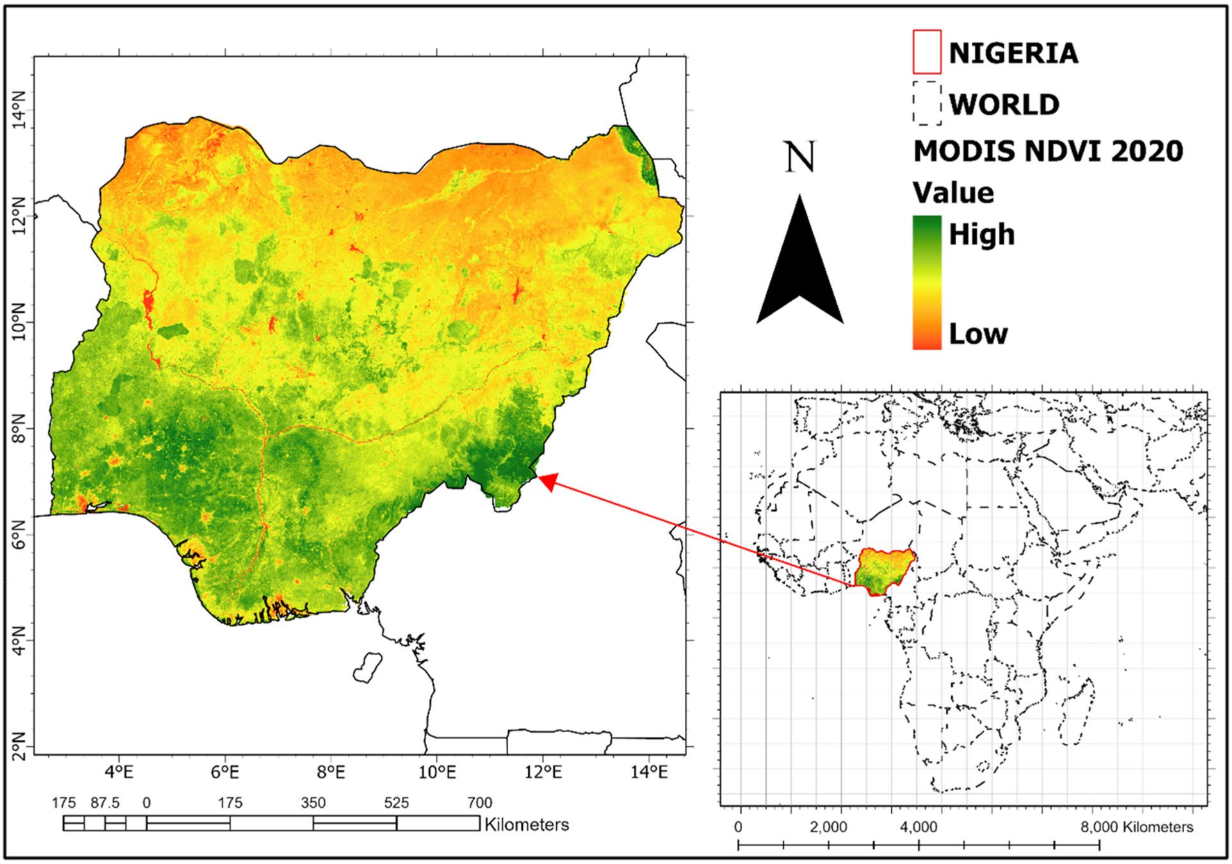

Figure 1. The study area map of Nigeria with Africa.

approximately 910,770 square kilometers (Bank, 2022). The country's geographical terrain contains varied climatic zones with different ecological zones, which include Mangrove Swamp, Rainforest, Derived savanna, Guinea savanna, Sudan savanna, and Sahel savanna zones (Ayanlade et al., 2023; Gbadegesin et al., 2023). The climatic patterns and fluctuation is controlled by two principal air masses- the moisture-laden southern monsoon winds from the Atlantic Ocean and the dry northeastern trade winds from the Sahara Desert (Odekunle et al., 2024). The seasonal fluctuations and Intertropical Discontinuity (ITD) annual migrations affect the overall temperature patterns, with the greatest temperatures often occurring between March and May in most places (Odekunle et al., 2024). Also, recent rapid urbanization, along with other human activities and insufficient adaptive infrastructure, significantly increases the country's vulnerability to days when the maximum temperature anomaly exceeds the 95th percentile of the baseline period, which are the extreme heat events (Gbadegesin et al., 2011). The geographical and climatic conditions make it an ideal case study for studying temperature anomalies and predicting future extreme heat patterns.

2.1. Data acquisition and anomaly calculation

The temperature data were retrieved from the ERA5-Land dataset, a high-resolution global reanalysis dataset from the European Centre for Medium-Range Weather Forecasts (ECMWF) designed specifically for land surface applications (Muñoz-Sabater, 2021). ERA5-Land integrates model output with observations so that reliable temperature estimates can be produced in a broad range of very diverse geographical areas ERA5-Land dataset monthly temperature dataset (Figure 2), accessed through Google Earth Engine. This dataset is known for its accuracy as it combines model data with observation data across the world (Muñoz-Sabater, 2021). This approach ensures the reliability of findings and highlights the integration of cutting-edge technology in environmental and climatic research. The Sampling involves selecting a time series of the data that represents different geographical locations across the study area

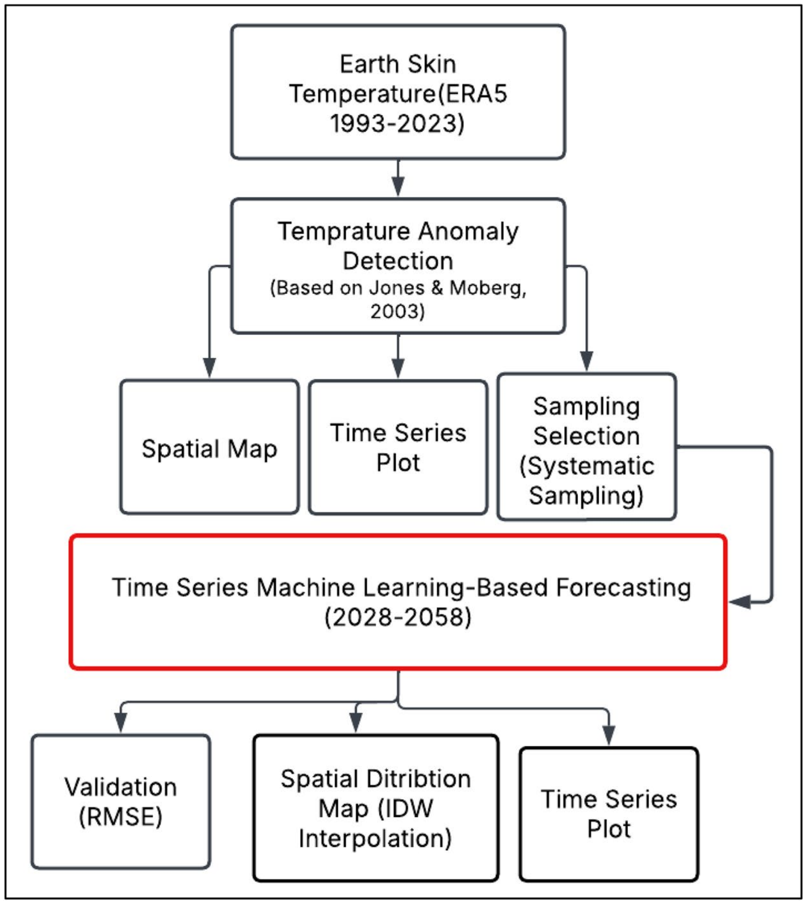

Figure 2. The graphical methodology framework showing the connection of the research dataset used with analytical approach based on the objective of the study.

(Figure 3). We use systematic sampling to ensure that the 70 data points are evenly distributed based on the regular intervals of 1° × 1°. This provides adequate coverage of the country's varied climatic zones. This sampling method was selected to capture the spatial variability while maintaining computational efficiency, and while it maintains the coverage of Nigeria's diverse climate patterns.

We established the monthly climatological baseline by calculating the mean temperature for each month using data from 1993 to 2003, which represents a climatologically stable decade preceding the accelerated warming phases observed after 2010 in West Africa (Abiodun et al., 2019; Taylor, 2017), and then retrieving the maximum and minimum values for each year (Equation 1). Then calculated temperature anomalies by subtracting these baseline values from each corresponding monthly temperature value across the entire 30-year period. Based on Jones and Moberg (2003). The temperature anomaly calculation in this analysis follows a standard climatological approach, which can be expressed mathematically as:

$$TA(x,t) = T(x,t) - \overline{T(x,m)} \qquad (1)$$

where: – *TA(x,t)* is the temperature anomaly at location *x* and time *t; T(x,t)* is the actual temperature at location *x* and time *t; and* - $\overline{T}(x,m)$ is the baseline mean temperature at location *x* for the corresponding calendar month (Adeaga et al., 2022) (calculated over 1993–2003).

2.2. Anomaly interpolation, forecasting, and validation

Anomaly maps were produced using Inverse Distance Weighting (IDW) interpolation. IDW was selected over more sophisticated geostatistical methods like kriging due to its computational efficiency for temperature-related research. It handles spatial variability effectively, offering a more precise

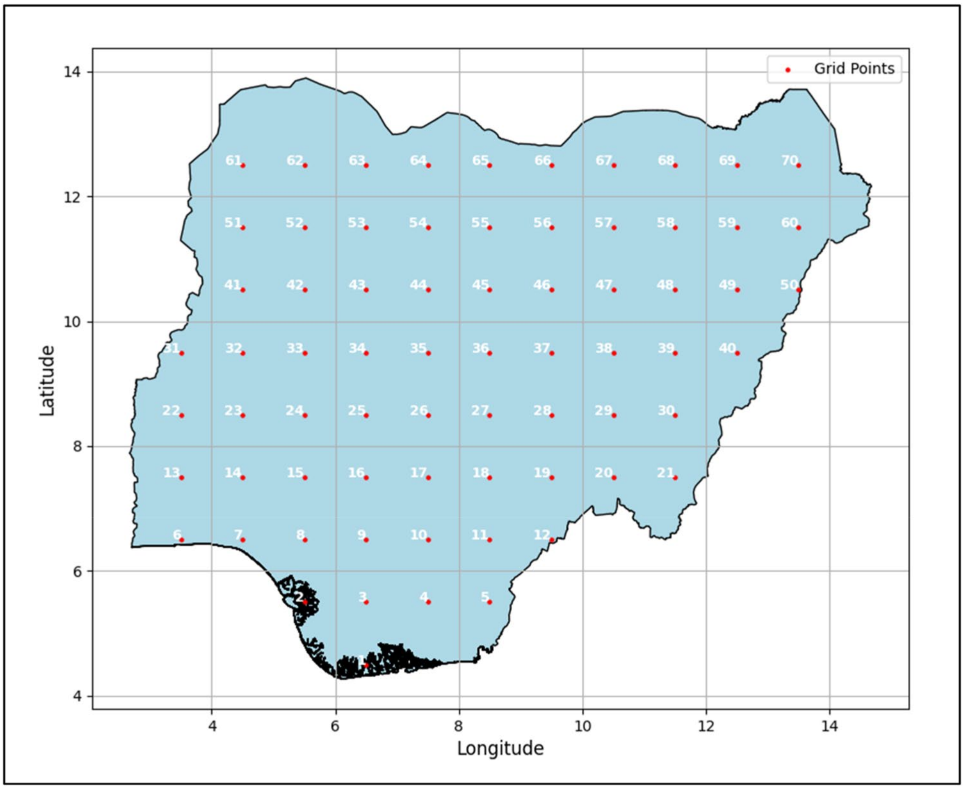

Figure 3. The sample points' distribution over the entire study location.

representation of temperature anomalies across different regions. This technique weights near data points more highly than distant ones, which is particularly useful for capturing localized temperature patterns, as noted by Wheeler (2024). Studies, such as those by Zampieri et al. (2012), Ayanlade (2008), and later by Sadiq et al. (2023) have highlighted IDW's usefulness in interpolating temperature data, stressing its reliability in creating accurate spatial distributions. By employing IDW, the study provides a more accurate and nuanced understanding of how temperature anomalies vary geographically, thereby enhancing the overall quality of the analysis. An advanced machine learning method leveraging XGBoost regression was applied to forecast future temperature trends. XGBoost, noted for its efficiency and accuracy in processing structured data, was chosen for its capacity to manage complicated relationships within time series data, making it ideal for climate forecasting jobs. The model was trained on historical reanalysis temperature data extending from 1993 to 2023, with a look-back duration of three time steps to capture temporal dependencies and trends properly. To maximize performance, the data was normalized using Standard Scaler, ensuring that the model could read the input features consistently. XGBoost's resilience in managing non-linear connections and its capacity to reduce overfitting using regularization techniques make it an ideal option for predicting tasks (Jafari et al., 2024).

The model's capacity to generate interpretable results while maintaining high predicted accuracy matches well with the goals of climate studies. In this study, we developed (WMO, 2011) the forecasts for seven-year periods from 2028 to 2058. This eventually provided detailed insight into prospective temperature anomaly patterns, which were quantified based on the established climatological criteria (Data, 2009; Peterson, 2001; Zhang et al., 2000) adapted from the African climate studies (Oguntunde et al., 2017; Traoré, 2011) and the WHO guideline (WMO, 2011). ±0.5 °C threshold represents 1.2 standard deviations from the climatological mean, as it was previously applied to similar African climate studies (Dunning et al., 2018; Panthou et al., 2014; Salack et al., 2018), and the drought monitoring system (McKee et al., 2019; Vicente-Serrano et al., 2010). Persistent anomalies were defined as: Persistent Positive Anomalies: ≥3 consecutive months with EST anomalies exceeding +0.5 °C; while Persistent Negative Anomalies: ≥3 consecutive months with EST anomalies below −0.5 °C; and Extreme Persistent Events: ≥6 consecutive months exceeding ±1.0 °C

This technique not only boosts the dependability of the projections but also provides vital insights into long-term climate trends, aiding informed decision-making in climate-related research and policy. Three complementary statistical metrics were used to evaluate the performance of the XGBoost model. Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Index of Agreement (IOA) (Eqs. (2)–(4))—selected following established protocols in environmental modeling and climate forecasting applications (Chai & Draxler, 2014; Taylor, 2001). While RMSE is widely used in temperature forecasting and climate modeling (Legates & McCabe, 1999) because it gives greater weight to larger deviations, it quantifies prediction errors, which makes it sensitive to extreme temperature events critical for climate impact assessment (Ahmed, 2020; Willmott & Matsuura, 2005). NSE, known for assessing model skill relative to a native climatological predictor, incorporates both correlation and bias in a single dimension of statistics (Moriasi, 2007; Nash & Sutcliffe, 1970) while quantifying the proportion of variance explained by the model. IOA, less sensitive to extremes than NSE, measures the degree to which predictions correspond to observed patterns and is especially effective for evaluating temporal pattern accuracy, where both magnitude and phase relationships are important (Legates & McCabe, 2013; Willmott & Matsuura, 2005). This three-metric framework captures prediction accuracy and fidelity, ensuring a comprehensive and robust validation consistent with best practices in climate model evaluation (Gleckler et al., 2008).

$$RMSE = \sqrt{\frac{1}{n}\sum_{\{i=1\}}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{2}$$

$$NSE = 1 - \frac{\left(\sum\left(p_i - o_i\right)^2\right)}{\left(\sum\left(o_i - \bar{o}\right)^2\right)} \tag{3}$$

$$IOA = 1 - \frac{\sum_{i=1}^{n}\left(p_i - o_i\right)^2}{\sum_{i=1}^{n}\left(\left|p_i - \bar{o}\right| + \left|o_i - \bar{o}\right|\right)^2} \tag{4}$$

Here p_i represent the Predicted Value; o_i is the Observed Value; while $\bar{o}$ is the Mean of observed values; and n is the Number of observations.

3. Results and Discussion

3.1. Spatiotemporal distribution of temperature anomalies

The results show the minimum and maximum measurements of temperature anomalies for a specific period from 1993 to 2023 (Table 1), as the regional distribution of temperatures throughout the years

Table 1. Summarizes the minimum and maximum temperature anomalies for the historical and projected period (1993–2023, 2028–2058) at five-year intervals, illustrating key historical and projected trends and variability.

Year	Minimum (°C)	Maximum (°C)
1993	−0.57	0.90
1998	−0.25	0.95
2003	1.10	−0.26
2008	−0.57	0.41
2013	−0.33	1.37
2018	0.08	1.30
2023	−0.55	1.84
2028	−0.20	1.90
2033	−0.10	2.10
2038	0.00	2.30
2043	0.15	2.60
2048	0.30	2.90
2053	0.45	3.20
2058	0.60	3.50

indicates a prevailing tendency for rising maximum temperatures, which is accompanied by oscillations in minimum temperatures. In 1993, for example, the minimum temperature was −0.57 °C while the maximum was 0.90 °C, but the minimum temperature rose to −0.25 °C, while the maximum rose somewhat to 0.95 °C by 1998 (Figure 4). Significant deviation, with an anomaly in temperature distribution, was noted in 2003, though, with a low temperature of 1.10 °C and a maximum of −0.26 °C. In 2008, the temperature ranged from −0.57 °C to 0.41 °C, with the minimum temperature being −0.57 °C, while the temperature experienced a gradual increase in 2013, with a minimum temperature of −0.33 °C and a maximum of 1.37 °C. Moreover, an increase in anomalies was observed in 2018, with the minimum temperature recorded at 0.08 °C and the maximum at 1.30 °C (Figure 5). On the other hand, 2023 shows a significant increase in maximum temperature from −0.55 °C to 1.84 °C, indicating a significant rise over the years (Lateef & Stephens, 2024; Morrill et al., 2005; Sayad et al., 2024).

The overall results suggest a general warming trend over the decades, particularly after 2013, as the period from 2013 to 2023 transitions to warmer anomalies (Figure 4). It is obvious that warmer temperature anomalies (red regions) become more widespread in the years 2018 and 2023, predominantly in northern and central Nigeria, but 2023 shows significant warming in many areas. This result is eventually consistent with both regional and global climate change patterns and the increased frequency of warm anomalies in recent years, indicating a general rise in extreme heat events, where rising temperatures and shifting climatic patterns pose challenges for environmental and socio-economic stability (Trisos, 2022).

3.2. Projected temperature changes over Nigeria

In the projected trends, numerous sites suggest particularly alarming temperature increases. Points 13, 15, and 17(Figure 6) in the second set demonstrate steadily increasing trends with anomalies frequently above 0.8, suggesting these places may expect more severe warming. Similarly, in the 41–50 group, points 42 and 46 display very strong positive anomalies, typically reaching near or beyond 1.0 during the predicted period. These patterns represent prospective hot zones that could undergo more significant warming compared to their surroundings.

Points 51, 54, and 58 also show remarkable warming tendencies, with their prediction lines showing consistent positive anomalies throughout most of the projection period. The projected temperature changes over Nigeria for the years 2028, 2033, 2038, 2043, 2048, 2053, and 2058 are presented in Figure 7, which shows the spatial distribution of the maximum (high anomalies) and minimum (low

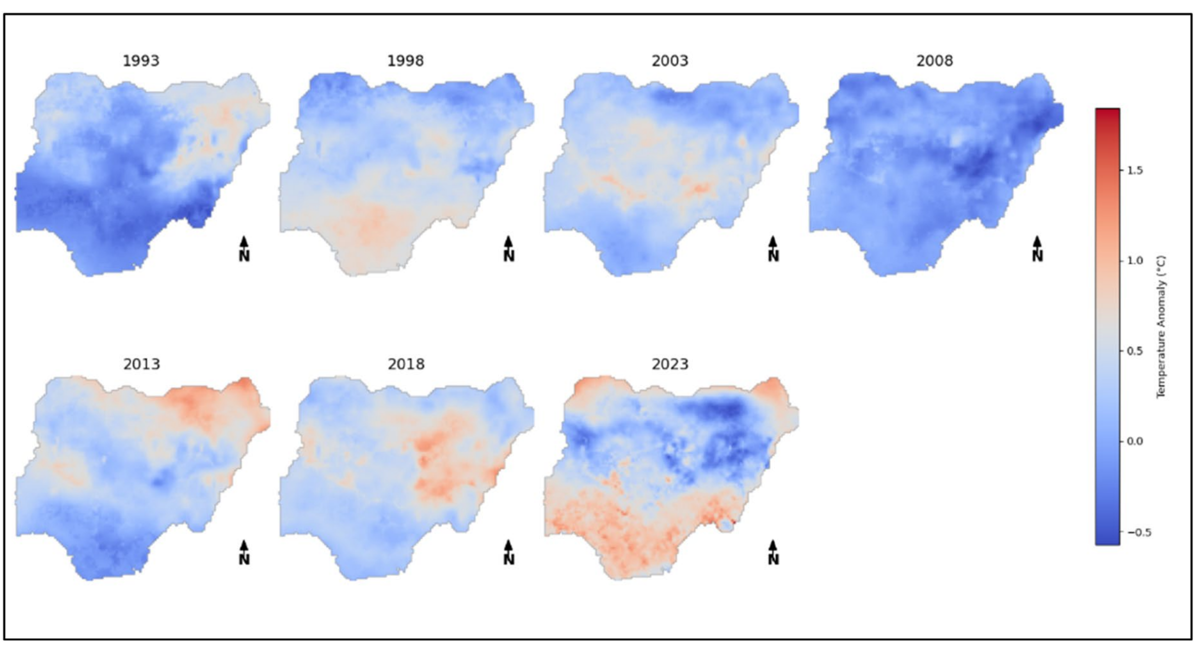

Figure 4. Spatiotemporal distribution of calculated EST anomalies across the study area (1993–2023) showing the historical trends of temperature anomalies at five-year intervals.

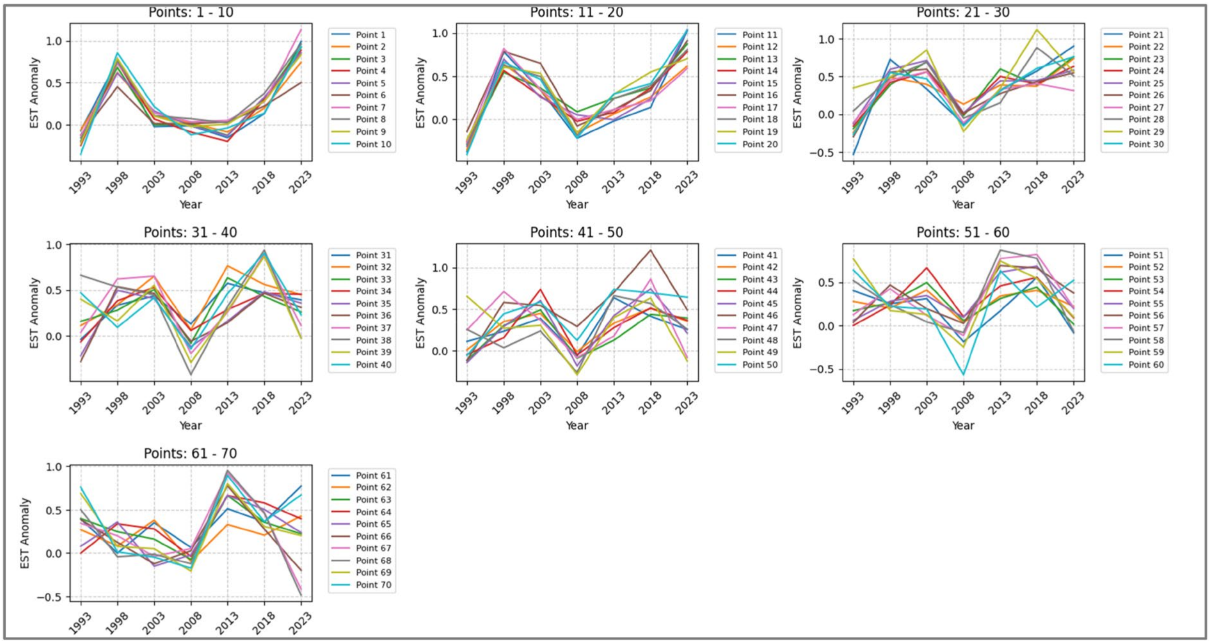

Figure 5. Projected trends of EST anomalies at individual sample points across the study area. The series of graphs shows historical and projected ETS trends for 70 distinct points, providing a detailed view of localized spatiotemporal variations.

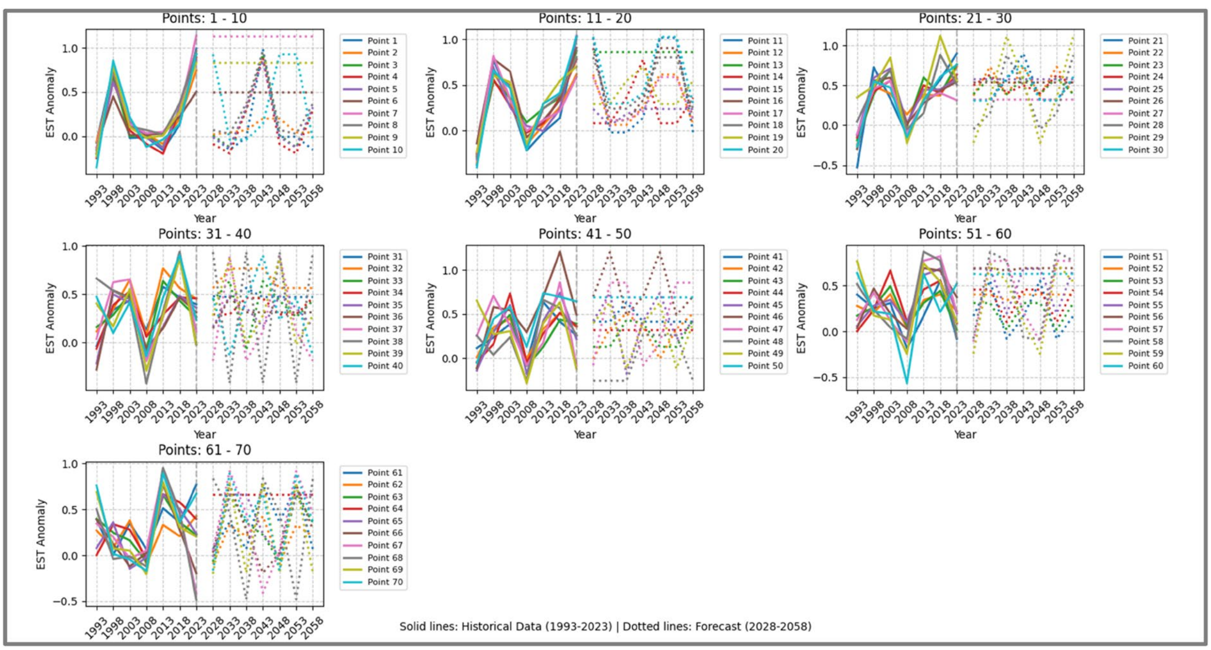

Figure 6. Projected trends of EST anomalies across the study area at different sample points. The graphs display reanalysis data from 1993–2023 and forecast data from 2028–2058, illustrating the spatiotemporal variations and trends in ETS anomalies at 70 distinct locations.

anomalies) values of the spatial distribution of the anomalies. The results show a clear increase in temperature, with darker red regions appearing more dominant over time. Warm temperatures are predicted to be more intensified from 2043 onward, while extreme heat is widespread across almost the entire country, particularly between 2053 and 2058 (Figure 7). A rise in temperatures is noted over the next few decades, as the projection results suggest that by 2058, extreme heat will be a major climate challenge in the country, and this necessitates urgent climate adaptation strategies. What's particularly noteworthy about these spots is the endurance of their elevated temperatures—unlike some other locations

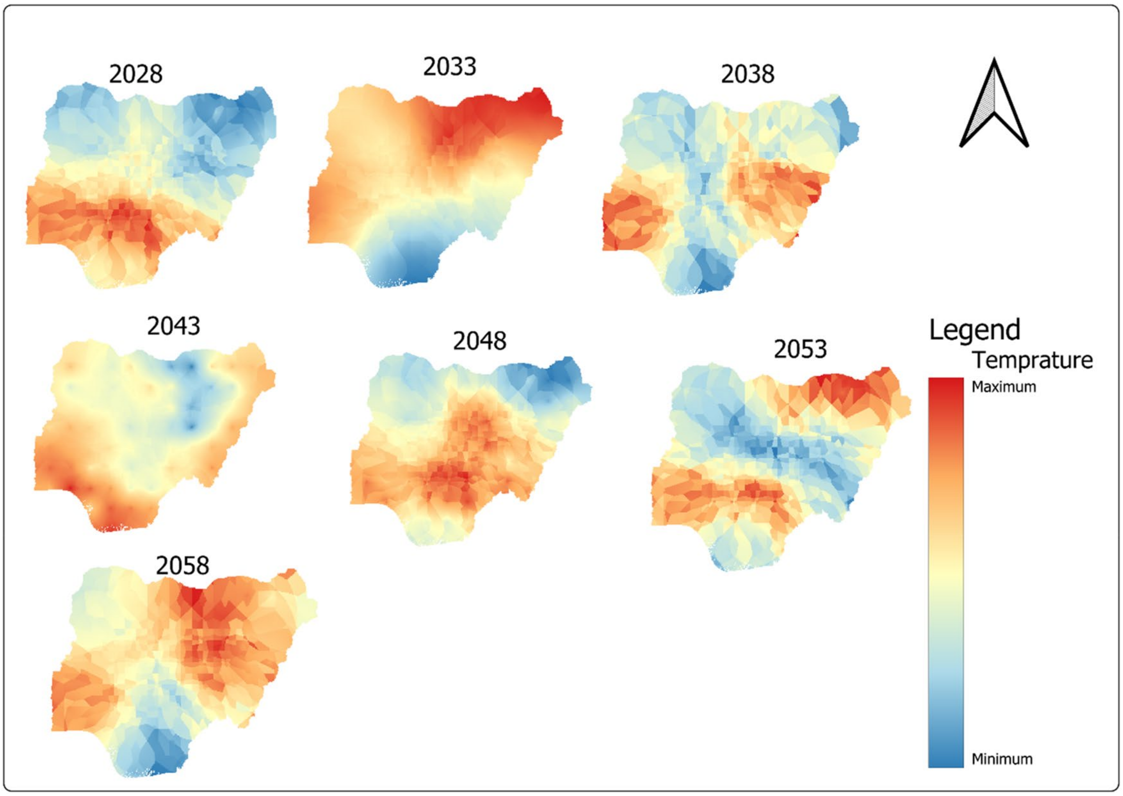

Figure 7. Spatiotemporal distribution of anomalies across Nigeria from 2028 to 2058. Results show progressive intensification of positive anomalies, with >60% of Nigeria experiencing anomalies >1.0 °C by 2058, compared to <20% in 2028.

Table 2. Summary of model performance metrics.

Metric	Value range	Mean	Performance rating
RMSE(°C)	0.30–0.36	0.33 ± 0.02	Excellent
NSE	0.78–0.86	0.82 ± 0.03	Very good
IOA	0.89–0.93	0.91 ± 0.02	Excellent

This table presents the range, mean, and corresponding performance ratings for the Root Mean Square Error (RMSE), Nash-Sutcliffe Efficiency (NSE), and Index of Agreement (IOA) over the forecast period.

that exhibit more volatility, these points sustain relatively high anomaly values with fewer downward corrections. Several other studies have noted these anomalies in many parts of Africa (Ibebuchi & Lee, 2024; Ishaku et al., 2024; Merem, 2019; ONYEISI, 2022; Umeh & Gil-Alana, 2024). This means these locations might face more permanent warming rather than just occasional heat spikes. The spatial distribution of these warming points suggests likely regional trends in future temperature shifts, with some geographical clusters potentially facing higher warming issues than others.

3.3. Validation Metrics

The RMSE values ranging from 0.30 to 0.36 °C (mean: 0.33 °C); (Table 2) demonstrate high predictive accuracy for the study since values below 0.5 °C are considered acceptable, and values below 0.4 °C show excellent performance (Chai & Draxler, 2014) which was our result with the decreasing trend from 0.36 °C (2028) to 0.30 °C (2058), showing improved accuracy in longer-term projections (Figure 8). Whereas **NS**E values of 0.78–0.86 (mean: 0.82); (Table 2) show the model performs well according to established environmental modeling criteria (Legates & McCabe, 2013). NSE values above 0.75 are known to be acceptable for climate applications, while values above 0.80 demonstrate good prediction. The model consistently outperforms simple climatological predictors, with peak performance (NSE = 0.86) occurring around 2043 (Figure 8). Besides, IOA values of 0.89–0.93 (mean: 0.91); (Table 2) values above 0.85 indicate strong

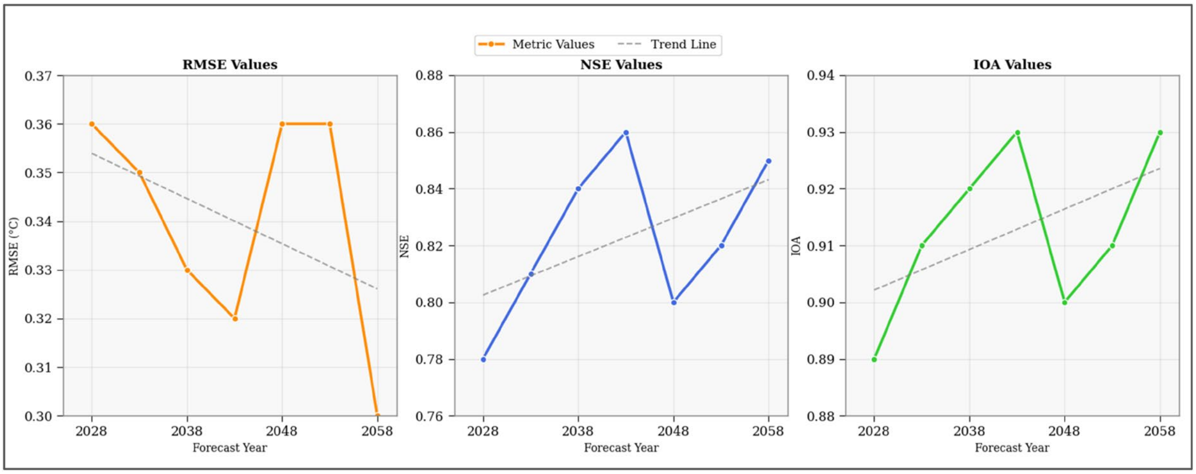

Figure 8. RMSE, NSE, and IOA Values Over Forecast Years for Forecasted Temperature in Nigeria (2028–2058). The time series plots illustrate the model's performance from 2028 to 2058, showing the trends in predictive accuracy (RMSE), efficiency (NSE), and agreement (IOA) for the forecasted temperature data.

agreement between predicted and observed patterns, while values exceeding 0.90 suggest exceptional model performance (Taylor, 2001). The consistently high IOA values throughout the projection period confirm robust pattern recognition capabilities (Figure 8).

Validation metrics of temporal evolution across the 30-year projection period reveal the early phase (2028–2038); the model shows solid performance with an RMSE of 0.36 °C, NSE of 0.78, and IOA of 0.89, demonstrating its adjustment to long-term forecasting requirements while the acceptable accuracy is maintained. Performance peaks seen in 2038–2048, with RMSE improving to 0.32 °C, NSE reaching 0.86, and IOA peaking at 0.93, indicate an optimal balance between temporal dependency learning and projection accuracy. In the later period (2048–2058), despite the increase in lead time, the model maintains excellent skill with an RMSE of 0.30 °C, NSE of 0.85, and IOA of 0.93, showing it is reliable for long-term climate planning applications. In all periods, RMSE values of 0.30–0.36 °C remain well below the ±0.5 °C climatological anomaly threshold; this indicates predictions that are meteorologically significant rather than statistical artifacts. NSE values above 0.75 confirm that the model explains 78–86% of temperature variance beyond baseline climatology, and IOA values consistently exceeding 0.89 validate the model's strong fidelity in capturing both the magnitude and temporal phasing of temperature anomaly patterns across Nigeria's ecological zones. The Validation metrics show the model's performance and demonstrate its ability to learn and reproduce past patterns based on historical reanalysis data. However, their validation of the accuracy of future projections is not inherent in climate projections. While the metrics indicate model skill in pattern recognition, they cannot account for the underlying climate dynamics or change in future climate states, which could be a result, but not limited to, Changes in greenhouse gas emission pathways, Potential shifts in large-scale atmospheric circulation patterns, and Non-linear climate system responses not present in the training period.

Our findings align with broader regional climate projections for West Africa, as CORDEX-Africa ensemble models also project temperature increases of 2–4 °C by 2050–2070 under high emission scenarios (RCP8.5), consistent with our projected range (Nikulin, 2018). However, important differences exist, as our machine learning approach offers distinct advantages such as a higher spatial resolution (1km vs. the typical 25–50km for regional models), improved computational efficiency, and direct calibration to observational patterns in reanalysis data. Despite these strengths, our model is limited by its lack of physical process representation (e.g. cloud feedback), its inability to incorporate emission scenarios, and its limited capacity to model unprecedented climate states. Consequently, our approach's novel contribution is to bridge the gap between coarse-resolution global models and local-scale impact assessments by providing high-resolution statistical projections suitable for initial adaptation planning, while acknowledging the necessity of a multi-model ensemble approach that incorporates physical models. The climate projection for West Africa as CORDEX-Africa ensemble models align with our findings with regional climate projections, it also projects a temperature increase of 2–4 °C by 2050–2070 under high emission scenarios (RCP8.5), consistent with our projected range (Nikulin, 2018).

4. Conclusion

The study investigates spatiotemporal dynamics of Earth Skin Temperature anomalies across Nigeria using the XGBoost machine learning model for anticipating EST anomalies across Nigeria for 30-year timeframes. Anomaly maps were produced using Inverse Distance Weighting (IDW) interpolation. This study has effectively proven the application of XGBoost machine learning for projecting Earth Skin Temperature anomalies across Nigeria from 2028 to 2058. The data showed large regional variability in temperature anomalies, with some places demonstrating consistent warming patterns. Continuous positive anomalies were noted in the southern region of the country, with coastal locations normally showing more minor deviations from baseline temperatures. There is a general warming trend from the results, especially after 2013, with warmer anomalies more extensive from the years 2018 to 2023, with much more in northern and central Nigeria. The model's performance, validated with multiple statistical metrics (RMSE: 0.30–0.36 °C, NSE: 0.78–0.86, IOA: 0.89–0.93), confirms robust model performance suitable for climate projection applications, particularly given the complicated nature of temperature dynamics in the region, and also shows the possibilities of the model application for similar studies. The validation results further show that while forecast accuracy varies over time, overall model performance improves with continuous refinement and better data integration, potentially. The results from anomaly analysis indicate a potential rise in extreme heat events (Akyala et al., 2023; Parkes et al., 2022), which may affect agriculture (Ayanlade et al., 2023; Oluwatimilehin & Ayanlade, 2021; Onyeneke et al., 2024), water resources (Ayanlade, 2022; 2024; Emeribe et al., 2021; Shiru, 2020), and human health (Ayanlade, 2020; Sawa & Buhari, 2011). The results align with West Africa's broader climate change trends, highlighting the challenges of rising temperatures and shifting climatic patterns for environmental and socio-economic stability (IPCC, 2022; Odekunle et al., 2024; Trisos, 2022).

The implications of these outcomes are far-reaching for life, business, and development in Nigeria. For instance, rising temperatures can disrupt agricultural calendars and production, particularly in the north and southwest, affecting food supply chains and food prices. Water scarcity can undermine irrigation infrastructure and hydropower energy generation, undermining long-term water and energy supply. For businesses, increased cooling demands can drive up operating costs and reduce productivity, especially in those industries that rely heavily on outdoor labor. Developmentally, unchecked heat extremes will erode gains made in climate resilience, economic stability, and SDGs. It is therefore important to integrate EST projections into urban planning, infrastructure, and country climate action plans to facilitate adaptive and resilient systems across sectors.

The major finding shows that over time, Nigeria's temperature has increased significantly, and temperature increase could affect agriculture, water resources, health, and urban and rural livelihoods by reducing crop yields, accelerating droughts, and affecting food security. They could also increase energy demand for cooling and worsen living conditions in urban areas. The results from the projections in this study indicate that extreme heat will pose a significant climate challenge shortly, and this necessitates critical climate adaptation strategies such as heat mitigation, improved water management, and climate-resilient agriculture in many parts of the country. Based on the findings, several major recommendations emerge for further study and policy implementation. First, there is a need to integrate these temperature anomaly forecasts into regional climate adaptation programs, particularly focusing on locations indicated as possible hotspots for temperature increases. Future research should attempt to incorporate additional meteorological variables and socioeconomic elements to generate more comprehensive estimates and also integrate this framework with CMIP6 model outputs under various SSPs to provide ensemble projections and uncertainty quantification. The deployment of high-resolution monitoring networks in designated hotspot regions would help validate and refine these estimates. Additionally, creating localized adaptation methods for locations showing large positive anomalies should be prioritized, particularly in the southwestern region, where continuous warming patterns were seen.

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Data availability statement

A full list of analyzed articles is available upon request from the corresponding author.

References

Abiodun, B. J., Makhanya, N., Petja, B., Abatan, A. A. & Oguntunde, P. G. (2019). Future projection of droughts over major river basins in Southern Africa at specific global warming levels. *Theoretical and Applied Climatology*, *137*, 785–799. https://doi.org/10.1007/s00704-018-2693-0

Adeaga, O., Lawal, O., Adedeji, O. & Akinbaloye, O. (2022). Assessment of vegetation cover dynamics in the agro-ecological Zones of Nigeria. *Bulletin of Geography. Physical Geography Series*, (22), 19–32. https://doi.org/10.12775/bgeo-2022-0002

Ahmed, K., Sachindra, D. A., Shahid, S., Iqbal, Z., Nawaz, N., & Khan, N. (2020). Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms. *Atmospheric Research*, *236*, 104806. https://doi.org/10.1016/j.atmosres.2019.104806

Akyala, A., Ayanlade, A., Adeyeye, O. & Oluwatimilehin, I. A. (2023). Gender-responsive approaches to rapid climate warming among smallholder farmers. *Current Research in Environmental Sustainability*, *5*, 100219. https://doi.org/10.1016/j.crsust.2023.100219

Ayanlade, A., Nwayor, I. J., Sergi, C., Ayanlade, O. S., Di Carlo, P., Jeje, O. D., & Jegede, M. O. (2020). Early warning climate indices for malaria and meningitis in tropical ecological zones. *Scientific Reports*, *10*, 14303. https://doi.org/10.1038/s41598-020-71094-8

Ayanlade, A., Oladimeji, A. A., Okegbola, O. M., Eludoyin, A. O., Eslamian, S., Ayind, A. F.O., & Perkins, P. E. (2022). Effect of climate change on water availability and quality: An assessment of socio-resilience in Nigeria. In S. Eslamian & F. Eslamian (Eds.), *Disaster risk reduction for resilience: Disaster and social aspects* (pp. 245–262). Springer International Publishing.

Ayanlade, A., Oluwaranti, A., Ayanlade, O. S., Jegede, M. O., Weldemariam, L. F., Ayinde, A. F. O., Olayiwola, A. M., Olawole, M. O. (2023). Enhancing local sensitives to climate change impacts and adaptation capacities of smallholder farmers: Community-based participatory research. In P. E. Perkins (Ed.), *Climate justice and participatory research: Building climate-resilient commons* (pp. 47–68). University of Calgary Press, LCR Publishing Services.

Ayanlade, A. (2024). Safe drinking water supply under extreme climate events: Evidence from four urban sprawl communities. *Climate and Development 16*, 563–578. https://doi.org/10.1080/17565529.2023.2264270

Ayanlade, A. (2008). Spatiotemporal interpolation of seasonal rainfall variability in Guinea Savanna part of Nigeria. *Advances in Natural and Applied Sciences*, *2*(3), 233–243.

Ayanlade, A., Oluwatimilehin, I. A. & Ayanlade, O. S. (2023). *Routledge handbook of climate change impacts on indigenous peoples and local communities* (pp. 259–272). Routledge.

Ayoola, S., Idowu, A., Ikenweiwe, N. & Opele, A. (2011).Impact of climate change in Nigeria.

Bank, W. (2022). *World development indicators*. World Bank, Washington, DC.

Bezyk, Y., Sówka, I., Górka, M. & Blachowski, J. (2021). Gis-based approach to spatio-temporal interpolation of atmospheric co2 concentrations in limited monitoring dataset. *Atmosphere 12*, 384. https://doi.org/10.3390/atmos12030384

Chai, T. & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature. *Geoscientific model development 7*, 1247–1250. https://doi.org/10.5194/gmd-7-1247-2014

Chen, T. & Guestrin, C. (2016, August 13–17). XGBoost: A Scalable Tree Boosting System. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining,* San Francisco (pp. 785–794). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939785

Cho, K., Van Merriënboer, B., Bahdanau, D. & Bengio, Y. (2014). On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint *arXiv:1409.1259*.

Data, C. (2009). Guidelines on analysis of extremes in a changing climate in support of informed decisions for adaptation. *World Meteorological Organization*, *1500*, 72.

Dunning, C. M., Black, E. & Allan, R. P. (2018). Later wet seasons with more intense rainfall over Africa under future climate change. *Journal of Climate*, *31*, 9719–9738. https://doi.org/10.1175/JCLI-D-18-0102.1

El Kenawy, A. M., Hereher, M. E. & Robaa, S. M. (2019). An assessment of the accuracy of MODIS land surface temperature over Egypt using ground-based measurements. *Remote Sensing*, *11*, 2369. https://doi.org/10.3390/rs11202369

Emeribe, C. N., Ezeh, C. U. & Butu, A. W. (2021). Modelling climatic water balance for water stress-detection for select crops under climate variability in the Sudano-Guinean Savanna, Nigeria. *Modeling Earth Systems and Environment*, *7*, 715–735. https://doi.org/10.1007/s40808-020-00919-2

Fowler, H. J., Blenkinsop, S. & Tebaldi, C. (2007). Linking climate change modelling to impacts studies: Recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, *27*(12), 1547–1578. https://doi.org/10.1002/joc.1556

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, *29*(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

Gbadegesin, A. S., Olorunfemi, F. B. & Raheem, U. A. (2011). *Coping with global environmental change*, *disasters and security: Threats*, *challenges*, *vulnerabilities and risks* (pp. 669–687). Springer.

Gbadegesin, A., Adesina, F., Orimoogunje, O. & Oderinde, F. (2023). *Landscapes and Landforms of Nigeria* (pp. 39–52). Springer.

Ghojogh, B. & Ghodsi, A. (2023). Recurrent neural networks and long short-term memory networks: Tutorial and survey. *arXiv preprint arXiv:2304.11461*.

Gillies, A. (2020). Corruption trends during Africa's oil boom, 2005 to 2014. *The Extractive Industries and Society 7*, 171–181. https://doi.org/10.1016/j.exis.2020.06.006

Giorgi, F., Jones, C. & Asrar, G. R. (2009). Addressing climate information needs at the regional level: the CORDEX framework. *World Meteorological Organization (WMO) Bulletin*, *58*, 175.

Gleckler, P. J., Taylor, K. E. & Doutriaux, C. (2008). Performance metrics for climate models. *Journal of Geophysical Research: Atmospheres*, *113*, 972. https://doi.org/10.1029/2007JD008972

Gu, H., Wang, G., Yu, Z. & Mei, R. (2012). Assessing future climate changes and extreme indicators in east and south Asia using the RegCM4 regional climate model. *Climatic Change*, *114*, 301–317. https://doi.org/10.1007/s10584-012-0411-y

Hochreiter, S. & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*, 1735–1780. https://doi.org/10.1162/neco.1997.9.8.1735

Ibebuchi, C. C. & Lee, C. C. (2024). Circulation pattern controls of summer temperature anomalies in Southern Africa. *Advances in Atmospheric Sciences*, *41*, 341–354. https://doi.org/10.1007/s00376-023-2392-3

Ishaku, D., Umaru, E. T., Adebayo, A. A., Löwner, R. & Okhimamhe, A. A. (2024). Analysis of the observed trends in rainfall and temperature patterns in North-Eastern Nigeria. *Climate*, *12*, 219. https://doi.org/10.3390/cli12120219

IPCC. (2022). Climate change 2022: Impacts, adaptation and vulnerability. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama,

(Eds.), *Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change*. Cambridge University Press. https://doi.org/10.1017/9781009325844
Jafari, S., Yang, J.-H. & Byun, Y.-C. (2024). Optimized XGBoost modeling for accurate battery capacity degradation prediction. *Results in Engineering*, *24*, 102786. https://doi.org/10.1016/j.rineng.2024.102786
Jones, P. D. & Moberg, A. (2003). Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001. *Journal of Climate*, *16*, 206–223. https://doi.org/10.1175/1520-0442(2003)016<0206:HALSSA>2.0.CO;2
Knauer, K., Gessner, U., Dech, S. & Kuenzer, C. (2014). Remote sensing of vegetation dynamics in West Africa. *International Journal of Remote Sensing*, *35*, 6357–6396. https://doi.org/10.1080/01431161.2014.954062
Lateef, M. B. & Stephens, M. (2024). An assessment of carbon Monoxide Emission in Nigeria and recommendations for sustainable mitigation strategies on climate impact. *FUTA Journal of Management and Technology*, *3*(2), 68–83. https://doi.org/10.2139/ssrn.5259185
Legates, D. R. & McCabeJr, G. J. (1999). Evaluating the use of "goodness-of-fit" measures in hydrologic and hydroclimatic model validation. *Water Resources Research*, *35*, 233–241. https://doi.org/10.1029/1998WR900018
Legates, D. R. & McCabe, G. J. (2013). A refined index of model performance: A rejoinder. *International Journal of Climatology*, *33*, 53–56. https://doi.org/10.1002/joc.3487
Lim, B. & Zohren, S. (2021). Time-series forecasting with deep learning: A survey. *Philosophical Transactions of the Royal Society A*, *379*, 20200209. https://doi.org/10.1098/rsta.2020.0209
Maraun, D. & Widmann, M. (2018). *Statistical downscaling and bias correction for climate research*. Cambridge University Press.
McKee, T. B., Doesken, N. J. & Kleist, J. (2019). *Proceedings of the 8th Conference on Applied Climatology* (pp. 179–183). California.
Merem, E. C., Twumasi, Y., Wesley, J., Alsarari, M., Fageir, S., Crisler, M., Romorno, C., Olagbegi, D., Hines, A., Ochai, G. S., Nwagboso, E., Leggett, S., Foster, D., Purry, V., & Washington, J. (2019)Regional assessment of climate change hazards in Southern Nigeria with GIS. *Journal of Safety Engineering*, *8*, 9–27. https://doi.org/10.5923/j.safety.20190801.02
Moriasi, D. N., Arnold, J. G., Van Liew, M. W., Bingner, R. L., Harmel, R. D., & Veith, T. L. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE*, *50*(3), 885–900. https://doi.org/10.13031/2013.23153
Morrill, J. C., Bales, R. C. & Conklin, M. H. (2005). Estimating stream temperature from air temperature: Implications for future water quality. *Journal of Environmental Engineering*, *131*, 139–146. https://doi.org/10.1061/(ASCE)0733-9372(2005)131:1(139)
Muñoz-Sabater, J., Dutra, E., Agustí-Panareda, A., Albergel, C., Arduini, G., Balsamo, G., Boussetta, S., Choulga, M., Harrigan, S., Hersbach, H., Martens, B., Miralles, D. G., Piles, M., Rodríguez-Fernández, N. J., Zsoter, E., Buontempo, C., & Thépaut, J.-N. (2021). ERA5-Land: A state-of-the-art global reanalysis dataset for land applications. *Earth System Science Data*, *13*, 4349–4383. https://doi.org/10.5194/essd-13-4349-2021
Nash, J. E. & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I – A discussion of principles. *Journal of hydrology*, *10*, 282–290. https://doi.org/10.1016/0022-1694(70)90255-6
Nikulin, G., Lennard, C., Dosio, A., Kjellström, E., Chen, Y., Hänsler, A., Kupiainen, M., Laprise, R., Mariotti, L., Maule, C. F., van Meijgaard, E., Panitz, H.-J., Scinocca, J. F., & Somot, S. (2018). The effects of 1.5 and 2 degrees of global warming on Africa in the CORDEX ensemble. *Environmental Research Letters*, *13(*6), 065003. https://doi.org/10.1088/1748-9326/aab1b1
O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., & Sanderson, B. M. (2016). The scenario model intercomparison project (ScenarioMIP) for CMIP6. *Geoscientific Model Development*, *9*, 461–482. https://doi.org/10.5194/gmd-9-3461-2016
Odekunle, T. O., Adesina, F. A., Gbode, I. E., Adeyefa, A. O. & Ajadi, S. O. (2024). Variabilities and trends in the onset, peak, and retreat of Intertropical Discontinuity (ITD) annual migrations over West Africa between 1979 and 2020. *Climate Dynamics*, *62*, 149–169. https://doi.org/10.1007/s00382-024-07270-7
Oguntunde, P. G., Abiodun, B. J. & Lischeid, G. (2017). Impacts of climate change on hydro-meteorological drought over the Volta Basin, West Africa. *Global and Planetary Change*, *155*, 121–132. https://doi.org/10.1016/j.gloplacha.2017.07.003
Oluwatimilehin, I. A. & Ayanlade, A. (2021). Agricultural community-based impact assessment and farmers' perception of climate change in selected Ecological Zones in Nigeria. *Agriculture & Food Security*, *10*, 1–17. https://doi.org/10.1186/s40066-020-00275-5
Onyeisi, J. O. (2022). *Characterisation of Spatio-temporal pattern of rainfall* and *temperature over the lower Niger River basin*.
Onyeneke, R. U., Ejike, R. D., Osuji, E. E. & Chidiebere-Mark, N. M. (2024). Does climate change affect crops differently? New evidence from Nigeria. *Environ. Dev. Sustainability*, *26*, 393–419. https://doi.org/10.1007/s10668-022-02714-8
Osman B., &Ayanlade, A. (2024). Climate change, gendered vulnerabilities and adaptation strategies: A participatory research in West Africa. In *Climate change and regional socio-economic systems in the global south: Resilience strategies for sustainable development* (pp. 191–211). Springer Nature Singapore.

Panthou, G., Vischel, T. & Lebel, T. (2014). Recent trends in the regime of extreme rainfall in the Central Sahel. *International Journal of Climatology*, *34*, 984. https://doi.org/10.1002/joc.3984

Parkes, B., Buzan, J. R. & Huber, M. (2022). Heat stress in Africa under high intensity climate change. *International journal of biometeorology*, *66*, 531–545. https://doi.org/10.1007/s00484-022-02295-1

Peterson, T. C., Folland, C., Gruza, G., Hogg, W., Mokssit, A., Plummer, N., Klein Tank, A., Parker, D., Alexander, L., Collins, D., Trewin, B., Haylock, N., Zhang, X., Easterling, D., Gleason, B., Liebmann, B., Vose, R., Horton, R., & Salinger, J. (2001). *Report on the activities of the working group on climate change detection and related rapporteurs 1998-2001 (WCDMP-47, WMO-TD 1071)*. World Meteorological Organization.

Sadiq, M. A., Sarkar, S. K. & Raisa, S. S. (2023). Meteorological drought assessment in northern Bangladesh: A machine learning-based approach considering remote sensing indices. *Ecological Indicators*, *157*, 111233. https://doi.org/10.1016/j.ecolind.2023.111233

Salack, S., Saley, I. A., Lawson, N. Z., Zabré, I. & Daku, E. K. (2018). Scales for rating heavy rainfall events in the West African Sahel. *Weather and climate extremes*, *21*, 36–42. https://doi.org/10.1016/j.wace.2018.05.004

Sawa, B. & Buhari, B. (2011). Temperature variability and outbreak of meningitis and measles in Zaria, northern Nigeria. *Research Journal of applied sciences, Engineering and Technology*, *3*, 399–402.

Sayad, B., Osra, O. A., Binyaseen, A. M. & Qattan, W. S. (2024). Analyzing urban climatic shifts in Annaba City: Decadal trends, seasonal variability and extreme weather events. *Atmosphere*, *15*, 529. https://doi.org/10.3390/atmos15050529

Shiru, M. S., Shahid, S., Shiru, S., Chung, E. S., Alias, N., Ahmed, K., Dioha, E. C., Sa'adi, Z., Salman, S., & Noor, M. (2020). Challenges in water resources of Lagos mega city of Nigeria in the context of climate change. *Journal of Water and Climate Change*, *11*(4), 1067–1083. https://doi.org/10.2166/wcc.2019.047

Shumway, R. H., Stoffer, D. S., Shumway, R. H. & Stoffer, D. S. (2017). ARIMA models. In *Time series analysis and its applications: With R examples* (pp. 75–163). https://doi.org/10.1007/978-3-319-52452-8_3

Taylor, C. M., Belušić, D., Guichard, F., Parker, D. J., Vischel, T., Bock, O., Harris, P. P., Janicot, S., Klein, C., & Panthou, G. (2017). Frequency of extreme Sahelian storms tripled since 1982 in satellite observations. *Nature*, *544*(7651), 475–478. https://doi.org/10.1038/nature22069

Taylor, K. E. (2001). Summarizing multiple aspects of model performance in a single diagram. *Journal of geophysical research: Atmospheres*, *106*, 183–192. https://doi.org/10.1029/2000JD900719

Teutschbein, C. & Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies: Review and evaluation of different methods. *Journal of hydrology 456*, 12–29. https://doi.org/10.1016/j.jhydrol.2012.05.052

Traoré, S. B., Alhassane, A., Muller, B., Kouressy, M., Somé, L., Sultan, B., Oettli, P., Siéné Laopé, A. C., Sangaré, S., Vaksmann, M., Diop, M., Dingkhun, M., & Baron, C. (2011). Characterizing and modeling the diversity of cropping situations under climatic constraints in West Africa. *Atmospheric Science Letters*, *12*(1), 89–95. https://doi.org/10.1002/asl.295

Trisos, C. H., Adelekan, I. O., Totin, E., Ayanlade, A., Efitre, J., Gemeda, A., Kalaba, K., Lennard, C., Masao, C., Mgaya, Y., Ngaruiya, G., Olago, D., Simpson, N. P., & Zakieldeen, S. (2022). Africa. In H.-O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, S. Löschke, V. Möller, A. Okem, & B. Rama (Eds.), *Climate Change 2022: Impacts, adaptation and vulnerability. Contribution of working group II to the sixth assessment report of the intergovernmental panel on climate change* (pp. 1285–1455). Cambridge University Press. https://doi.org/10.1017/9781009325844.011

Udo, R. K. (2023). *Geographical regions of Nigeria*. Univ of California Press.

Umeh, S. C. & Gil-Alana, L. A. (2024). Trends in temperatures in Sub-Saharan Africa. Evidence of global warming. *Journal of African Earth Sciences*, *213*, 105228. https://doi.org/10.1016/j.jafrearsci.2024.105228

Vicente-Serrano, S. M., Beguería, S. & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *Journal of climate*, *23*, 696–718. https://doi.org/10.1175/2009JCLI2909.1

Wheeler, R. L., Miller, J. S., Smith, G. N., Lambert, J. H., Pennetti, C. A., & Louis, G. E. (2024). Geospatial analysis of extreme temperature impacts in agricultural systems using machine learning. In *2024 IEEE International Symposium on Systems Engineering (ISSE)* (pp. 1–8). IEEE. https://doi.org/10.1109/ISSE63315.2024.10741115

Willmott, C. J. & Matsuura, K. (2005). Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. *Climate Research*, *30*, 79–82. https://doi.org/10.3354/cr030079

WMO. (2011). *Guide to climatological practices*. World Meteorological Organization.

Zampieri, M., Serpetzoglou, E., Anagnostou, E. N., Nikolopoulos, E. I. & Papadopoulos, A. (2012). Improving the representation of river–groundwater interactions in land surface modeling at the regional scale: Observational evidence and parameterization applied in the Community Land Model. *Journal of Hydrology*, *420*, 72–86. https://doi.org/10.1016/j.jhydrol.2011.11.041

Zhang, J., Zeng, Y. & Starly, B. (2021). Recurrent neural networks with long term temporal dependencies in machine tool wear diagnosis and prognosis. *SN Applied Sciences*, *3*, 442. https://doi.org/10.1007/s42452-021-04427-5

Zhang, X., Vincent, L. A., Hogg, W. & Niitsoo, A. (2000). Temperature and precipitation trends in Canada during the 20th century. *Atmosphere-ocean*, *38*, 395–429. https://doi.org/10.1080/07055900.2000.9649654