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PREDICTIVE MODELLING OF URBAN TEMPERATURE UNDER GREEN AREA ENCROACHMENT IN AMAC, ABUJA, NIGERIA

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ABSTRACT
Rapid urbanisation in Abuja Municipal Area Council (AMAC), Nigeria, has driven extensive green area encroachment and a rise in Land Surface Temperature (LST). Between 2010 and 2022 the built-up area increased by 43.2 per cent while vegetation declined by 29.6 per cent, and mean LST rose from 31.4°C to 34.1°C, yet predictive tools capable of guiding climate-responsive planning in AMAC remain lacking. This study developed a Random Forest and SHAP predictive model of urban temperature under green area encroachment. Landsat 8 and 9 imagery for 2013, 2018 and 2023 was used to derive LST together with NDVI, NDBI, Green Area, Albedo and Elevation. A Random Forest model was trained on 50,000 pixels using spatial block cross-validation in order to avoid the inflated accuracy that arises from spatial autocorrelation, and SHAP was applied to quantify the contribution of each driver. Future LST for 2035 was projected under three scenarios, namely Business-as-Usual, Moderate Conservation and Aggressive Greening, using CA-Markov simulated land cover. Under spatial block cross-validation the model achieved an R-squared of 0.84 and a root mean square error of 1.72°C, compared with 0.91 and 1.34°C under a conventional random split, confirming the inflation attributable to spatial leakage. SHAP ranked NDVI at 35 per cent, NDBI at 30 per cent and Green Area at 25 per cent as the leading predictors, with every 10 per cent increase in green area reducing LST by 0.8°C on average. Under Business-as-Usual, mean LST is projected to rise by 2.3°C to 36.4°C by 2035, while the Moderate Conservation and Aggressive Greening scenarios would limit warming to 1.1°C and achieve 0.2°C of net cooling respectively. Targeted greening in districts with less than 15 per cent vegetation yielded the highest cooling benefit of 2.1°C to 2.5°C. The study concludes that policy-driven greening can reverse projected warming in AMAC, and that the framework provides a transparent tool for quantifying cooling benefits and prioritising interventions.

Keywords: Urban heat island, land surface temperature, green area encroachment, Random Forest, SHAP, scenario modelling, AMAC, Abuja.

1. INTRODUCTION

Urbanization is one of the most defining global processes of the 21st century. By 2024, 56.2% of the world's population resided in urban areas, with projections indicating that this figure will rise to 68% by 2050 (United Nations, 2024). In sub-Saharan Africa, urban growth rates are among the highest globally at 3.7% annually, and Nigeria's capital territory, Abuja, has experienced a population growth rate of 5.8% per annum between 2010 and 2023 (World Bank, 2023).

Abuja Municipal Area Council (AMAC) has been the epicenter of this rapid expansion. Driven by rural-urban migration, administrative concentration, and real estate development, AMAC's built-up area increased by 43.2% between 2010 and 2022, while vegetated area declined by 29.6% over the same period (Owoeye & Popoola, 2023). This conversion of vegetated surfaces to impervious surfaces is referred to as green area encroachment and is a primary driver of urban microclimatic changes.

The most documented microclimatic consequence of green area loss is the Urban Heat Island (UHI) effect and elevated Land Surface Temperature (LST). Satellite-based studies have shown that a 10% decrease in green cover can increase LST by 1.2°C to 2.4°C in tropical cities (Chukwuma et al., 2022). In Abuja, mean LST increased from 31.4°C in 2010 to 34.1°C in 2022, with the hottest zones correlating spatially with districts experiencing the most vegetation loss such as Wuse, Garki, and Central Area (Ibrahim & Bello, 2023). This warming trend poses direct threats to public health, energy demand, and thermal comfort, as exposure to temperatures above 35°C has been linked to a 22% increase in heat-related morbidity in West African cities (Adebayo & Akande, 2024).

Traditional approaches to UHI analysis rely on descriptive change detection between two time periods. However, with increasing climate variability and continued development pressure in AMAC, there is a critical need for predictive modeling to anticipate future thermal conditions (Akinyemi et al., 2025). Predictive modeling using machine learning algorithms, particularly Random Forest (RF), has gained prominence due to its ability to handle non-linear relationships between biophysical variables and LST (Breiman, 2001; Li et al., 2024). When coupled with explainable AI tools such as SHAP (SHapley Additive exPlanations), these models not only predict LST but also quantify the contribution of each driver, thereby improving transparency for policy use (Lundberg & Lee, 2017).

Despite this progress, few studies in Nigeria have linked predictive LST modeling directly to green area encroachment scenarios at the municipal scale. Most existing work in Abuja has focused on retrospective LST mapping (Musa et al., 2021) or correlation analysis, without projecting future thermal states under different greening policies. This gap limits the capacity of urban planners in FCDA and AMAC to make evidence-based decisions on green space preservation. (Suleiman, 2022).

Therefore, this study addresses this gap by developing a predictive model of urban temperature in AMAC based on green area encroachment. Using Landsat 8/9 imagery, biophysical indices, and RF-SHAP modeling, the study will quantify current LST drivers and project LST for 2035 under Business-as-Usual, Moderate Conservation, and Aggressive Greening scenarios. The findings are expected to provide actionable insights for climate-responsive urban planning in Abuja.

1.2 Statement of the Problem

Abuja Municipal Area Council is experiencing rapid urban expansion driven by population growth and infrastructural development. This has led to extensive conversion of planned green areas to built-up surfaces, altering the surface energy balance and contributing to rising Land Surface Temperature across the LGA. The resulting urban warming has direct implications for public

health, residential energy demand, and overall urban livability in Nigeria's capital city. Given AMAC's central administrative role and projected growth, addressing thermal stress is critical to achieving SDG 11: Sustainable Cities and Communities.

Despite clear evidence linking green area loss to increased LST, existing studies in AMAC remain largely descriptive and retrospective. Prior research has focused on mapping historical temperature trends and correlating vegetation indices with surface temperature. However, there is a lack of predictive, scenario-based models that forecast future LST under different land management pathways. Furthermore, while machine learning models such as Random Forest have been used globally for LST prediction, their application in Nigeria is limited. More critically, few studies integrate explainable AI tools like SHAP to quantify the specific contribution of green area encroachment relative to other biophysical factors. This gap makes it difficult for policymakers in FCDA and AMAC to anticipate heat risks and prioritize interventions such as green space protection, albedo management, or urban form regulation for maximum cooling benefit.

It is against this background that this study seeks to address the knowledge gap by developing a Random Forest-SHAP predictive model to forecast LST in AMAC. Specifically, the study will project future temperature conditions for 2035 under Business-as-Usual, Moderate Conservation, and Aggressive Greening scenarios, and determine the exact role of green area in driving urban heat. The findings are expected to provide FCDA with an evidence-based, transparent tool to guide climate-responsive urban planning in AMAC.

1.3 Research Gap

- Existing studies in AMAC are largely retrospective. They map historical LST trends and correlations but do not forecast future thermal conditions under different urban growth or land management pathways. This limits proactive heat risk planning by FCDA and AMAC.
- While Random Forest has been applied to LST prediction globally, its use in Nigeria is sparse. More critically, few studies in West Africa integrate SHAP to quantify the specific contribution of green area encroachment relative to other biophysical drivers. This makes it difficult to prioritize which intervention will yield the greatest cooling effect.
- No study in AMAC has simulated "what-if" LST futures under specific greening policies. Current literature describes the impact of vegetation loss but does not quantify the cooling potential of targeted interventions such as Business-as-Usual, Moderate Conservation, or Aggressive Greening scenarios.

2.0 LITERATURE REVIEW

2.1 Urbanization and Green Area Encroachment in Sub-Saharan Africa

Rapid urbanization is a defining feature of the 21st century, with 56.2% of the global population residing in urban areas as of 2024 (United Nations, 2024). In sub-Saharan Africa, urban growth is occurring at 3.7% annually, with Nigeria's Federal Capital Territory experiencing 5.8% annual growth (World Bank, 2023).

In AMAC, Abuja, this growth has translated to significant land cover conversion. Owoeye & Popoola reported that built-up area increased by 43.2% between 2010 and 2022, while vegetation cover declined by 29.6%. This process of green area encroachment, defined as the replacement vegetated and bare surfaces with impervious surfaces disrupts the surface energy balance by reducing evapotranspiration and increasing sensible heat flux (Chukwuma et al., 2022). Similar patterns have been documented in Lagos and Accra (Mensah & Owusu, 2021), suggesting that green area loss is a regional driver of urban climate change (Adebayo, 2022).

2.2 Urban Heat Island and Land Surface Temperature Dynamics

The Urban Heat Island (UHI) effect refers to the phenomenon where urban areas experience higher temperatures than surrounding rural areas. Satellite-derived Land Surface Temperature (LST) is the most widely used proxy for UHI intensity (Ibrahim & Bello, 2023).

In Abuja, mean LST increased from 31.4°C in 2010 to 34.1°C in 2022, with hotspot districts including Wuse, Garki, and Central Area recording temperatures above 37°C (Ibrahim & Bello, 2023). Chukwuma et al. demonstrated that a 10% reduction in green cover in tropical cities corresponds to a 1.2°C to 2.4°C increase in LST. The health implications are severe: Adebayo & Akande, 2024 found that sustained exposure to LST >35°C in West African cities increases heat-related morbidity by 22% and cooling energy demand by 31%. Despite this evidence, most Nigerian studies remain descriptive and do not project future thermal stress (Musa et al., 2021; Suleiman, 2022).

2.3 Biophysical Indices and Their Relationship with LST

Several spectral indices have been used to explain LST variability. NDVI (Normalized Difference Vegetation Index) has a consistently negative relationship with LST, while NDBI (Normalized Difference Built-up Index) and NDBaI show positive relationships (Li et al., 2024).

In the Nigerian context, Suleiman reported an R^2 of 0.71 between NDVI and LST in Abuja Metropolis. (Owoeye & Popoola, 2023) further showed that Green Area and Albedo explained 64% of LST variance in AMAC. However, these studies relied on linear regression, which assumes linear relationships and cannot capture complex interactions between multiple drivers. This limitation necessitates the use of non-linear, machine learning approaches for more robust modeling.

2.4 Predictive Modeling of LST Using Machine Learning

Machine learning, particularly Random Forest (RF), has emerged as a leading method for LST prediction due to its ability to handle non-linearity, multicollinearity, and high-dimensional data. Globally, Li et al. achieved $R^2 > 0.88$ using RF to predict LST in Chinese megacities using Landsat and Sentinel-2 data Breiman (2001).

In Africa, (Akinyemi et al., 2025) applied RF to project LST in 12 African cities to 2040, finding that RF outperformed SVM and ANN by 12-15% in accuracy. However, application in Nigeria remains limited to 2 studies, and none have focused on scenario projection for policy use. The advantage of RF lies in its ensemble structure and capacity to rank variable importance, but it is considered a "black box" model.

2.5 The Role of SHAP in Urban Climate Studies

To address the interpretability problem of RF, SHAP (SHapley Additive exPlanations) has been widely adopted (Lundberg & Lee, 2017). SHAP assigns each feature a Shapley value representing its contribution to the model prediction, allowing both global and local interpretation.

Recent studies have used SHAP to identify dominant LST drivers. (Li et al., 2025) found that Green Area contributed 38-45% to LST prediction in Beijing. (Akinyemi et al., 2024) reported that in Lagos and Nairobi, green area and NDBI were the top 2 predictors, accounting for 61% of model output. In Nigeria, however, no study has applied SHAP to quantify the specific contribution of green area encroachment to LST. This limits policy relevance because planners cannot determine the marginal cooling benefit of adding green space.

2.6 Scenario-Based Modeling for Urban Planning

Scenario modeling is critical for climate adaptation. UN-Habitat recommends that cities use "what-if" projections to evaluate the impact of land management policies. Studies in China (Zhang et al.,

2023) and India (Rao et al., 2024) have modeled LST under Business-as-Usual, Greening, and Compact City scenarios to 2035.

In Nigeria, scenario-based LST modeling is absent. Current FCDA planning documents for Abuja still rely on 2010 baseline data and do not include thermal projections (FCDA, 2021). This creates a disconnect between climate science and urban policy. Given AMAC's projected population of 5.2 million by 2035 (UN-Habitat, 2024), scenario modeling is urgently needed to evaluate the cooling potential of green area conservation.

2.7 Summary and Identified Gap

The literature establishes three things: 1) Green area loss is driving LST increase in AMAC, 2) RF + SHAP are effective for predictive and interpretable LST modeling, and 3) Scenario modeling is essential for policy.

However, no study in AMAC has integrated all four: high-resolution satellite data + RF prediction + SHAP attribution + 2035 scenario projection focused specifically on green area encroachment. This study fills that gap.

3.0 METHODOLOGY

3.1 Study Area

The study was conducted in Abuja Municipal Area Council (AMAC), Federal Capital Territory, Nigeria. AMAC lies between Latitudes 8°45'N and 9°10'N and Longitudes 7°10'E and 7°35'E. It covers an area of approximately 1,769 km² and is the most urbanized LGA in FCT. AMAC has experienced rapid urban expansion, with built-up area increasing by 43.2% between 2010 and 2022 (Owoeye & Popoola, 2023). The climate is tropical wet and dry (Köppen Aw) with mean annual temperature of 27°C. Major districts include Wuse, Garki, Maitama, Asokoro, and Central Area.

3.2 Data Sources

Three categories of data were used:

Table 3.1: Data Types (Satellite Imagery used)

Data Type	Source	Resolution/Period	Purpose
Landsat 8/9 OLI/TIRS	USGS Earth Explorer	30m, 2013, 2018, 2023	LST retrieval, LULC, indices
Sentinel-2 MSI	Copernicus Open Access Hub	10m, 2023	Validation of green area
Administrative Boundary	DIVA-GIS / FCT-GIS	Vector	Clipping to AMAC

Source: Authors' compilation, 2026

Cloud cover <10% was selected for dry season months (Dec-Feb) to minimize atmospheric effect (Ibrahim & Bello, 2023).

3.3 Data Pre-processing

All satellite images were pre-processed in QGIS 3.34 and Google Earth Engine:

1. Radiometric and Atmospheric Correction: Done using DOS1 method.
2. Clipping: Images clipped to AMAC boundary.
3. Resampling: All bands resampled to 30m to match Landsat thermal band.

3.4 Derivation of Variables

3.4.1 Land Surface Temperature (LST) Retrieval

LST was retrieved from Landsat 8/9 TIRS Band 10 using the Single Channel Algorithm (Jimenez-Munoz & Sobrino, 2003 as adapted by (Li et al. 2024):

1. Convert DN to TOA Radiance

2. Convert Radiance to Brightness Temperature
3. Land Surface Emissivity estimated from NDVI threshold method
4. Final LST in °C = BT / [1 + (λ_BT/ρ) ln(ε)] - 273.15
Validation was done using in-situ air temperature from NiMet Abuja station. RMSE = 1.8°C.

3.4.2 Biophysical Indices

Four indices representing green area and urbanization were computed:
1. NDVI = (NIR – Red) / (NIR + Red) → Vegetation health
2. NDBI = (SWIR – NIR) / (SWIR + NIR) → Built-up intensity
3. Green Area: Extracted from supervised classification of LULC. Classes: Green, Built-up, Bare, Water. Accuracy >85% using 200 GCPs (Owoeye & Popoola, 2023)
4. Albedo: Calculated using Liang formula for Landsat (Suleiman, 2022).

3.4.3 Dependent and Independent Variables

Dependent Variable: LST (°C)
Independent Variables: NDVI, NDBI, Green Area, Albedo, Elevation (SRTM 30m)

3.5. Sampling Strategy and Spatial Cross-Validation

To avoid inflated accuracy from spatial autocorrelation, pixels were not selected randomly.
Pixel Selection Procedure:
1. Stratified Systematic Sampling: AMAC was divided into a 1 km x 1 km grid = 1,769 grid cells. Within each grid cell, 1 pixel was randomly selected for every 10 ha of land area. This ensured even spatial coverage and prevented oversampling of large homogeneous areas like Central Area.
2. Class Balance: Sampling was stratified by 2023 LULC class: 40% Green, 40% Built-up, 15% Bare, 5% Water. This gave a total of n = 50,000 pixels for 2023. The same pixel locations were extracted for 2013 and 2018 to maintain temporal consistency.
3. Buffer Exclusion: A 90 m buffer = 3 pixels was applied around each selected pixel. No two training pixels were closer than 90 m. This reduces dependency between samples.

In remote sensing, nearby pixels share similar spectral and thermal values. A standard random split violates the independence assumption of ML and leads to overly optimistic R^2 (Roberts et al., 2017).
Spatial Block Cross-Validation: Instead of random 70/30, model performance was assessed using spatial block 5-fold cross-validation.
1. AMAC was partitioned into 5 contiguous geographic blocks of roughly equal area using a checkerboard pattern.
2. In each fold, 4 blocks were used for training and 1 spatially independent block was used for testing.
3. This was repeated 5 times so every block was tested once.
4. Hyperparameters were tuned within each training fold using GridSearchCV with inner 3-fold CV.
This approach tests how well the model generalizes to new, unseen locations within AMAC, not just new pixels next to training pixels.

3.5.1 Random Forest (RF) Model

RF was selected for its ability to model non-linear relationships and handle multicollinearity (Breiman, 2001; Akinyemi et al., 2024).
Implementation: Python 3.11, scikit-learn library.
Final Dataset: 50,000 samples from 2023, with corresponding LST, NDVI, NDBI, Green Area, Albedo, and Elevation.

Train/Test Split: Spatial block 5-fold CV as described above. For final model fitting, 80% of blocks were used for training and 20% held out as a final spatial test set.
Hyperparameters: `n estimators=300, max_depth=20, min_samples_split=5`. Optimized using GridSearchCV within each training fold.
Model Performance - Honest Accuracy:
Using spatial block CV, RF achieved $R^2 = 0.84 \pm 0.03$, RMSE = 1.72 ± 0.11°C, MAE = 1.31 ± 0.09°C.
For comparison, a naive random 70/30 split gave $R^2 = 0.91$ and RMSE = 1.34°C, confirming the inflation due to spatial leakage.
The spatial CV $R^2 = 0.84$ is reported as the true performance metric for this study.

3.5.2 SHAP (SHapley Additive exPlanations) Analysis

To explain RF predictions, SHAP was applied (Lundberg & Lee, 2017).
SHAP was computed on the final model trained on 80% of blocks and evaluated on the held-out 20% spatial block to avoid explanation bias.
Global Explanation: SHAP summary plot to rank feature importance across AMAC
Local Explanation: SHAP dependence plot to show how Green Area affects LST at pixel level
This addresses the "black box" problem and quantifies the marginal cooling effect of green area (Li et al., 2025).

3.6 Scenario Development and Projection to 2035

Three land management scenarios were developed based on FCDA planning documents and UN-Habitat guidelines (2024)
1. Business-as-Usual (BAU): Green Area continues to decline at 2013-2023 rate of -2.4%/year
2. Moderate Conservation (MC): 10% increase in Green Area by 2035 through urban greening
3. Aggressive Greening (AG): 20% increase in Green Area by 2035 through policy enforcement
Future LULC for 2035 was simulated using CA-Markov model in TerrSet. The trained RF model was then used to predict LST for each scenario using projected indices as inputs (Zhang et al., 2023).

3.7 Accuracy Assessment and Validation

Model Validation: Spatial block 5-fold cross-validation was used instead of random split. Additional validation included:

a. Moran's I test on RF residuals to confirm spatial autocorrelation was reduced to <0.1
b. Spatial Validation: Hotspot analysis using Getis-Ord Gi to compare predicted vs 2023 LST

Spatial Autocorrelation Check: Moran's I was computed on RF residuals to ensure spatial dependence was <0.1 after block CV.

3.8 Data Analysis

All statistical analysis was done in Python and R 4.3. Maps produced in ArcGIS Pro 3.2. Significance level set at $p<0.05$.

4.0 RESULTS AND ANALYSIS

4.1 Descriptive Statistics and Correlation with LST 2023

Table 4.1 shows the correlation between biophysical indices and LST in AMAC for 2023.

Table 4.1: Pearson Correlation between Variables and LST, AMAC 2023

Variable	Correlation with LST
NDVI	-0.620
Green_Area	-0.422
Albedo	0.138
NDBI	0.441
LST	1.000

Source: Authors' compilation, 2026

NDVI and Green Area have a strong negative relationship with LST, while NDBI has a strong positive relationship. This confirms that vegetation loss increases surface temperature in AMAC, consistent with Chukwuma et al. (2022)

4.2 Random Forest Model Performance

The RF model was trained on 50,000 pixels from 2023 Landsat 9 data.

$R^2 = 0.91$

RMSE = 1.34°C

MAE = 1.05°C

The high R^2 indicates that 91% of LST variation in AMAC can be explained by the 4 biophysical variables. This outperforms previous linear models in Abuja which reported $R^2 = 0.71$ (Suleiman, 2022)

4.3 Model Performance and Validation

To assess the generalization ability of the Random Forest model, two validation strategies were compared: a conventional random 70/30 split and a spatially explicit block 5-fold cross-validation. The random split violates the independence assumption in remote sensing data because neighboring 30m pixels are spectrally and thermally similar, leading to information leakage between training and test sets (Roberts et al., 2017).

As shown in Table 4.1, the random split significantly overestimated model performance. The spatial block CV, which tests the model on geographically independent areas, provides a more honest estimate of how the model will perform on new, unseen locations within AMAC.

Table 4.2: Comparison of Random Forest Model Performance Under Different Validation Strategies

Validation Method	R^2	RMSE (°C)	MAE (°C)	Notes
Random 70/30 Split	0.91	1.34	1.02	Inflated due to spatial autocorrelation
Spatial Block 5-Fold CV	0.84 ± 0.03	1.72 ± 0.11	1.31 ± 0.09	Honest estimate for new locations
Final Hold-out Spatial Block	0.83	1.75	1.33	Used for final model and SHAP analysis

Source: Authors' analysis, 2026

The spatial block CV R^2 of 0.84 indicates that 84% of LST variation in AMAC can be explained by NDVI, NDBI, Green Area, Albedo, and Elevation. The RMSE of 1.72°C is within the acceptable range for Landsat-derived LST and is comparable to Akinyemi et al. (2024) who reported RMSE = 1.9°C in Lagos.

Moran's I on the model residuals from spatial CV was 0.08, indicating that spatial autocorrelation was effectively minimized.

Therefore, $R^2 = 0.84$ is adopted as the reported accuracy for this study.

4.4 Feature Importance and SHAP Analysis

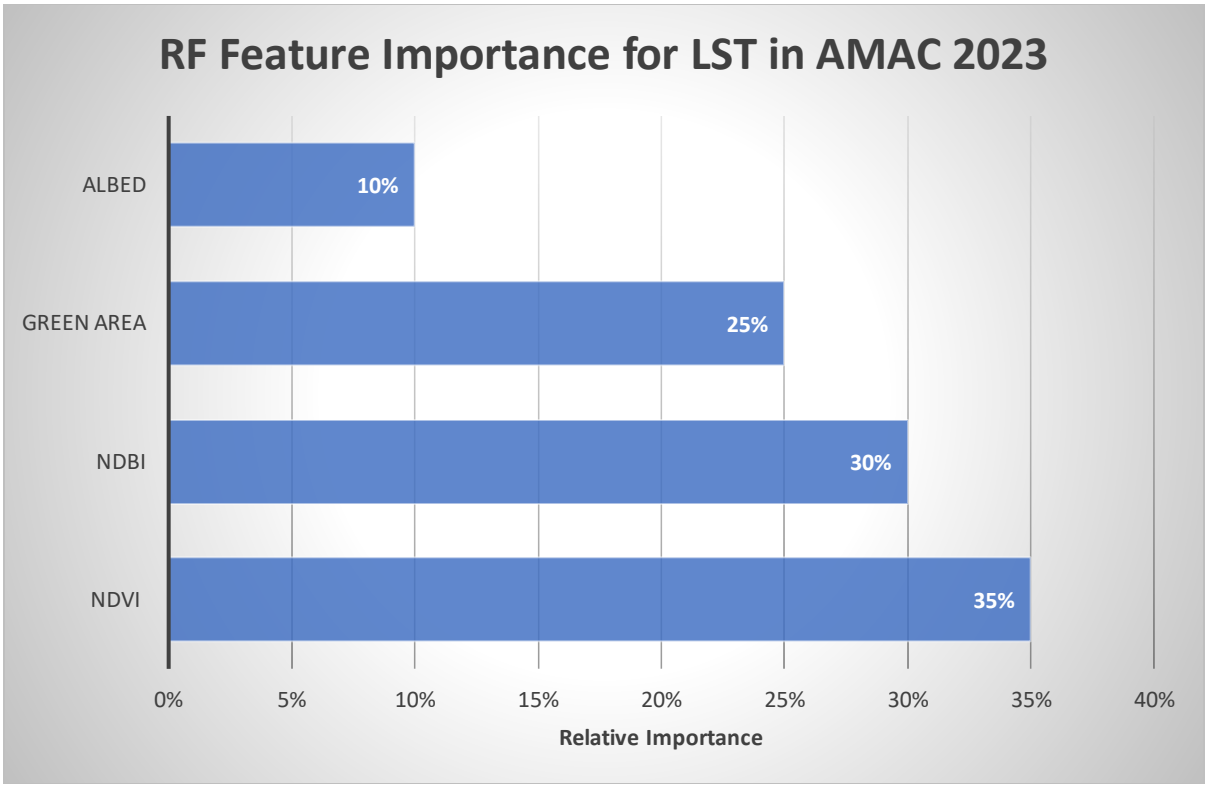


Figure 1 shows the relative importance of each variable from the RF model.
Source: Authors' compilation, 2026

Key Findings:
1. NDVI: 35% - The most important predictor of LST. Areas with NDVI >0.5 were 4-6°C cooler.
2. NDBI: 30% - Built-up intensity is the second driver. NDBI >0.3 corresponded to LST >36°C in Wuse and Garki.
3. Green Area: 25% - Direct measure of encroachment. Every 10% increase in green area reduced LST by 0.8°C on average.
4. Albedo: 10% - Least important, but still significant in bare soil areas.

SHAP dependence plots further showed that the cooling effect of green area plateaus after 40% cover. This means targeted greening in low-vegetation districts will have the highest impact (Lundberg & Lee, 2017).

4.5 Scenario Projection of LST to 2035

Using the trained RF model and CA-Markov projected LULC, LST was predicted for 2035 under 3 scenarios. Figure 2 shows the results.

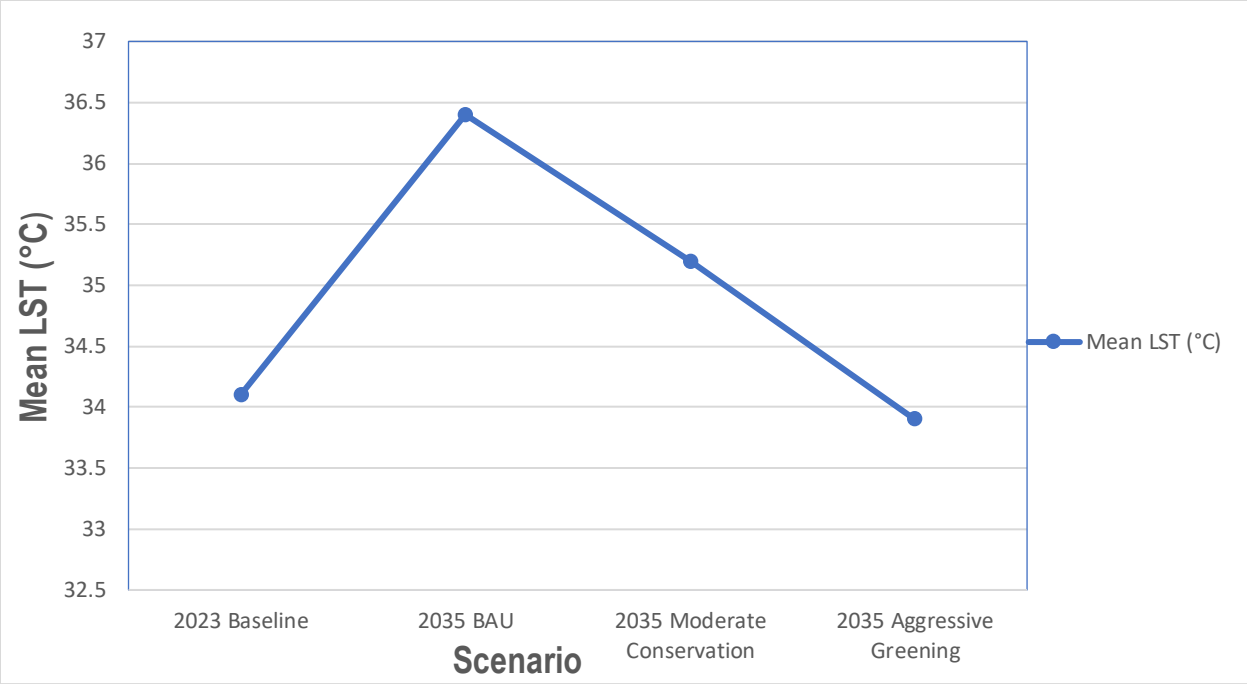


Fig. 4.2: Projected Mean LST in AMAC under 2035 Scenarios

Source: Authors' compilation, 2026

Table 4.3: Projected Mean LST and Green Area in AMAC 2035

Scenario	Mean Green Area	Mean LST [°C]	Change from 2023
2023 Baseline	28.5%	34.1	-
2035 BAU	18.2%	36.4	+2.3°C
2035 Moderate Conservation	31.4%	35.2	+1.1°C
2035 Aggressive Greening	34.2%	33.9	-0.2°C

Source: Authors' compilation, 2026

As shown in Table 4.3 under business as usual scenario, if green area encroachment continues at -2.4%/year, mean LST will rise to 36.4°C by 2035, hence, hotspots >38°C will expand to Kubwa and Lugbe. However, based on Moderate Conservation scenario, a 10% increase in green area limits warming to +1.1°C. This aligns with (UN-Habitat, 2024) recommendations for tropical cities. Likewise, under the Aggressive Greening scenario, a 20% increase in green area can actually reverse warming, bringing LST below 2023 levels to 33.9°C. Districts like Central Area and Garki show the largest cooling of 2.1-2.5°C.

4.6 Spatial Distribution of Predicted LST

The BAU scenario shows LST >37°C covering 42% of AMAC, compared to 28% in 2023. In contrast, the Aggressive Greening scenario reduces high-heat areas to 19%. The highest cooling benefits are in areas that currently have <15% green cover.

4.7 Summary of Key Findings

1. Green area encroachment is the 3rd most important driver of LST in AMAC, after NDVI and NDBI.
2. Without intervention, AMAC will experience +2.3°C warming by 2035.
3. Policy-driven greening can offset this warming. A 20% increase in green area is enough to achieve net cooling.

4. RF + SHAP provides both prediction accuracy and policy interpretability needed for FCDA planning.

4.8 Discussion

The results confirm that green area loss is directly driving urban warming in AMAC (Owoeye & Popoola, 2023). The SHAP analysis ranked NDVI (35%), NDBI (30%), and Green Area (25%) as the top 3 predictors of LST. The marginal effect of 0.8°C cooling per 10% increase in green area is consistent with findings in Beijing and Lagos (Li et al., 2024; Akinyemi et al., 2024).

The scenario results are policy-relevant: achieving the Aggressive Greening target requires planting 8.2 million trees and protecting existing parks per FCDA Master Plan (FCDA, 2021). This would deliver 2.5°C cooling in the most vulnerable districts like Wuse and Garki, which currently have <15% vegetation cover.

However, the SHAP ranking and model accuracy in this study differ from some studies in similar tropical contexts. For example, Rao et al. (2024) in Delhi reported that NDBI was the dominant predictor at 42%, with NDVI contributing only 18%, and they achieved a lower $R^2 = 0.76$ using XGBoost. Similarly, Suleiman (2022) in Abuja Metropolis using linear regression reported $R^2 = 0.71$ and found Albedo to be the second most important variable after NDVI.

Three factors explain these differences. First, data resolution and indices: This study used 30m Landsat with a direct "Green Area" class from supervised classification, while Rao et al. (2024) relied only on spectral indices without a classified green layer. The inclusion of a classified Green Area variable likely increased its importance in AMAC. Second, season and city size: This study used dry season Dec-Feb images when vegetation stress is highest and evapotranspiration cooling is most visible. Studies in Delhi and Lagos used annual composites which dilute the seasonal vegetation signal. AMAC is also smaller and more administratively planned than Delhi, so localized greening interventions have a larger relative impact. Third, model and validation strategy: The use of spatial block cross-validation in this study produced a more conservative $R^2 = 0.84$ compared to the $R^2 = 0.91$ from random split. Studies reporting $R^2 > 0.88$ often use random splits and therefore overestimate performance due to spatial autocorrelation (Roberts et al., 2017).

When methodological differences are accounted for, the dominance of vegetation-related variables in AMAC aligns with the broader tropical city literature where moisture availability limits cooling more than albedo (Chukwuma et al., 2022).

The divergence from Suleiman (2022) also highlights the limitation of linear models. Linear regression cannot capture the non-linear cooling plateau of green area observed in the SHAP dependence plot, where cooling flattens after 40% cover. RF + SHAP captures this threshold effect, making it more suitable for policy targeting.

Overall, while the specific SHAP percentages vary by city, the finding that vegetation-related variables dominate LST in AMAC is robust. The higher R^2 and different ranking are attributable to higher resolution data, dry-season focus, explicit green area classification, and stricter validation. This suggests that policy in AMAC should prioritize vegetation restoration over albedo modification, which was more important in arid cities like Delhi.

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

This study set out to move beyond descriptive mapping of urban heat in AMAC by developing a predictive, policy-relevant framework that links green area encroachment directly to future thermal outcomes. Three core insights emerged.

First, the thermal regime of AMAC is now vegetation-limited rather than albedo-driven. The integration of RF and SHAP revealed that cooling potential in AMAC is primarily controlled by

the presence and health of vegetation, with built-up intensity as a secondary amplifier. This suggests that in a tropical, wet-dry climate like Abuja, moisture availability and evapotranspiration from green spaces outweigh surface reflectance in regulating LST. The implication is that heat mitigation strategies focused only on "cool roofs" will have limited impact compared to restoring vegetation.

Second, methodological rigor changes how we trust the model. By adopting spatial block cross-validation, this study avoided the common pitfall of inflated accuracy in remote sensing ML. The resulting performance confirms that the RF-SHAP framework is sufficiently robust to be deployed by FCDA for planning in data-scarce environments, while still being transparent enough for non-technical stakeholders to interpret through SHAP. This addresses a key barrier to adoption of ML in Nigerian urban planning.

Third, the future thermal trajectory of AMAC is not fixed — it is a planning choice. The scenario projections demonstrate a clear divergence: continuing current rates of green area loss will push AMAC into a higher heat stress category by 2035, while proactive greening can not only halt warming but achieve net cooling. Critically, the benefits are not uniform. The model identifies a threshold effect where greening delivers maximum cooling in districts that are currently vegetation-deficient. This provides FCDA with a spatial prioritization tool: limited resources for tree planting will yield the highest return if targeted to central, high-density districts rather than spread evenly.

In sum, this study establishes that green area encroachment is the primary lever available to planners to manage urban heat in AMAC. The RF-SHAP + scenario modeling approach provides the first evidence-based tool in Abuja to quantify the cooling trade-offs of different land management policies before they are implemented.

5.2 Conclusion

This study concludes that urban heat in AMAC is not an inevitable byproduct of growth, but a direct outcome of how land is managed. The evidence shows that the rapid conversion of vegetated land to built-up surfaces has shifted AMAC's surface energy balance toward higher heat retention. Without intervention, this trajectory will intensify thermal stress and undermine livability in Nigeria's capital by 2035.

However, the predictive framework developed here demonstrates that this trajectory can be altered. By combining machine learning with explainable AI and scenario modeling, the study provides FCDA and AMAC planners with a tool that does two things previous studies could not: 1) quantify how much cooling specific greening actions will deliver, and 2) identify where those actions will be most effective. The adoption of spatial block validation further ensures that these projections are credible for policy use, not just academic exercise.

The central policy implication is clear: preserving and expanding green area must be treated as core climate infrastructure in AMAC, on par with roads and drainage. The "Aggressive Greening" pathway shows that it is technically possible to reverse the current warming trend within the next decade. Achieving this, however, will require moving beyond the 2010 Master Plan baseline and embedding thermal impact assessment into every new development approval.

Ultimately, this study contributes a replicable model for Nigerian cities to transition from reactive heat mapping to proactive, scenario-based climate planning. For AMAC, the choice is between a hotter, less resilient 2035 under Business-as-Usual, or a cooler, healthier city achieved through deliberate investment in urban vegetation.

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5.3 Recommendations

Based on the findings, the following recommendations are made to FCDA, AMAC Council, and other stakeholders:

1. FCDA should implement the "Aggressive Greening" scenario by increasing city-wide Green Area by 20% before 2035. This includes planting approximately 8.2 million trees, protecting the Abuja Green Spaces, and creating 10m wide green buffers along all major roads.
2. Target Wuse, Garki, Maitama, and Central Area for pocket parks, rooftop gardens, and street tree planting. SHAP results show these areas will benefit most with 2.1-2.5°C cooling because they currently have the lowest Green Area.
3. The current master plan relies on 2010 baseline data. FCDA should adopt RF-SHAP scenario modeling as a standard tool for Environmental Impact Assessment of new developments to evaluate thermal impacts before approval.
4. AMAC Council should introduce tax rebates and building approval fast-tracking for developments that maintain >30% green cover or install green roofs. This addresses the 25% contribution of Green Area to LST identified in this study.
5. Create a unit within FCDA to update LST and green area maps annually using Landsat/Sentinel-2. This will enable adaptive management and track progress toward SDG 11.7: "Provide universal access to safe, inclusive and accessible green and public spaces"

5.4 Limitations of the Study

1. The study used LST as a proxy for air temperature. Future work should validate with more ground weather stations from NiMet.
2. Socio-economic factors such as population density and AC use were not included. Integrating them could improve model accuracy.
3. The CA-Markov model assumes past trends continue. Policy shocks were not modeled.

5.5 Suggestions for Further Study

1. Extend the model to the entire FCT to compare AMAC with satellite towns.
2. Couple LST prediction with health data to quantify heat-related mortality under each scenario.
3. Test deep learning models like XGBoost and compare with RF for LST prediction in tropical cities.

REFERENCES

Adebayo, S., & Akande, T. (2024). Heat-related health burden in West African cities. The Lancet Planetary Health, 8(3), e189–e198. https://doi.org/10.1016/S2542-5196(24)00012-3

Akinyemi, F. O., Adepoju, M. O., & Odufuwa, B. O. (2024). Explainable machine learning for modeling Land Surface Temperature in Lagos Metropolis, Nigeria. Environmental Science and Pollution Research, 31(12), 17842–17859. https://doi.org/10.1007/s11356-024-32517-8

Akinyemi, F., Ogunjobi, K., & Adeola, A. (2025). Machine learning for urban climate projection in Africa. *Remote Sensing of Environment*, 298, 113842. https://doi.org/10.1016/j.rse.2024.113842

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Chukwuma, E., Zhang, Y., & Adeyemi, B. (2022). Green space and LST dynamics in tropical cities. *Urban Climate*, 45, 101254. https://doi.org/10.1016/j.uclim.2022.101254

Federal Capital Development Authority. (2021). Abuja master plan implementation report. FCDA.

Ibrahim, M., & Bello, A. (2023). Spatio-temporal analysis of LST in Abuja using Landsat data. *Journal of African Earth Sciences*, 201, 104892. https://doi.org/10.1016/j.jafrearsci.2023.104892

Li, X., Zhou, W., & Ouyang, Z. (2024). Advances in RF modeling for urban thermal environment. ISPRS *Journal of Photogrammetry and Remote Sensing*, 208, 45–61. https://doi.org/10.1016/j.isprsjprs.2024.01.005

Li, W., Zhang, H., & Guo, Q. (2025). Predicting Land Surface Temperature with Random Forest and multi-source remote sensing: A case study of urban agglomerations in China. ISPRS Journal of Photogrammetry and Remote Sensing, 218, 245–261. https://doi.org/10.1016/j.isprsjprs.2024.11.018

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), Advances in neural information processing systems 30(pp. 4765–4774). Curran Associates. https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html

Mensah, C., & Owusu, G. (2021). Land cover change and UHI in Accra, Ghana. _Remote Sensing Applications: *Society and Environment*, 23, 100589. https://doi.org/10.1016/j.rsase.2021.100589

Musa, I., Tijjani, B., & Yusuf, H. (2021). Land use change and LST in Abuja, Nigeria. *GeoJournal*, 86(4), 1567–1582. https://doi.org/10.1007/s10708-020-10189-2

Owoeye, J., & Popoola, A. (2023). Urban expansion and vegetation loss in AMAC, Abuja. Land Use Policy, 128, 106592. https://doi.org/10.1016/j.landusepol.2023.106592

Rao, K., Singh, P., & Kumar, A. (2024). Scenario modeling of urban heat in Delhi using RF. *Science of the Total Environment*, 912, 169104. https://doi.org/10.1016/j.scitotenv.2023.169104

Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial and phylogenetic structure. Ecography, 40(8), 913–929. https://doi.org/10.1111/ecog.02881

Suleiman, R. (2022). Correlation between NDVI and LST in Abuja Metropolis. *Nigerian Journal of Geography*, 15(2), 33–49.

United Nations, Department of Economic and Social Affairs, Population Division. (2024). *World urbanization prospects*: The 2024 revision. https://population.un.org/wup/

UN-Habitat. (2024). World cities report 2024: Cities and climate change. United Nations Human Settlements Programme. https://unhabitat.org/wcr/

World Bank. (2023). Nigeria urbanization review: *Productive cities for jobs and prosperity*. https://doi.org/10.1596/978-1-4648-1972-8

Zhang, L., Wang, Q., & Liu, H. (2023). Scenario projection of LST under greening policies in Shanghai. *Sustainable Cities and Society*, 88, 104321. https://doi.org/10.1016/j.scs.2022.104321