

Quantifying the Spatiotemporal Nexus between Deforestation and Land Surface Temperature Rise in a Semi-Arid African City: A 20-Year Geospatial Analysis of Katsina Metropolis, Nigeria

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ABSTRACT

Rapid urbanization in semi-arid Africa often triggers deforestation, raising concerns about its impact on urban microclimates and the intensification of the Urban Heat Island (UHI) effect. This study provides a rigorous 20-year geospatial analysis of the relationship between deforestation and Land Surface Temperature (LST) in Katsina Metropolis, Nigeria, a rapidly growing city in the semi-arid Sudan Savanna. Using Landsat satellite imagery (2002, 2012, 2022), we quantified vegetation cover change via the Normalized Difference Vegetation Index (NDVI) and retrieved LST using the mono-window algorithm. Our findings reveal a significant degradation of dense vegetation, which declined by 23.1% (a loss of 5.51 km²), while non-vegetated areas expanded by 59.6% (a gain of 17.13 km²). This land cover transformation was accompanied by a pronounced rise in LST, with the mean temperature increasing by 2.5°C and the minimum temperature rising sharply by 5.6°C, indicating an intensified and persistent UHI effect. Critically, regression analysis demonstrated a strong and strengthening negative relationship between NDVI and LST, with the coefficient of determination (R^2) increasing to 0.81 by 2022. This confirms that vegetation loss is the dominant driver of urban warming in this semi-arid setting. The study concludes that unchecked urban expansion at the expense of green spaces poses a significant environmental threat, and it underscores the urgent need for integrated urban greening strategies as a primary component of climate-resilient planning in semi-arid African cities.

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1 Introduction

The 21st century is characterized by rapid urbanization, a global trend with profound environmental consequences, particularly in the Global South (Kookana et al., 2020). A critical yet often overlooked impact of this urban expansion is the alteration of local and regional climates, primarily through the modification of land surface properties (Yu et al., 2024). The conversion of natural landscapes, such as forests and grasslands, to impervious surfaces like asphalt and concrete, fundamentally disrupts the surface energy balance. This process is a key driver of the Urban Heat Island (UHI) effect, a well-established phenomenon where urban areas experience significantly warmer temperatures than their rural surroundings (Oke, 1982; Manoli et al., 2019). The UHI effect exacerbates energy consumption, elevates pollutant concentrations, and, most critically, poses severe risks to human health and well-being through increased heat stress (He et al., 2021).

In semi-arid regions of Africa, these challenges are intensified by climatic preconditions and anthropogenic pressures (Serdeczny et al., 2017). Cities in these zones already face high baseline temperatures and water scarcity, making them exceptionally vulnerable to additional warming. A primary anthropogenic pressure

driving this warming is deforestation, defined as the permanent conversion of forested lands to non-forest uses according to the Food and Agriculture Organization (FAO, 2020). In the African context, deforestation is frequently driven by agricultural expansion, uncontrolled urbanization, and a heavy reliance on biomass for energy, leading to the loss of the critical ecosystem services that vegetation provides for microclimate regulation (Hein et al., 2018). Vegetation cools the environment through shade and evapotranspiration, and its removal leads to increased solar radiation absorption and a consequent rise in Land Surface Temperature (LST) (Wang et al., 2024). LST, the radiative skin temperature of the Earth's surface, is a more direct indicator of surface energy balance and UHI intensity than near-surface air temperature (Chakraborty & Lee, 2019; Zhou et al., 2019).

The situation in Nigeria, Africa's most populous nation, is particularly alarming. The country has one of the highest deforestation rates globally, with a loss of approximately 3.7% of its primary forest between 2002 and 2020 (Global Forest Watch, 2023). In Northern Nigeria's semi-arid Sudan Savanna belt, this trend is amplified by high population growth and pervasive dependence on fuelwood, placing immense pressure on remaining vegetation covers (Abaje et al., 2015). Katsina Metropolis,

the political and economic hub of Katsina State, epitomizes this crisis. This trend of land cover transformation is persistent, as confirmed by a recent state-wide analysis, which documented ongoing changes driven by infrastructural development to meet the needs of a growing population (Gandapa et al., 2023). Furthermore, Mmaduabuchi et al. (2020) reported a decadal vegetation loss of 19.3 km² in Katsina State, attributing it to agricultural and settlement expansion. This rapid land use/land cover (LULC) change is expected to have a significant impact on the city's thermal environment, yet a comprehensive, long-term spatiotemporal analysis specifically linking deforestation to LST dynamics in Katsina Metropolis remains limited.

Remote sensing technology has revolutionized the monitoring of environmental change, providing synoptic, repetitive, and cost-effective data for analyzing LULC and LST dynamics over time (Manoli et al., 2019). The Normalized Difference Vegetation Index (NDVI), derived from the red and near-infrared bands of satellite sensors like Landsat, has become a standard tool for quantifying vegetation density and health (Tucker, 1979). Declining NDVI values are a reliable proxy for deforestation and vegetation stress, enabling the tracking of green cover loss across urban landscapes (Huang et al., 2021).

Concurrently, thermal infrared data from the same satellite platforms allow for the retrieval of LST, providing a direct measurement of surface heating, as facilitated by the use of pre-processed Landsat Collection 2 Level-2 products (USGS, 2021). The inverse relationship between NDVI and LST is well-established in urban climatology; as vegetation cover decreases (lower NDVI), the cooling effects of shade and evapotranspiration diminish, leading to elevated LST. This relationship has been consistently demonstrated in diverse geographical contexts, from global-scale analyses (Chakraborty & Lee, 2019) to regional studies in semi-arid Africa (Isioye et al., 2020).

However, many existing studies in Nigeria have focused on larger metropolitan areas or have not employed the latest, atmospherically corrected Landsat Collection 2 data, which offers improved accuracy for time-series analysis (USGS, 2021). There is a critical need for localized, high-resolution studies in rapidly growing secondary cities like Katsina Metropolis, where the pace of environmental change is swift and the impacts on livability are immediate. Such studies are essential for generating city-specific evidence to guide sustainable urban planning and climate adaptation strategies.

To bridge this gap, this study conducts a rigorous 20-year (2002-2022) geospatial analysis to quantify the spatiotemporal extent of deforestation using NDVI, examine the concomitant changes in Land Surface

Temperature (LST), and assess the statistical relationship between vegetation loss and surface warming in Katsina Metropolis. By quantifying this nexus, the study provides critical empirical evidence on the environmental consequences of urban growth, which is a prerequisite for promoting sustainable and climate-resilient urban development in semi-arid Africa.

2 Materials and methods

2.1 Study area

Katsina Metropolis (Fig. 1) is the capital of Katsina State, Nigeria, and is situated in the semi-arid northwestern part of the country. It is located within latitudes 12° 55' 30" N and 13° 4' 30" N and longitudes 7° 33' 0" E and 7° 40' 30" E, covering a land area of approximately 142 km² (Ibrahim & Halliru, 2022). The city lies within the Sudan Savanna ecological zone, characterized by a tropical wet and dry climate (Köppen *Aw*) with a distinct seasonal pattern. The region experiences a single rainy season from June to September, with an average annual rainfall of about 780 mm, and a prolonged dry season from October to May (K. Abubakar et al., 2024).

Daytime temperatures are consistently high, often ranging from 29°C to 38°C, and can exceed 40°C during the pre-rainy months (March-May). The metropolis serves as the administrative and commercial hub of the state, experiencing rapid population growth and urban expansion, which has accelerated land use changes and placed significant pressure on the local vegetation cover (Ibrahim & Halliru, 2022; Ahmad et al., 2023).

2.2 Data Sources and Pre-processing

This study utilized multi-temporal satellite imagery from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS). To ensure consistency in the time series analysis and minimize the influence of seasonal phenology, all images were acquired during the peak of the dry season (January-February) when vegetation is least lush and cloud cover is minimal. Specifically, the scenes for February 13, 2002 (Landsat 7), January 24, 2012 (Landsat 7), and February 12, 2022 (Landsat 8) were downloaded from the United States Geological Survey (USGS) Earth Explorer portal (<https://earthexplorer.usgs.gov/>).

A significant strength of this analysis is the use of Landsat Collection 2 Level-2 products. These datasets are pre-processed to provide surface reflectance (SR) and surface temperature (ST) values, which are derived using advanced algorithms that account for atmospheric conditions, thereby enhancing the inter-comparability of data across different years and sensors (USGS, 2021). The specifications of the data used are summarized in Table 1.

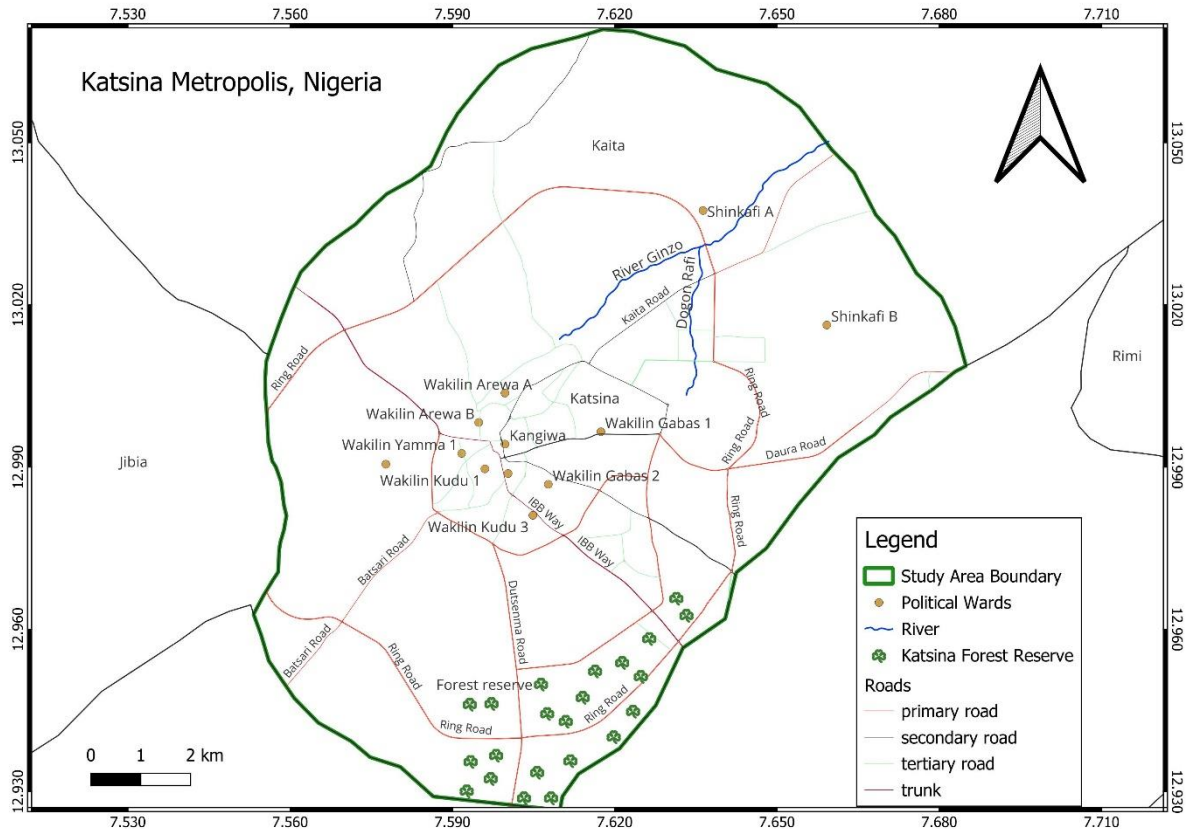


Figure 1: Map of the study area showing the location and boundary of Katsina Metropolis, Nigeria, within its regional context.

Table 1: Specifications of Landsat Satellite Data Used

Parameter	Landsat 7 ETM+ (2002, 2012)	Landsat 8 OLI/TIRS (2022)
Sensor	ETM+	OLI & TIRS
Data Level	Collection 2 Level-2	Collection 2 Level-2
Spatial Resolution (SR)	30 m	30 m
Spatial Resolution (ST)	60 m (resampled to 30 m)	100 m (resampled to 30 m)
Bands for NDVI	Red: Band 3, NIR: Band 4	Red: Band 4, NIR: Band 5
Band for LST	Thermal: Band 6	Thermal: Band 10

2.3 Data Analysis

Analysis of Vegetation Cover (NDVI)

The Normalized Difference Vegetation Index (NDVI) was calculated to assess vegetation density and its changes over time. NDVI is computed using the standard formula (Huang et al., 2021):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

For Landsat 7, the Red and Near-Infrared (NIR) bands are Band 3 and Band 4, respectively. For Landsat 8, they are

Band 4 and Band 5. The calculation was performed using the Raster Calculator tool in ArcGIS 10.8. The resulting NDVI values range from -1 to +1, where higher values indicate denser and healthier vegetation, values near zero represent bare soil, and negative values typically correspond to water bodies (Huang et al., 2021). The NDVI rasters for each year were then clipped to the boundary of Katsina Metropolis. To quantify changes, the NDVI images were classified into three land cover classes based on established thresholds for semi-arid regions (Dey et al., 2021): non-vegetated (-1 to 0.1), sparse vegetation (0.1 to 0.25), and Vegetated (0.25 to 1). The area in square kilometres for each class was calculated for each epoch (2002, 2012, 2022).

Retrieval of Land Surface Temperature (LST)

Land Surface Temperature (LST) was derived from the thermal infrared bands of the Landsat Collection 2 Level-2 data. The retrieval process leverages the principle that the intensity of thermal radiation emitted by the Earth's surface is a function of its temperature, as described by Planck's law. While the Collection 2 data provides surface temperature values, the raw data from the thermal bands are provided as Digital Numbers (DN). These DNs were converted to top-of-atmosphere (TOA) spectral radiance and subsequently to brightness temperature in Kelvin, using the scaling parameters provided in the metadata file (MTL.txt) for each scene (USGS, 2021). This step is crucial for standardizing the data across different sensors and

acquisition dates.

The following formula was applied uniformly across all scenes using the Raster Calculator tool in ArcGIS 10.8 to convert the DN values to Kelvin:

$$LST (Kelvin) = (DN \times Scale_Factor) + Add_Offset \quad (2)$$

Where:

- DN is the pixel value from the thermal band (Band 6 for Landsat 7; Band 10 for Landsat 8).
- Scale_Factor is a multiplicative rescaling factor (0.00341802 for both sensors in this collection).
- Add_Offset is an additive rescaling factor (149.0 for both sensors in this collection).

It is important to note that this brightness temperature represents the temperature of a blackbody emitting the same radiance and does not account for the land surface's emissivity (ϵ). However, the use of Landsat Collection 2 Level-2 products, which are generated using advanced algorithms, implies that atmospheric corrections and emissivity adjustments have been applied to derive a more physically accurate surface temperature, as recommended by the USGS (2021) and supported by recent methodological reviews (Avdan & Jovanovska, 2016; Wang et al., 2024).

The resulting values were in Kelvin. To convert to degrees Celsius ($^{\circ}C$), the following standard conversion was applied:

$$LST (^{\circ}C) = LST (Kelvin) - 273.15 \quad (3)$$

This two-step calculation, directly utilizing the scene-specific scaling parameters, ensures a precise and physically robust retrieval of LST, accounting for the radiometric calibration of each sensor. The final LST rasters for each year, now in degrees Celsius, were clipped to the study area boundary for subsequent analysis.

Regression Analysis between NDVI and LST

To quantitatively assess the influence of vegetation cover on surface temperature, a simple linear regression analysis was performed, with Land Surface Temperature (LST) as the dependent variable and the Normalized Difference Vegetation Index (NDVI) as the independent variable. The regression model is expressed as:

$$LST = \beta_0 + \beta_1(NDVI) + \epsilon \quad (4)$$

where β_0 is the intercept, β_1 is the slope coefficient, and ϵ is the error term.

A systematic sampling approach was employed to avoid spatial autocorrelation bias (Chakraborty & Lee, 2019). A fishnet of 30 by 30 grid cells (total 900 points) was

created over the study area. The "Extract Multi Values to Points" tool in ArcGIS was used to extract the corresponding NDVI and LST values for each point in the fishnet for each of the three years. The extracted data were then exported to statistical software, where the linear regression model was fitted.

The strength of the relationship was quantified using the coefficient of determination (R^2), which indicates the proportion of variance in LST explained by NDVI. The slope of the regression line (β_1) was also examined to confirm the expected negative relationship.

3 Results

3.1 Spatiotemporal Dynamics of Vegetation Cover (2002-2022)

The analysis of the Normalized Difference Vegetation Index (NDVI) reveals a significant decline in vegetation cover in Katsina Metropolis over the two-decade study period. The spatial distribution of NDVI for the years 2002, 2012, and 2022 is presented in Fig. 2, while the quantitative changes in vegetation cover classes are summarized in Table 2.

Table 2: Areal Extent (km²) of NDVI-based Land Cover Classes in Katsina Metropolis

NDVI Class	2002	2012	2022	Net Change (2002-2022) (km ²)
Non-vegetated	28.72	34.38	45.85	+17.13
Sparse Vegetation	92.30	89.88	80.61	-11.69
Vegetated	23.87	20.55	18.36	-5.51

In 2002, the landscape was characterized by a more extensive distribution of vegetated areas, particularly in the periphery. The NDVI values ranged from -0.027 to 0.352, with a mean of 0.144. The classified NDVI map (Fig. 2a) shows that Dense Vegetation covered 23.87 km² (16.8% of the study area), while non-vegetated areas accounted for 28.72 km² (20.2%).

By 2012, a clear reduction in vegetation density was observed. The maximum NDVI value decreased to 0.337, and the spatial extent of the Dense Vegetation class contracted to 20.55 km² (14.5%). Concurrently, non-vegetated areas expanded to 34.38 km² (24.2%), indicating a conversion of green spaces to built-up or bare land. The trend of vegetation loss continued through 2022. The vegetated class further diminished to 18.36 km² (12.9%), representing a net loss of 5.51 km² over the 20 years. In contrast, non-vegetated areas expanded dramatically to 45.85 km² (32.3%), a net increase of 17.13 km² since 2002. This signifies a substantial transformation of the urban landscape, with a clear shift from vegetated to non-vegetated land cover.

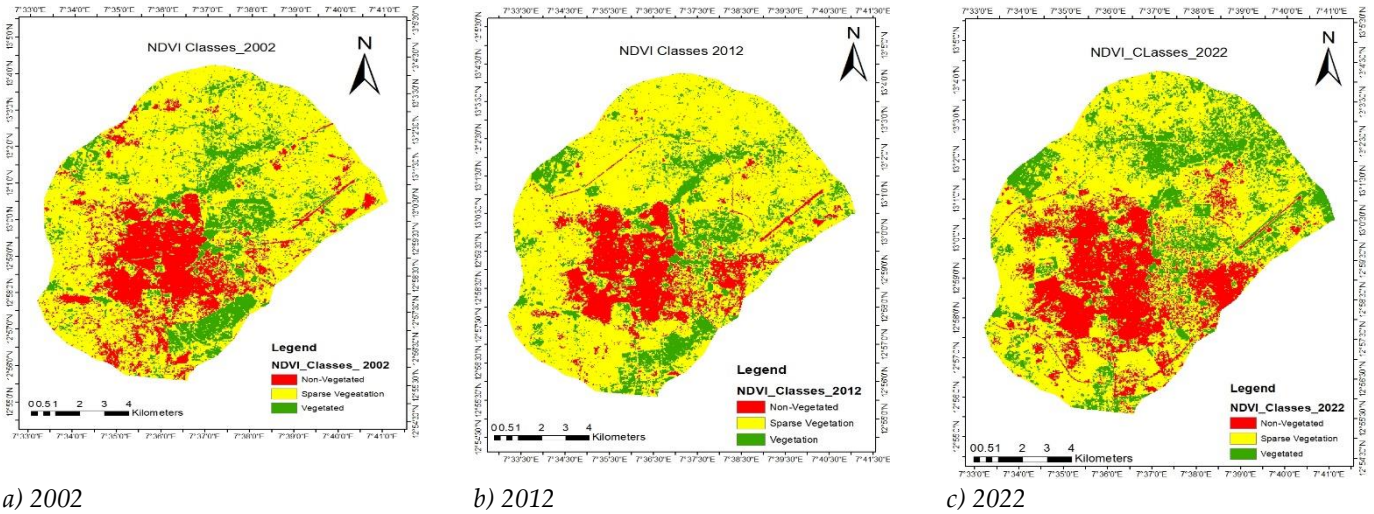


Figure 2: NDVI Class Map a) 2002, b) 2012, and c) 2022

Temporal Trends in Land Surface Temperature (LST)

The retrieval of Land Surface Temperature (LST) shows a corresponding warming trend across Katsina Metropolis from 2002 to 2022 (Fig. 3). The statistical summary of LST for the three epochs is provided in Table 3.

Table 3: Statistical Summary of NDVI and LST in Katsina Metropolis (2002-2022)

Year	NDVI Statistics			LST Statistics		
	Min	Max	Mean	Min	Max	Mean
2002	-0.03	0.352	0.144	28.22	36.47	34.08
2012	-0.09	0.337	0.154	31.85	40.35	38.31
2022	-0.03	0.329	0.158	33.83	39.45	36.58

In 2002, the LST ranged from 28.22°C to 36.47°C, with a mean of 34.08°C. The spatial pattern showed more localized and less intense heat islands. A significant intensification of surface heating was evident in 2012. The minimum LST rose to 31.85°C, and the maximum LST peaked at 40.35°C. The mean LST increased sharply to 38.31°C, reflecting a substantial warming of 4.23°C compared to the 2002 baseline.

By 2022, while the maximum LST (39.45°C) was slightly lower than in 2012, the baseline temperatures were consistently higher. The minimum LST in 2022 was 33.83°C, which is 5.61°C warmer than the 2002 minimum. The mean LST for 2022 was 36.58°C, indicating that the metropolis retained a significantly warmer thermal regime compared to the start of the study period.

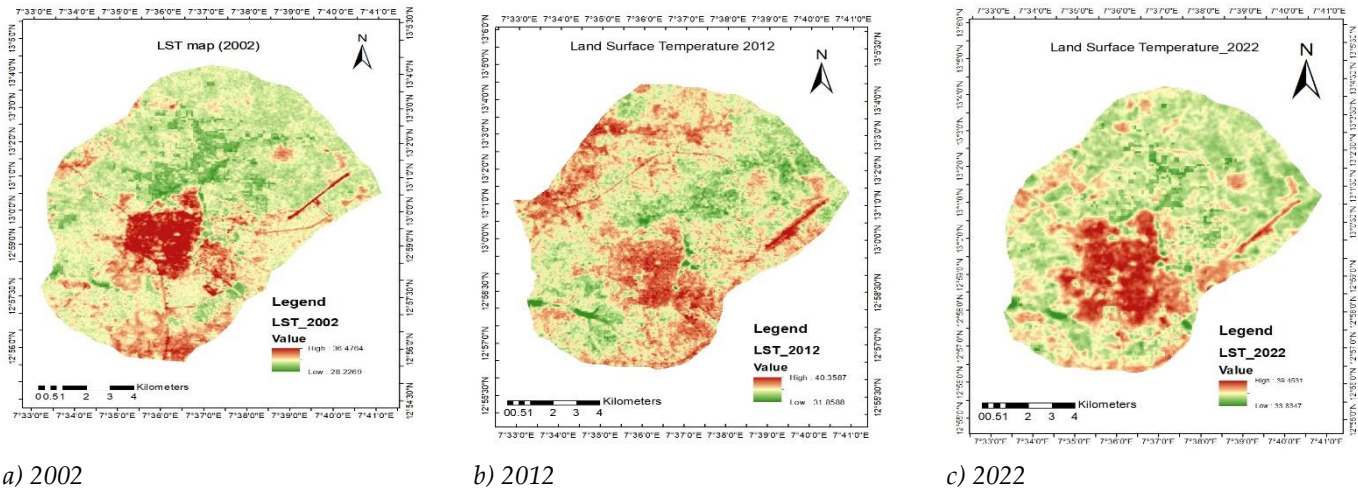


Figure 3: LST Map for a) 2002, b) 2012, and c) 2022

Relationship between NDVI and LST

The regression analysis demonstrates a strong, persistent negative relationship between NDVI and LST throughout the study period. The scatter plots and regression statistics for 2002, 2012, and 2022 are presented in Fig. 4.

In 2002, the regression analysis revealed a strong

negative relationship, with the NDVI variable being a highly significant predictor of LST ($R^2 = 0.7705$), indicating that 77% of the variability in LST could be explained by variations in NDVI. This strong inverse relationship was maintained in 2012, with a similarly high coefficient of determination ($R^2 = 0.7597$).

By 2022, the strength of the relationship increased

further, yielding the strongest correlation of the study period ($R^2 = 0.8143$). This signifies that over 81% of the variation in land surface temperature was attributable to the density and health of vegetation cover. The consistently high R^2 values across all three epochs robustly confirm that vegetation loss is a primary driver of land surface temperature increase in Katsina Metropolis.

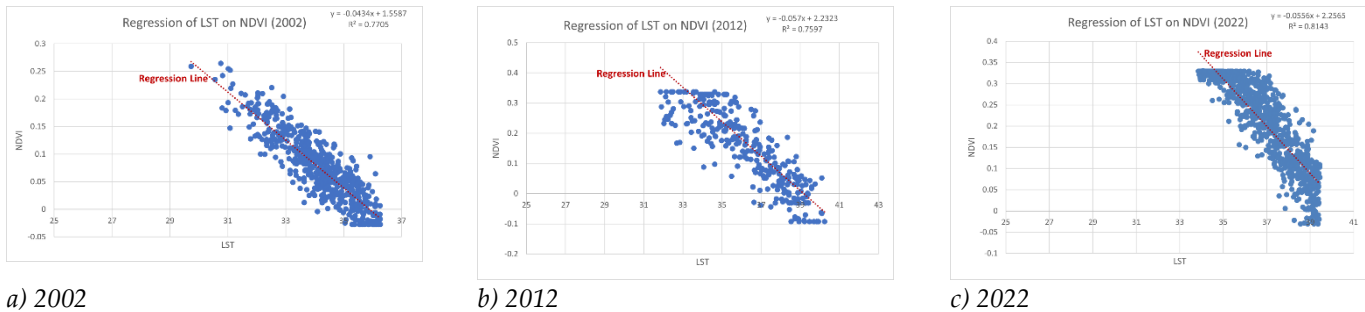


Figure 4: The Negative Relationship Between NDVI and LST in a) 2002, b) 2012, and c) 2022

4 Discussion

This study provides a robust, quantitative assessment of the spatiotemporal nexus between deforestation and land surface temperature (LST) rise in Katsina Metropolis, a rapidly urbanizing city in semi-arid Nigeria. Our findings confirm a significant transformation of the urban landscape over 20 years, characterized by extensive vegetation loss and a corresponding intensification of the urban thermal environment, with a consistently strong negative correlation between these two variables.

4.1 Escalating Vegetation Loss and Urban Expansion

The observed decline in dense vegetation cover, from 23.87 km² in 2002 to 18.36 km² in 2022, coupled with the dramatic expansion of non-vegetated areas by 17.13 km², underscores a rapid process of urbanization at the direct expense of green spaces. This trend aligns with the broader pattern of rapid urbanization in West Africa, where population growth often outpaces effective land-use planning (United Nations, 2019; Gandapa et al., 2023).

The specific drivers in Katsina, as indicated by local studies, include high demand for fuelwood, agricultural expansion on the urban fringes, and direct land conversion for housing and infrastructure (Ladan, 2014; Ahmad et al., 2023). The slight increase in mean NDVI from 2002 to 2022 (Table 3) likely reflects the growth of drought-resistant shrubs or small-scale regrowth in interstitial areas, but this does not offset the critical loss of dense, mature vegetation and its associated ecosystem services. This net loss of vegetative cover is the primary catalyst for the altered surface energy balance observed in this study.

4.2 Intensification of the Urban Heat Island (UHI) Effect

The significant rise in land surface temperature,

particularly the 4.23°C increase in mean LST from 2002 to 2012 and the consistently elevated baseline in 2022, provides clear evidence of an intensifying Urban Heat Island (UHI) effect. The replacement of natural, vegetated land with impervious surfaces like asphalt, concrete, and bare soil reduces albedo (reflectivity) and diminishes cooling through evapotranspiration (Manoli et al., 2019). This shifts the surface energy balance from latent heat flux (cooling) to sensible heat flux (warming), leading to the higher LST values we have documented (Chakraborty & Lee, 2019). The finding that the minimum LST increased more sharply (by 5.61°C) than the maximum LST highlights a critical aspect of UHI intensification: built-up areas not only heat up more during the day but also retain heat more effectively throughout the night, offering less respite from thermal stress (Manoli et al., 2019). This pattern of warming is consistent with studies in other semi-arid cities, such as those in Northern Nigeria, where Isioye et al. (2020) also reported a strong and growing UHI effect linked to land cover changes.

4.3 The Robust Nexus between Deforestation and Warming

The core finding of this research is the persistent and strong negative relationship between NDVI and LST, with the coefficient of determination (R^2) strengthening to 0.8143 by 2022. This signifies that over 81% of the spatial variability in surface temperature can be explained by the presence or absence of vegetation. This result is consistent with a growing body of regional literature from semi-arid Nigerian cities, which consistently identifies vegetation loss as a primary driver of urban warming.

For instance, a recent study in Kaduna Metropolis, located within the same Sudan Savanna ecological zone, also demonstrated a strong inverse correlation between

MODIS-derived NDVI and LST (Abubakar et al., 2024). Similarly, research in the Bwari Area Council of Abuja confirmed that significant vegetation loss was directly linked to increased land surface temperatures (Ekanem & Bukuromo, 2025). Our study from Katsina Metropolis empirically consolidates these findings, confirming that the nexus between deforestation and rising LST is a dominant and widespread environmental challenge across the semi-arid cities of Northern Nigeria.

4.4 Implications for Urban Planning and Climate Resilience

The synergistic trends of deforestation and rising LST pose a direct threat to the livability and public health of Katsina Metropolis. Elevated LSTs exacerbate heat stress for residents, increase energy demand for cooling, and can worsen air pollution levels (He et al., 2021). In a region already facing water scarcity and high baseline temperatures, these effects disproportionately impact vulnerable populations. Therefore, urban planning must prioritize the conservation of existing green spaces and the strategic integration of new ones.

The LST and NDVI maps generated in this study can serve as direct tools for planners, identifying "hotspots" that should be prioritized for targeted interventions such as the creation of urban parks, green corridors, and the promotion of "cool" building materials (Mushore et al., 2017). Policies aimed at providing alternative energy sources to reduce fuelwood dependence are also crucial to address a root cause of deforestation.

5 Conclusion

This study successfully employed a multi-temporal remote sensing approach to quantify the spatiotemporal dynamics of deforestation and its direct impact on land surface temperature (LST) in Katsina Metropolis from 2002 to 2022. The analysis yielded three unequivocal findings. First, the city experienced substantial vegetation degradation, with a net loss of 5.51 km² of dense vegetation and a concurrent 60% expansion of non-vegetated areas. Second, this land cover transformation triggered a significant warming trend, characterized by a

sharp rise in mean LST and a particularly alarming increase in minimum temperatures, signaling an intensified and persistent urban heat island (UHI) effect. Third, and most critically, a robust and strengthening negative relationship (R^2 reaching 0.81 by 2022) was established between NDVI and LST, confirming that vegetation loss is a primary driver of urban warming in this semi-arid context.

The implications of these findings extend beyond academic interest; they represent a pressing environmental and public health concern. The unchecked conversion of vegetated land to impervious surfaces is actively degrading the city's microclimate, thereby increasing the population's vulnerability to heat stress. Consequently, urban planning and environmental policy must prioritize ecological infrastructure as a core component of climate resilience strategies. Specifically, we recommend: (1) using the generated LST maps to identify thermal hotspots for targeted urban greening through tree-planting and the creation of parks and green corridors; (2) the stricter enforcement of laws against indiscriminate tree felling and the integration of green space requirements into urban development codes; and (3) promoting clean and affordable alternative energy sources to reduce reliance on fuelwood, a key driver of local deforestation. In the face of rapid urbanization and a changing climate, this study underscores that preserving and enhancing urban greenery is not a luxury but a necessity for sustainable urban development in semi-arid Africa.

For future research, we recommend integrating higher-resolution satellite imagery, exploring the impact of specific tree species on localized cooling, and coupling these geospatial findings with in-situ microclimate and socio-economic data to conduct a comprehensive vulnerability assessment. This study underscores that in the face of rapid urbanization and a changing climate, preserving and enhancing urban greenery is not a luxury but a necessity for sustainable urban development in semi-arid Africa.

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