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Impact of Forest Cover Loss on Surface Temperatures in Yakurr Local Government Area, Cross River State, Nigeria (2010–2025): A Remote Sensing Approach

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Abstract **Original Research Article**

The transformation of forest cover alters surface-energy exchanges on the earth's surface and may lead to extreme thermal conditions in the tropical environment. Although the dynamism of the environment is appreciated by most users, the role of forest cover transformation, surface thermal variability and community perceptions to environmental change is poorly documented at the local level. This study combines remote sensing and surveys to analyze the dynamics of forest cover and thermal land surface and perceived environmental change in the Yakurr Local Government Area of Cross River State, Nigeria from 2010 to 2025. Data on land-use/ land-cover for 2010, 2015 and 2025, along with satellite derived land surface temperatures and surveys conducted on 507 participants were analyzed using descriptive statistics, change detection and multivariable linear regression. The results showed a net reduction of 10,779 ha (28.9 %) in forest cover from 2010 to 2015, with a partial recovery to 26,509 ha in 2025. The mean land surface temperature increased from 30.93 °C in 2010 to 33.66 °C in 2015 before declining to 30.31 °C in 2025, indicating a non-monotonic thermal trend. Most respondents identified agricultural expansion (85.0%) and timber extraction (76.7%) as the key drivers of forest degradation. Simultaneously, 88.4% indicated increased daytime heat. Multivariable regression showed a significant positive relationship between the perception of forest loss and the intensity of warming (standardized $\beta = 0.298$; $p < 0.001$). The lowest extent of forest cover was correlated to the highest mean LST in 2015. Despite a subsequent drop in temperature, forest cover remained below its 2010 extent. This case illustrates the various relations forest and temperature may have and the role other variables may play. While complete and consistent information about land cover changes would have been useful, the data that were available showed a significant correlation between community perception of changing environment and remote sensing data. The study highlights the potential of fusing community-based data with geospatial data. This case emphasizes the importance of environment monitoring, participatory forest management and planning climate-responsive land use in the tropics.

Keywords: Deforestation; Land Surface Temperature; Land-Use/Land-Cover Change; Remote Sensing; Household Perceptions.

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1. INTRODUCTION

Tropical forests help regulate the climate in two ways. First, the carbon and other greenhouse gas cycles. Second, biophysical modification of radiation, evapotranspiration and turbulent heat. Trees intercept radiation. They transpire water if available, and alter aerodynamic roughness. Forest removal redirects energy to surface heat, resulting in warmer surface and other microclimatic changes. However, the net effect is controlled by other factors such as albedo, moisture, and the characteristics of the new land cover. Therefore, changes in the forested area do not always impact the climate (Zhu *et al.,* 2023; Zhang *et al.,* 2024; Ruijsch *et al.,* 2024). Although significant progress has been made in Earth Observation, changing forest conditions are one of the main environmental challenges in the tropics. The World Resources Institute's (2026) assessment predicted that 4.3 million hectares of primary tropical forest was lost in 2025. As remote sensing becomes more advanced, the distinction between fully intact forest, degraded canopy, tree cover outside forest, and secondary regrowth becomes more important in assessing changes in a landscape. In addition, Liu *et al.,*(2025) showed that finer resolution data can identify tree-cover changes that are not discernible from coarser data. Such information

adds methodological insights for the estimation of surface temperature changes due to deforestation.

Better understanding of the relationships between forests and climate has come from recent studies. It has been found that tropical forest loss and regrowth have different impacts on land surface temperature (LST) and that the temperautre response to forest removal is time varying and distinct to the type of disturbance. One study in Africa found that there exists both temporal and spatial variation in the relationships of vegetation and temperature and emphasized that the benefits of restoration depend on the environmental conditions in that region. Another study focused on the relationship between LST and tree canopy height showed there are differences by latitude and once again called for consideration of the structure of vegetation and local conditions instead of assuming all mapped forests are similar.

Changes in biophysical processes have many impacts that reach beyond surface temperature. For many rural communities in the tropics, the removal of forests for agriculture means a loss of an important source of livelihoods and a change in exposure to direct solar radiation and heat. One study found that deforestation is associated with local warming and consequently diminished worker productivity. While deforestation is associated with an increase in temperature at the surface, this does not mean surface temperature is the same as near-surface air temperature. There is a need to use local knowledge and reported experiences of communities for heat and health instead of assuming changes in the local temperature as reported by satellites are a good proxy for changes in the local climate.

Southeastern Nigeria is home to Cross River State, a place of great biological importance that is experiencing an increased demand for space for settlements and agriculture. Recent studies have documented changes in different forests of central Cross River State, and the socio-ecological pressures in Okwangwo Division of Cross River National Park. Though these studies place great emphasis on the need for improved governance of forests, they did not analyze the interrelationships of local-scale land-use changes, changes in remote-sensing-based surface temperature and household-level environmental perceptions in Yakurr Local Government Area. Yakurr Local Government Area is important to study because various land uses (i.e., forest, farms, settlements, and water bodies) coexist in a predominantly rural livelihood landscape. Of particular relevance is the potential for measuring three-date changes to identify shifts from a simple linear trajectory (i.e., an initial loss of forest, followed by a restoration of forest, and vice versa). The reasons for changes in forest extent may vary over time and may differ from changes in land-surface temperature (LST) of the surrounding area. It is important to exclude these factors when interpreting land-use change in a given area. Incorrect classification of the forest cover may occur if there is inadequate assessment of the changing perceptions of the local inhabitants about the environment.

Assessments of forest cover changes now identify loss, degradation and regrowth at a finer scale, but differences still exist. Vancutsem *et al.,*(2021) illustrated how repeated observations can resolve cases of deforestation from other disturbances and recovery in humid tropical forests. Reiner *et al.,*(2023) found that much of the tree cover in Africa is outside of previously mapped areas, and Bourgoin *et al.,*(2024) found that forest degradation can occur even in areas where forest cover is nominally present. New higher-resolution methods have also shown tree cover changes that are not documented by traditional maps (Liu *et al.,* 2025). These studies illustrate that the classification of areas into ‘forest’ and ‘non-forest’ may hide significant differences in canopy height, previous disturbance and potential for evaporative cooling.

Transformations in the drivers of forest loss are also heterogeneous. While agriculture and commodity supply chains are leading causes of global forest loss, their local salience varies by location and land tenure systems (West *et al.,* 2025; Singh & Persson, 2026). Gupta *et al.,*(2025) showed the type and configuration of replacement land cover influences the trajectory of forest recovery. Xu *et al.,*(2026) found that even small, persistent, forest cover clearings can have a large impact on tropical forest carbon, and may take a long time to recover. Fire-related disturbances are also a significant cause of canopy loss (Tyukavina *et al.,* 2022). Recently thermal studies show forest-conversion signals vary by location and type of disturbance. Li *et al.,*(2025) show that post-disturbance LST response varies with type of forest loss. Liao *et al.,*(2026) show that in the case of biodiversity loss, there are asymmetric responses for forest loss and gain. Different from biodiversity loss, in the case of conversion to plantation, Smith *et al.,*(2026) show that conversion to plantation has a different warming signal from that of shifting agriculture. At a broader scale, Li *et al.,*(2026) also mention that fragmentation of the landscape may affect the relationship between forest and climate. They state that due to multiple drivers of forest loss, relying on the total forested area may not be sufficient and we may need to integrate other variables, like cover, structure, fragmentation and the environment.

Local challenges with measurement, especially with respect to the temperature and experience of air near the ground (2m) versus the radiative temperature of the land surface, include the impact of instrument characteristics, sample date, atmospheric conditions, rainfall, soil moisture, and other variables. Zhao *et al.,*(2026) underscore the significance of differentiating local effects of land-cover change from the nonlocal effects when making physical interpretations. African

examples further underscore context-dependence. Urban expansion in some parts of East Africa has been associated with strong thermal changes (Ebaju *et al.,* 2026), while other studies in Ethiopia have documented seasonal variations and the importance of directly comparing land cover and LST (Keno *et al.,* 2025; Abafogi *et al.,* 2026). While more rigorous comparisons require access to source imagery, these studies motivate the description and comparative analyses undertaken herein.

This study combines geospatial and temporal evidence streams to examine land cover changes over Yakurr between 2010 and 2025, including the loss of forest cover and associated surface thermal conditions. The aims are: (i) to determine the quantum and net changes of the four land cover classes in study area; (ii) to document the land cover persistence and changes over the study period; (iii) to analyze the spatial distribution and statistics of LST for the years 2010, 2015 and 2025; (iv) to understand the beliefs of 507 respondents regarding forest degradation, its impacts and the adaptations undertaken; and (v) to examine the association between socioeconomic variables and the respondents' perceptions of warming. The study provides a local perspective regarding environmental change and distinguishes temporal co-occurrence from demonstrable forest-driven temperature effects.

2. MATERIALS AND METHODS

2.1 Study Area

The study focused on Yakurr Local Government Area (LGA), which is located in the central region of Cross River State, in the South-South geopolitical region of Nigeria (Figure 1). The administrative headquarters of Yakurr is Ugep and it shares boarders with Obubra LGA to the north, Biase LGA to the south, Abi LGA to the west and Akamkpa LGA to the east. The area is composed of several rural and urbanizing settlements including Ugep, Ekori, Mkpani, Nko, Idomi, Inyima, Assiga, Agoi-Ibami and Agoi-Ekpo. Figure 1 shows the location of Yakurr within Nigeria and Cross River State, and the various administrative wards (Bassey, 2022). It provides the context for assessing environmental changes within the study area. Climatically, Yakurr is within the humid tropical region of Nigeria, and has high temperatures and humidity, with distinct wet and dry seasons. The dry season is from November to March, and the wet season is from April to October. Relief in the area is generally flat, with the exception of the Agoi-Ekpo and Agoi-Ibami forests. The area is predominantly cleared for cultivation, leaving remnants of tropical rainforests and secondary vegetation (Bassey, 2022). Changes in environmental characteristics influence the productivity of the vegetation, availability of soil moisture, and surface water and changes in land surface temperatures and thermal conditions.

Agriculture is the main source of livelihood in Yakurr, but other important economic activities like settlement and transportation developments, as well as forest resource utilization enhance land use diversification. Therefore, the area's landscape consists of croplands, forests and other vegetation, settlements and commercial areas, bare lands and water features. These land cover units differ in a number of biophysical aspects, including surface reflectance, density of vegetation, evapotranspiration, thermal inertia and moisture retention. Consequently, changes in these land cover units affect the surface energy balance and result in variations in surface temperature of land.

Yakurr is a representative area of varying landscapes including forests, agriculture, and buildings, and, therefore, is good for studying land use change and land cover change and their effects on local climate. In addition, the replacement of vegetation by built-up or exposed land surface covers offers opportunities to assess changes in surface heating and thermal regulation of the ecosystem. It is imperative to understand these processes to identify new or emerging pressures on the environment and to develop sustainable land use, vegetation conservation and climate-responsive built environment and spatial land use planning.

2.2. Research design and analytical framework

The study employed an integrated geospatial and quantitative survey research design to analyze the interrelationships between land-use/land-cover (LULC) dynamics, forest-cover change, land surface temperature (LST) and the perception of the community on environmental change, in Yakurr LGA of Cross River State, Nigeria. The research designs incorporated multi-temporal remote sensing and household survey, to assess transformations in the environment and then juxtapose it with the experiences and perceptions of residents on changing ecological conditions. The research design employed in the study is a mixed methods approach and is consistent with theoretical principles of integrated research (Creswell & Plano Clark, 2018). The geospatial research design employed to analyze land cover conditions for the years 2010, 2015 and projected conditions for 2025, covered a 15 year research period. Changes in forest cover, constructed and settlement surfaces, bare lands and water bodies for the period were analyzed as well as surface temperature. The household survey was on 507 respondents and assessed socio-economic conditions, and changes in forest cover, drivers of environmental degradation, heat stress conditions, the impacts and adaptation to heat stress as well as the perception on the management of forest resources.

The analytical framework consisted of four interconnected stages. The first stage was to define and quantify the spatial and temporal distributions of the major land cover categories. The second stage was to analyze the spatial and temporal patterns of LST for the

study period. The third stage was to analyze community perceptions and socioeconomic factors associated with perceived environmental warming using descriptive and multivariable statistics. The final stage was to integrate evidence from the geospatial and socioeconomic assessments to locate areas of alignment and conflict between environmental changes observed remotely and those mentioned by the community. The integration of geospatial and socioeconomic data was meant to provide different points of view, rather than to create direct causal relationships. Changes in the physical condition of land surfaces were captured by remote sensing, while residents' retrospective perspectives on environmental conditions and how they responded to environmental pressures were captured in the surveys. These interpretations were made to separate community perceptions from satellite-derived data.2.3. Land-use/land-cover assessment and change detection

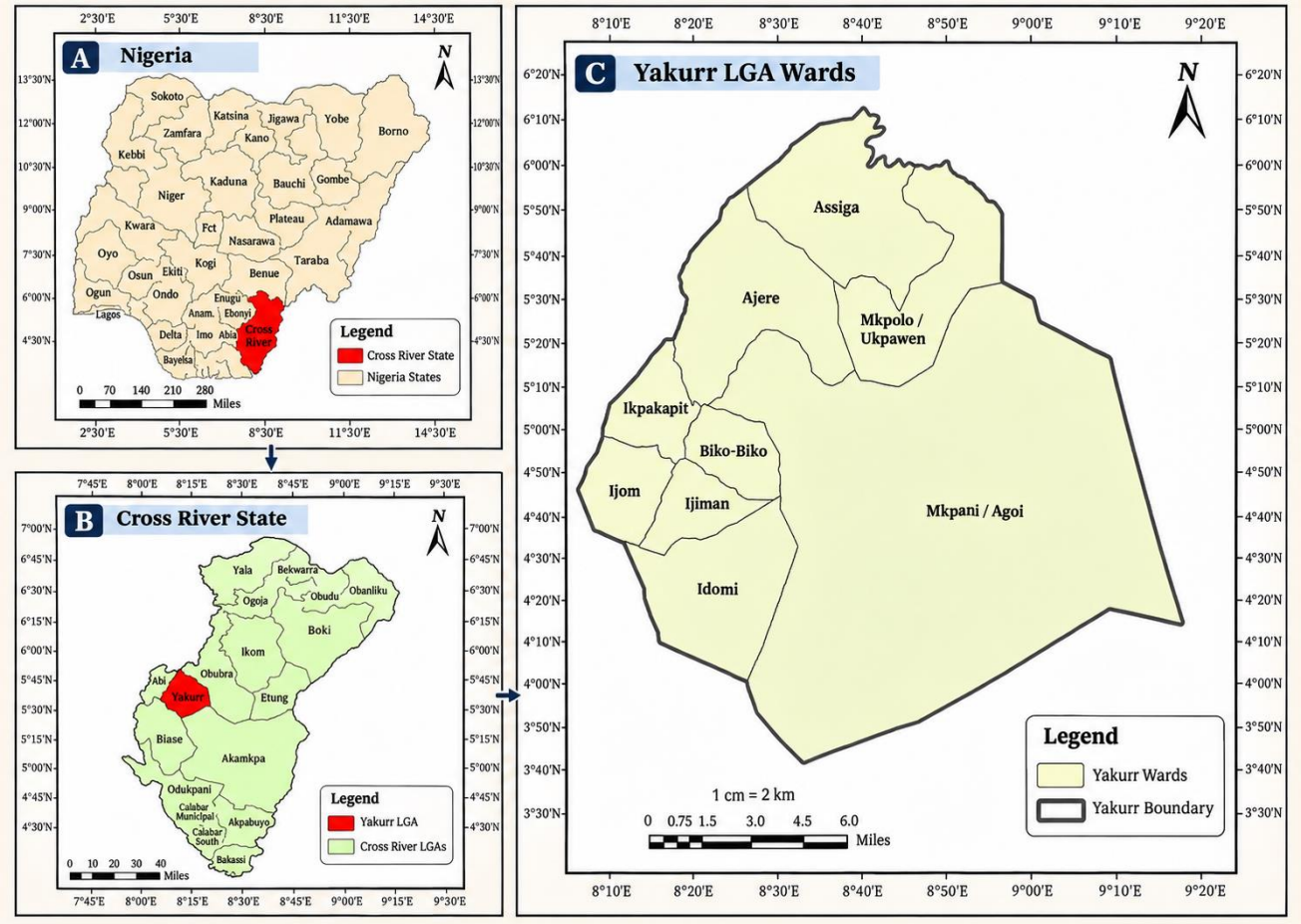


Figure 1. Location of Yakurr Local Government Area in Nigeria and Cross River State, showing ward boundaries. Source: study-area figure supplied with the research results

2.3.1. Land-cover characterization and spatial analysis

The basis of the spatial assessment was a set of land cover layers corresponding to 2010, 2015 and 2025. The comparison of different land-cover conditions was done within a fixed extent of 67,921 hectares (679.21 km^2). The consideration was given to four land-cover classes, namely: forest, developed land, barren land and water bodies. For the land cover classification, developed land included both settlements and other constructed land-use. Barren land included all lands with very little or no vegetation. Water bodies included all lakes and other artificial and natural water bodies. The classification facilitated analysis of vegetation loss, built-up land expansion and other land cover change potentially induced by surface thermal modification.

The areal extent of each class was given in hectares and as a proportion of the total mapped area. The areal extent of each class was determined as,

$$A_i,t = (A_k,t / A_t) \times 100 \quad (1)$$

where A_k,t is the areal extent of class i in year t and A_t is total area (67921 hectares). A major emphasis was on the changes that occurred in forest cover and developed and barren lands, since these land-use changes might have an effect on vegetation-related evapotranspiration, soil moisture and surface energy balance.

2.3.2. Quantification of land-cover change

Comparisons of the changes in class-specific areas from the periods 2010-2015, 2015-2025 and the overall period 2010-2025 were used to evaluate changes in land cover for the study. For each of these periods, absolute and relative changes were estimated to determine the direction and magnitude of changes that occurred to the landscape.

Absolute change was calculated as:

$$\Delta A_i = A_i,t_2 - A_i,t_1 \quad (2)$$

where ΔA_i is the change in area of class i and A_i,t_1 and A_i,t_2 are the extent of the class at time t_1 and time t_2, respectively.

Relative percentage change was determined as:

$$\Delta P_i = [(A_i,t_2 - A_i,t_1) / A_i,t_1] \times 100 \quad (3)$$

Positive values of ΔP_i indicate an expansion of class i area from the initial condition, and negative values indicate a contraction. These values were used to determine the extent of land cover change and also to evaluate the direction of change in the four land cover classes.

To adjust for different time spans of the observation intervals, net changes were also determined on an annualized basis as:

$$R_i = (A_i,t_2 - A_i,t_1) / (t_2 - t_1) \quad (4)$$

where R_i is the average annual change in hectares and $t_2 - t_1$ is the number of years between the observation dates. The annualized change provides a measure of the average change between the observation dates, and does not represent the change that occurred during each year. Dominant patterns of land cover change and expansion were determined using these values.

2.3.3. Land-cover transition analysis

Land-cover transition analysis studies potential changes between various landscape states. This method is based on the concept of "origin-destination" cross-tabulation, which involves comparing each land-cover class in a given year to the class in the next year. In the case of a four-category classification scheme, a complete transition matrix would contain 16 "origin-destination" cases, of which four cases represent persistence and 12 cases represent conversion. Persistence indicates that the land-cover class in a given year remains the same in the following year, and conversion indicates that the land-cover class has changed in a given year. The principal transitions of land-cover classification in this study were forest to developed land, forest to barren land, and barren land to developed land, as well as changes involving water bodies. Other principal land-cover transitions of interest were forest to developed land, forest to barren land, and barren land to developed land. Forest to developed land, and forest to barren land transitions indicate loss of vegetation cover and changes in surface thermal characteristics.

The transition matrix can be written as:

$$M = [A_{ij}] \quad (5)$$

where A_{ij} refers to the area transitioning from land-cover class i at the initial date to class j at the following date. In the case of a diagonal element (i = j), persistence is indicated, and in the case of an off diagonal element ($i \neq j$), conversion is indicated. In this study, to differentiate net changes in land-cover classes, gross changes were first estimated. Further, to maintain class-level integrity, certain restrictions have been placed to ensure that class-level gains or losses are not automatically interpreted as specific conversions. land-cover change analysis was conducted following Olofsson *et al.,*(2014) guidelines for transparent area estimation and accuracy assessment. In particular, the guidelines addressed the distinction between map-based area estimates and independently corroborated land-cover change assessments.

2.4 Land Surface Temperature Assessment

2.4.1 Spatial and Temporal Characterization of LST

The assessment of land surface temperature (LST) in Yakurr was done to study the thermal aspects of the area's changing landscape. The focus of this LST assessment was on observations for the years 2010, 2015 and 2025, to ensure compatibility with the land-cover assessment. LST is the radiometric temperature of the land surface and, to a first order, is determined by the energy exchange between the land surface and the atmosphere. Therefore, it is highly dependent on the land cover and land use conditions (Weng *et al.,*, 2004).

Temperature maps were produced for each of the assessment years, to illustrate the spatial patterns of LST, and to compute minimum and maximum values, mean and standard deviation. All temperature values were expressed in degree Celsius (°C) to facilitate comparison. Mean LST was used to represent the average thermal condition of the area, while the maximum and minimum values showed the highest and the lowest observed conditions, respectively. Standard deviation, on the other hand, was used to assess the level of heterogeneity in the landscape.

2.4.2. Variation in Surface Temperature over Time

Mean LST differences between successive years and for the entire study period were determined to assess temporal variability. Changes in mean LST were calculated using the following equation.

$$\Delta LST = LS\bar{T}_{t2} - LS\bar{T}_{t1} \quad (6)$$

Where ΔLST is the difference in mean surface temperature between two successive years and $LS\bar{T}_{t1}$ and $LS\bar{T}_{t2}$ are the mean LST for the two years, respectively. Positive ΔLST values indicate a warmer mean surface

temperature in the later of the two years being compared. The temperature differences were analyzed for the periods of 2010 to 2015, 2015 to 2025 and 2010 to 2025. Changes in the thermal characteristics of the study area were assessed by analyzing mean, minimum and maximum LST. Spatial variability in the thermal characteristics of the study area was assessed using standard deviation. Spatial analysis focused on identifying hotter and cooler zones in the landscape and understanding the possible influence of these zones on the distribution of forest and developed land, barren land and water. This analysis was based on the role of vegetation in the moderation of land surface temperature, for example, by shading or evapotranspiration, in contrast to built-up and other impervious surfaces (Weng *et al.,*, 2004).

The analysis was able to identify differences in temperatures observed by satellites between their acquisition dates. Long-term climatic warming cannot be differentiated from these temperature differences. Many factors, including seasonal changes in vegetation, soil moisture, and the condition of the atmosphere can all affect the differences in LSTs from one year to the next. The thermal assessment was thus interpreted as showing changes in surface temperature conditions in the study region rather than as proof of climatic changes resulting exclusively from the loss of forests in the study region.

2.5 Household survey and statistical analysis

2.5.1 Household survey variables

The socioeconomic component of the study used a cross-sectional survey, based in Yakurr LGA, to capture 507 respondents. The survey aimed to analyze the connections between changes in the forest cover, environmental warming, and associated ecological and social changes. The survey covered a wide range of themes pertaining to respondents' socioeconomic and demographic status, their perceptions on the causes and consequences of changes in the vegetation cover as well as their attitudes and perceptions on adaptation and the policies aimed at conservation and sustainable management of forests.

2.5.2. Descriptive statistical analysis

Through descriptive statistics, characterization of respondents, perception towards the environment, drivers of forest loss and its impacts, and adaptations were done. The distribution of response categories was presented in terms of frequencies and percentages. Percentages were represented in terms of equation (7). In cases where respondents were allowed to select multiple options, frequencies were treated as non-mutually exclusive and single-choice response frequencies were interpreted independently. This was particularly relevant when respondents indicated more than one driver of forest loss and adaptation as well as environmental impacts. The objective of descriptive analysis was to give a socioeconomic context to the community's experience regarding environmental changes and to assess the community's perceptions regarding environmental changes and compare them to the outcomes of geospatial analysis.

2.5.3. Multivariable regression analysis

Association between select socioeconomic and environmental perceptions was determined using multivariable linear regression and respondents' perceived intensity of environmental warming. The response scale for the perceived intensity of warming was 1 to 4, where 1 was the least and 4 was the greatest intensity. The remaining six independent variables were: perceived forest loss, farming, duration of residence, education, perceived effectiveness of forest management policies and perceived heat-related health impacts.

The regression model is expressed as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \varepsilon_i \quad (8)$$

where:

Y_i = level of environmental warming perceived by respondent i;
β_0 = intercept of the regression;
β_1 to β_6 = regression coefficients;
X_1 to X_6 = factors included in the regression;
ε_i = random error term.

Estimations made by the regression model were summarized using unstandardised coefficients, standard errors, standardised coefficients, t-statistics, p-values and 95% confidence intervals. The objective was to find out what factors caused variation in perceived warming level, taking into consideration all other factors in the model. Perceived warming level was measured using an ordered four-category response scale, and, for the purpose of this analysis, the linear form of the model is taken to be an exploratory approximation. Coefficients therefore indicate association to the ordered response category, not change in the measured environment temperature. An ordinal logistic regression model would provide a better approximation if the original respondent-level observations are available.

Additionally, the survey was cross-sectional. Therefore, causal inferences cannot be made from the regression analysis. Consequently, the regression analysis was taken to indicate a conditional relationship between reported environment changes and level of perceived warming.

2.6. Integration of geospatial and socioeconomic evidence

The last stage of analysis integrated the geospatial and household survey data to understand the dynamics of Yakurr LGA forest cover, surface thermal variability and the community's experience of environmental change. There were three main areas of comparison: (i) what changes occurred in the nature and extent of land cover and how did LST vary over time and

space; (ii) how did local communities perceive forest degradation and warming; what do they think are the environmental impacts; and what adaptive measures do they take; and (iii) do local people think environmental conditions have changed. Whenever there was a match in time between LST and land cover, and where change was observed in the built up or barren areas of the study area, the thermal characteristics of the study area were assessed. The two were then cross-examined to assess the match between remotely sensed and locally observed environmental change.

Specific focus was given to changes in forest cover, development-related transformation of the landscape, perceived changes in the climate, and the vulnerability of the households. The objective of the assessment was to determine whether the household observations, and the perceived changes over time, corroborated, complemented, or contradicted, the trends indicated by the remote sensing data. It is worth mentioning that the integration did not assume that the changes in aggregate LST were entirely due to the conversion of the forests. Other environmental processes may have contributed to the changes in land surface temperatures. Retrospective assessments of households may have limitations due to individual experiences and memories, as well as differences in household exposure to environmental changes. Therefore, the purpose of the integration was to triangulate various sources of evidence in a way that supported and strengthened existing contexts, while preserving their intrinsic differences. The integrated framework allowed understanding environmental and socioeconomic changes of the Yakurr landscape, with related implications for the conservation of forests, as well as for climate-responsive and land use-planning, ecosystem management and community adaptation.

3. RESULTS

3.1. Land-use/land-cover composition and net change

In the Yakurr study area delineated in Figure 1, Table 1 shows the distribution of the four mapped land-cover classes in 2010, 2015 and 2025. Forest occupied 37,288 ha, or 54.9% of the total 67,921 ha, in 2010; developed land accounted for 14,807 ha (21.8%), barren land for 11,376 ha (16.7%) and water bodies for 4,450 ha (6.6%). The forest category was therefore the largest mapped component at the beginning of the study period.

Between 2010 and 2015, forest area decreased to 21,856 ha, a net loss of 15,432 ha (41.4% of its 2010 extent). Over the same interval, developed land increased by 9,575 ha, barren land by 4,570 ha and water by 1,287 ha (Table 1). Between 2015 and 2025, mapped forest recovered by 4,653 ha (21.3% relative to 2015), while developed land contracted by 5,691 ha and barren land by 504 ha; the water category increased by another 1,542 ha.

The resulting 2025 forest extent of 26,509 ha remained 10,779 ha (28.9%) below the 2010 baseline. Conversely, barren land, developed land and water showed net increases over the full observation period of 4,066 ha (35.7%), 3,884 ha (26.2%) and 2,829 ha (63.6%), respectively (Table 1). The shifts demonstrate a decline followed by partial recovery in mapped forest area, rather than a monotonic trajectory of progressive annual forest loss. No explanation for the water increase is inferred from class totals alone.

The 2010, 2015 and 2025 classification maps (Figures 2–4) provide the spatial context for the class-area values in Table 1. They display visually heterogeneous distributions of vegetation, developed surfaces, exposed land and water rather than a uniform transition across the LGA. Figure 2 illustrates extensive mapped vegetation in the baseline year; Figure 3 depicts a larger distribution of non-vegetated classes, particularly in central and northern areas; and Figure 4 shows an altered pattern in 2025, with retained and re-established mapped vegetation amid developed and barren surfaces. Because image-specific classification accuracy and map cross-tabulation checks are unavailable, these patterns are descriptive rather than validated fine-scale conversion estimates.

The study-area locator (Figure 1) situates the environmental assessment within Cross River State and Yakurr's administrative wards, while the dated LULC maps (Figures 2–4) visualise the landscape context for the four-class area statistics in Table 1. These references are important for distinguishing the spatial extent of mapping from the distribution of respondents described later in Table 4.

Table 1. Mapped land-cover area in Yakurr LGA by observation year (ha).

Class Name	Yakuur 2010	Yakuur 2015	Yakuur 2025
Barren	11376	15946	15442
Developed	14807	24382	18691
Forest	37288	21856	26509
Water	4450	5737	7279
Total	67921	67921	67921

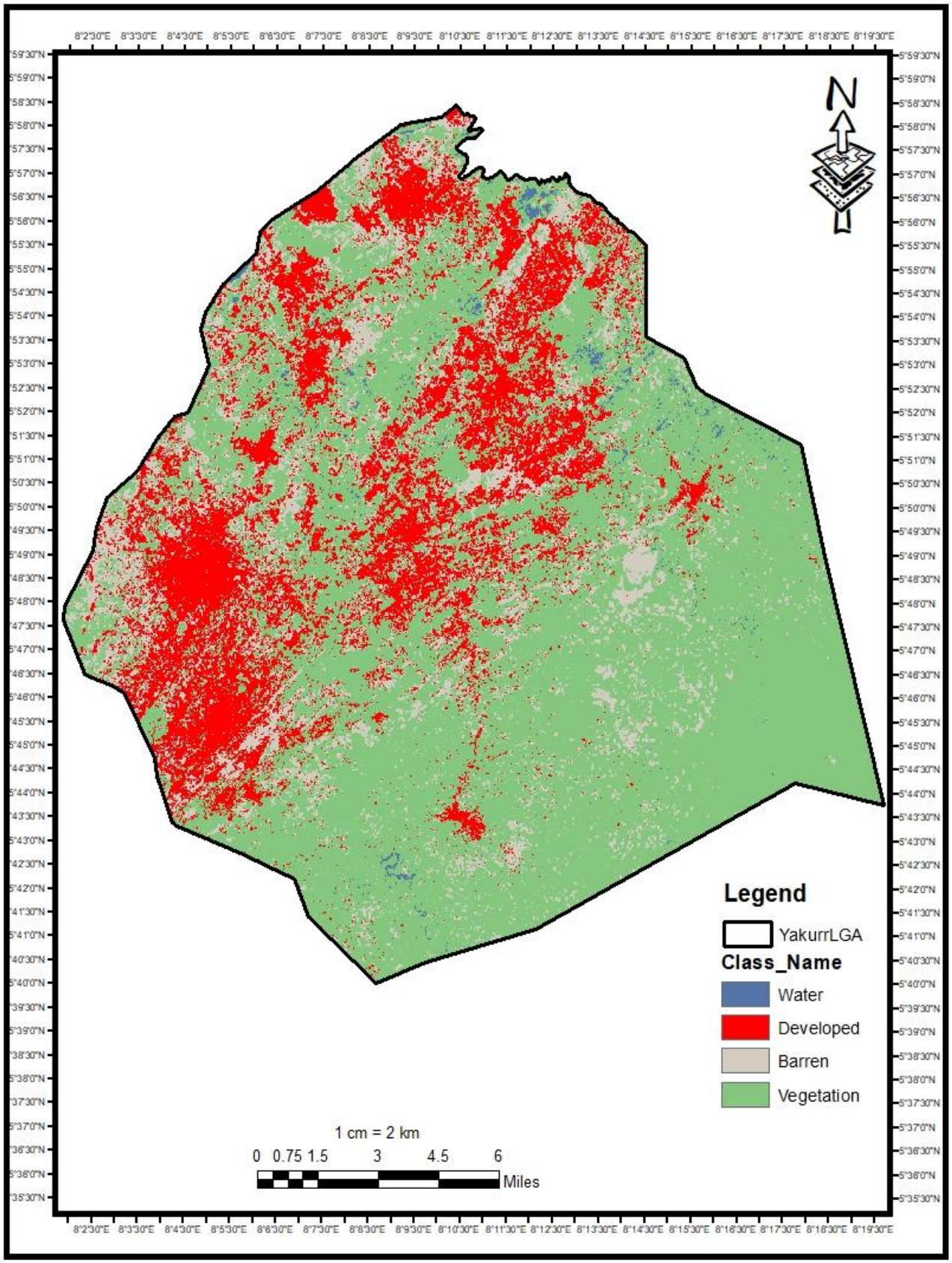


Figure 2. Land-use/land-cover map of Yakurr Local Government Area, 2010.

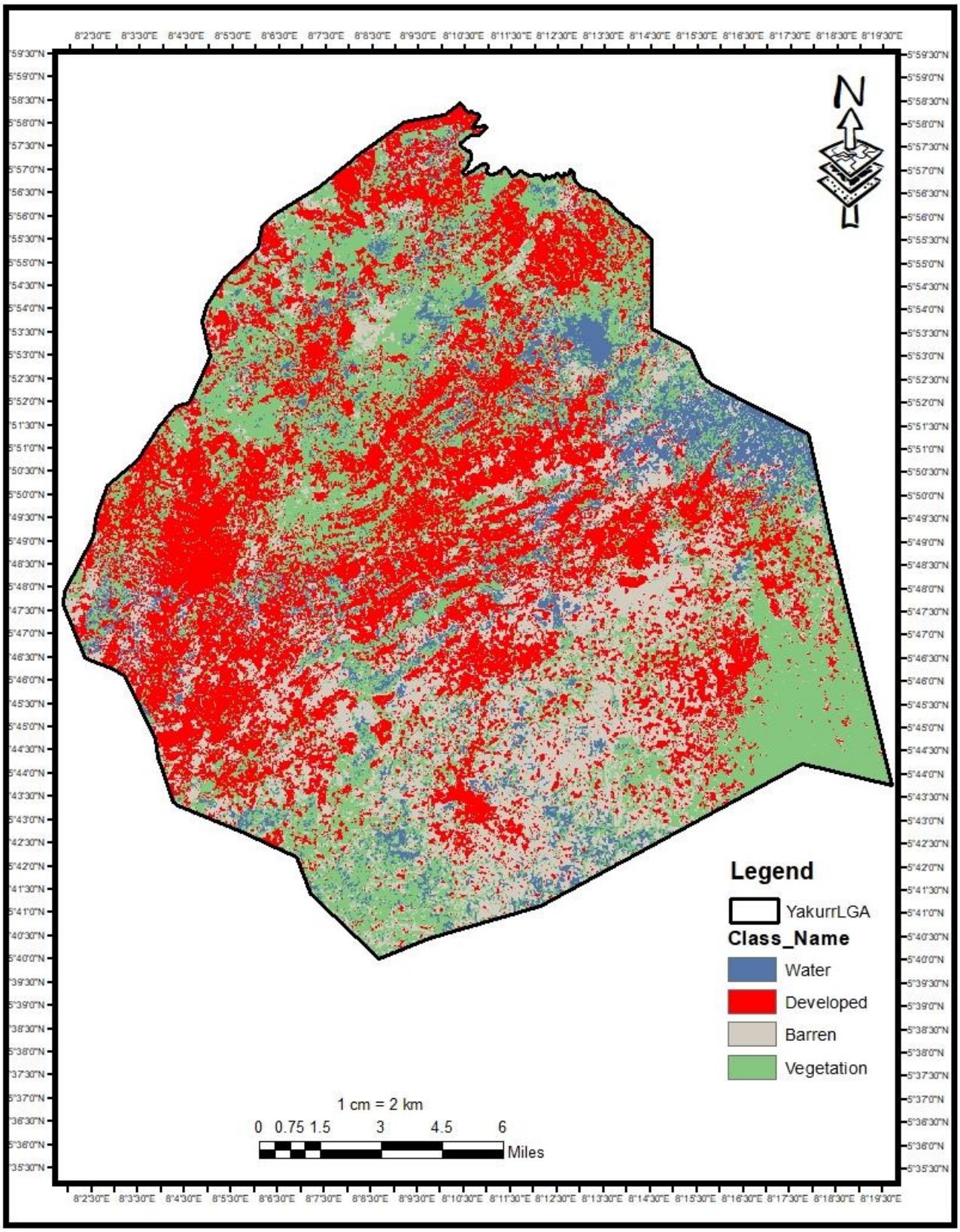


Figure 3. Land-use/land-cover map of Yakurr Local Government Area, 2015.

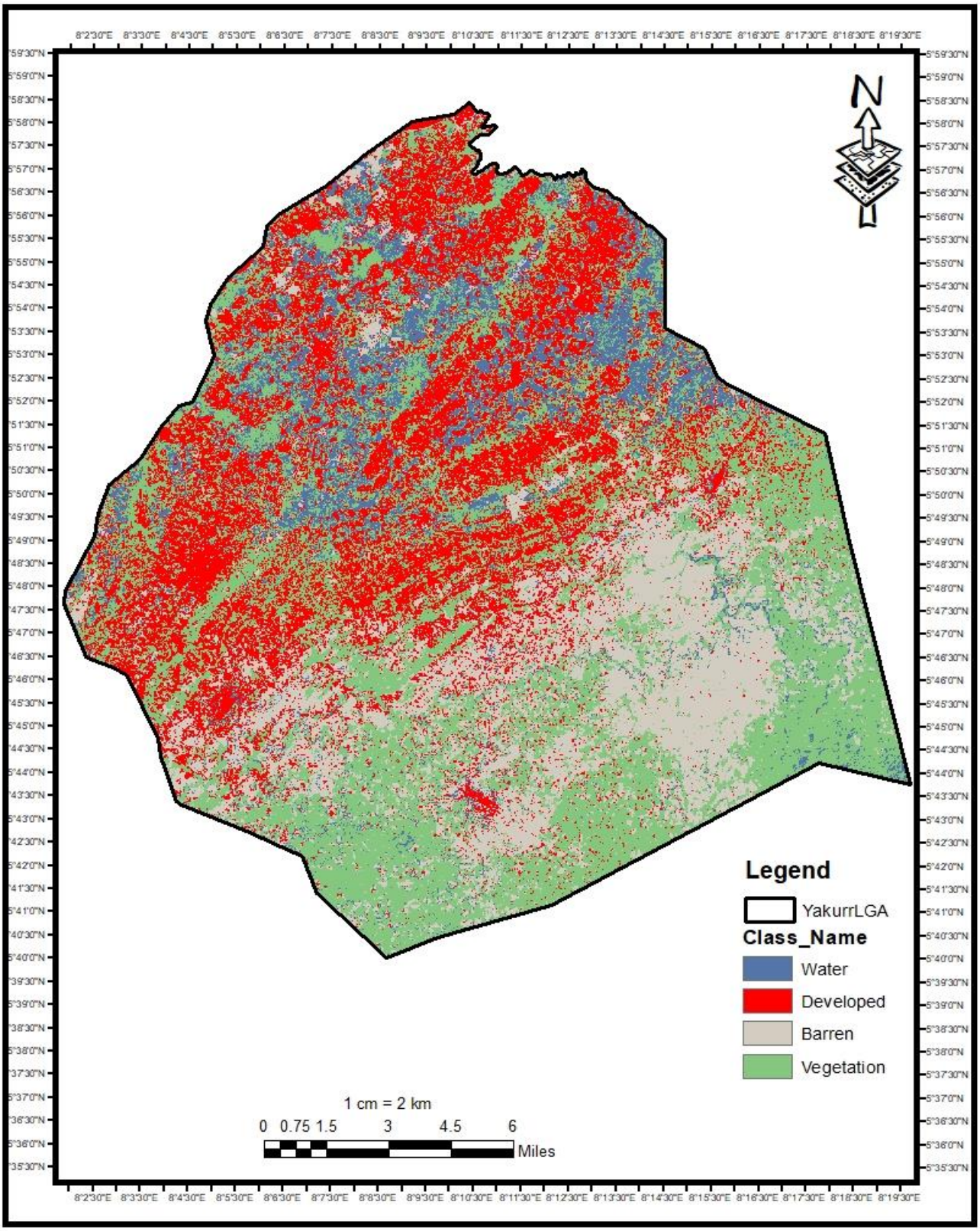


Figure 4. Land-use/land-cover map of Yakurr Local Government Area, 2025.

3.2. Reported land-cover transitions

The land-cover transition matrix (Table 2) represents persistence and conversion among barren, developed, forest and water classes for three labelled intervals. Its corresponding graphical summary (Figure 5) highlights the relative prominence of several reported transitions. The mapped change products (Figures 6 and 7) display spatial heterogeneity in the distribution of

change categories for the labelled periods 2010–2025 and 2015–2025. In combination, Table 2 and Figures 5–7 are intended to distinguish stable classes from areas classified differently through time. However, an internal accounting check reveals important discrepancies. For example, the row totals of the reported 2010–2015 transition matrix for barren, developed, forest and water are 11,395, 14,440, 41,643 and 443 ha, respectively, whereas Table 1 reports 2010 class areas of 11,376, 14,807, 37,288 and 4,450 ha. The year labels in Table 2 and Figure 5 also refer to 2020, for which no annual land-cover summary was supplied. Thus, although Figure 6 and Figure 7 illustrate the reported location and pattern of land-cover change, they cannot independently establish validated gross areas of specific transitions.

The figures are retained in their original form for completeness and traceability, but Table 2 and Figures 5–7 are treated as provisional outputs until origin–destination counts are recalculated directly from original, spatially aligned classification rasters. The class totals in Table 1 are used for the net-area comparisons reported in this article; no unverified transition quantities are promoted into substantive findings.

Table 2. Reported land-cover transition matrix across three intervals (ha).

Transition pathway	**2010-2015**	**2015-2020**	**2020-2025**
Units: hectares	Area Changed	Area Changed	area changed
Barren-Barren	3554	7401	3385
Barren-Developed	5378	3223	4291
Barren-Forest	2041	4801	2736
Barren-Water	422	539	983
Developed-Barren	1764	5715	1273
Developed-Developed	9547	10983	8009
Developed-Forest	2727	6388	4119
Developed-Water	402	1290	1039
Forest-Barren	10627	1800	10782
Forest-Developed	9399	3443	6336
Forest-Forest	16944	12562	19495
Forest-Water	4673	4042	5030
Water-Barren	18	545	21
Water-Developed	52	1038	50
Water-Forest	135	2747	149
Water-Water	238	1404	223
Total	67921	67921	67921

Note. Values and date labels are preserved from the source table. Marginal totals are inconsistent with Table 1 for some years; intervals labelled 2015–2020 and 2020–2025 require confirmation against the underlying classified rasters.

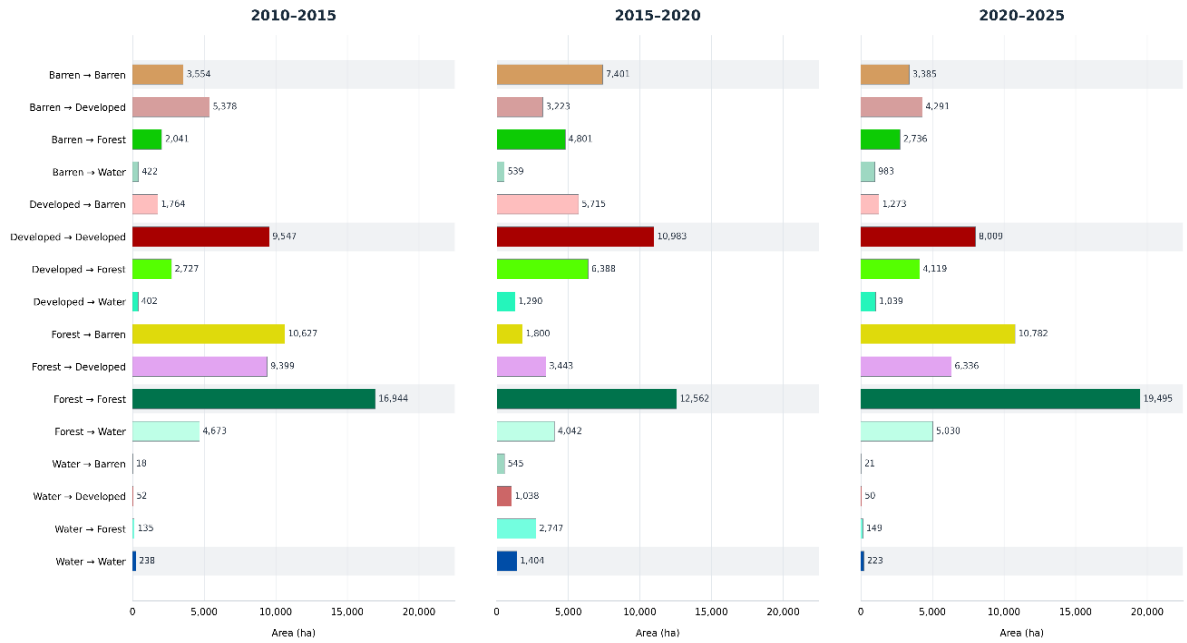


Figure 5. Reported land-cover persistence and conversion pathways for three intervals, 2010–2015, 2015–2020 and 2020–2025.

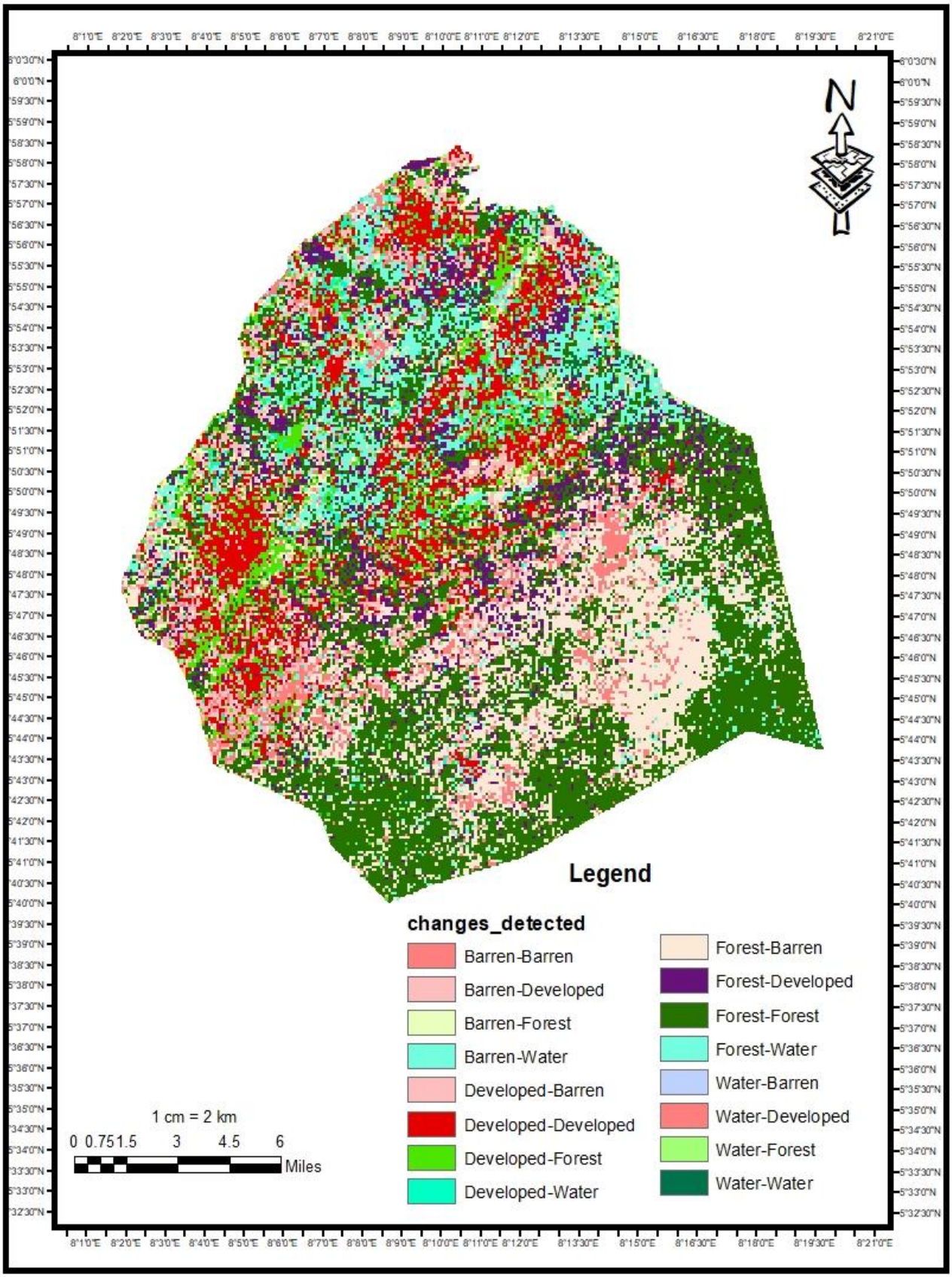


Figure 6. Supplied land-cover change-detection map labelled 2010–2025 for Yakurr LGA.

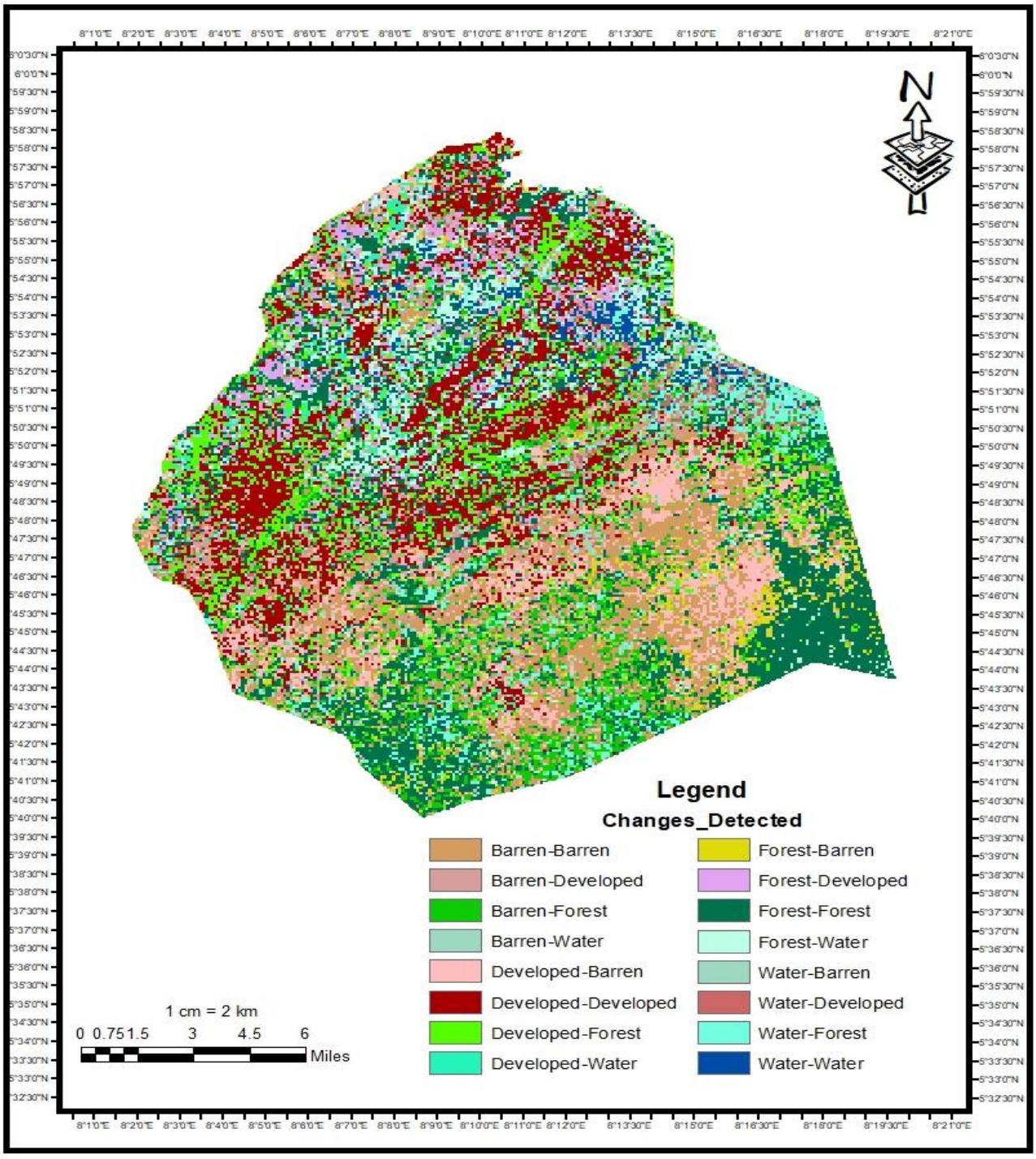


Figure 7. Supplied land-cover change-detection map labelled 2015–2025 for Yakurr LGA.

3.3. Temporal variation in land surface temperature

Table 3 presents the minimum, maximum, mean and standard deviation of the supplied LST data for the three observation years. Mean LST increased from 30.93 °C in 2010 to 33.66 °C in 2015, a difference of +2.73 °C. The reported maximum rose from 42.98 to 46.08 °C, and the spatial standard deviation from 2.17 to 2.51 °C. The temperature range widened from 16.67 °C to 25.04 °C during the same interval.

By 2025, mean LST had decreased to 30.31 °C, 3.35 °C below the 2015 mean and 0.62 °C below the 2010 mean. The 2025 maximum was 40.24 °C, while the standard deviation was 2.10 °C (Table 3). The three-date pattern is therefore non-monotonic, with the highest mean and maximum in 2015 rather than 2025. These differences are between observation-year composites or scenes and should not be represented as independently tested long-term climate trends.

The corresponding mapped temperature patterns are shown individually for 2010 (Figure 8), 2015 (Figure 9) and 2025 (Figure 10). All three figures display within-LGA thermal heterogeneity and clusters of relatively warmer and cooler pixels. Figure 9 also uses a higher upper temperature legend than Figures 8 and 10, consistent with the 2015 maximum listed in Table 3. Since the figure scales span different observed extrema, identical hues across years are not necessarily equal temperatures; direct visual comparison requires a harmonised legend.

The observed rise and subsequent decline in LST occur alongside the decline and partial recovery of forest extent in Table 1. This is a descriptive temporal coincidence only: the available data do not include matched pixel-level LST by land-cover class, rainfall or soil-moisture controls, or uncertainty estimates sufficient to isolate the magnitude of forest-associated surface warming.

Table 3. Reported descriptive statistics of land surface temperature, 2010–2025.

Year	Minimum (°C)	Maximum (°C)	Mean (°C)	SD (°C)
2010	26.3112	42.9843	30.92935471275521	2.165516796671708
2015	21.0475	46.0845	33.66097969968425	2.509359163958725
2025	24.6843	40.2362	30.31077101157794	2.097274871359334

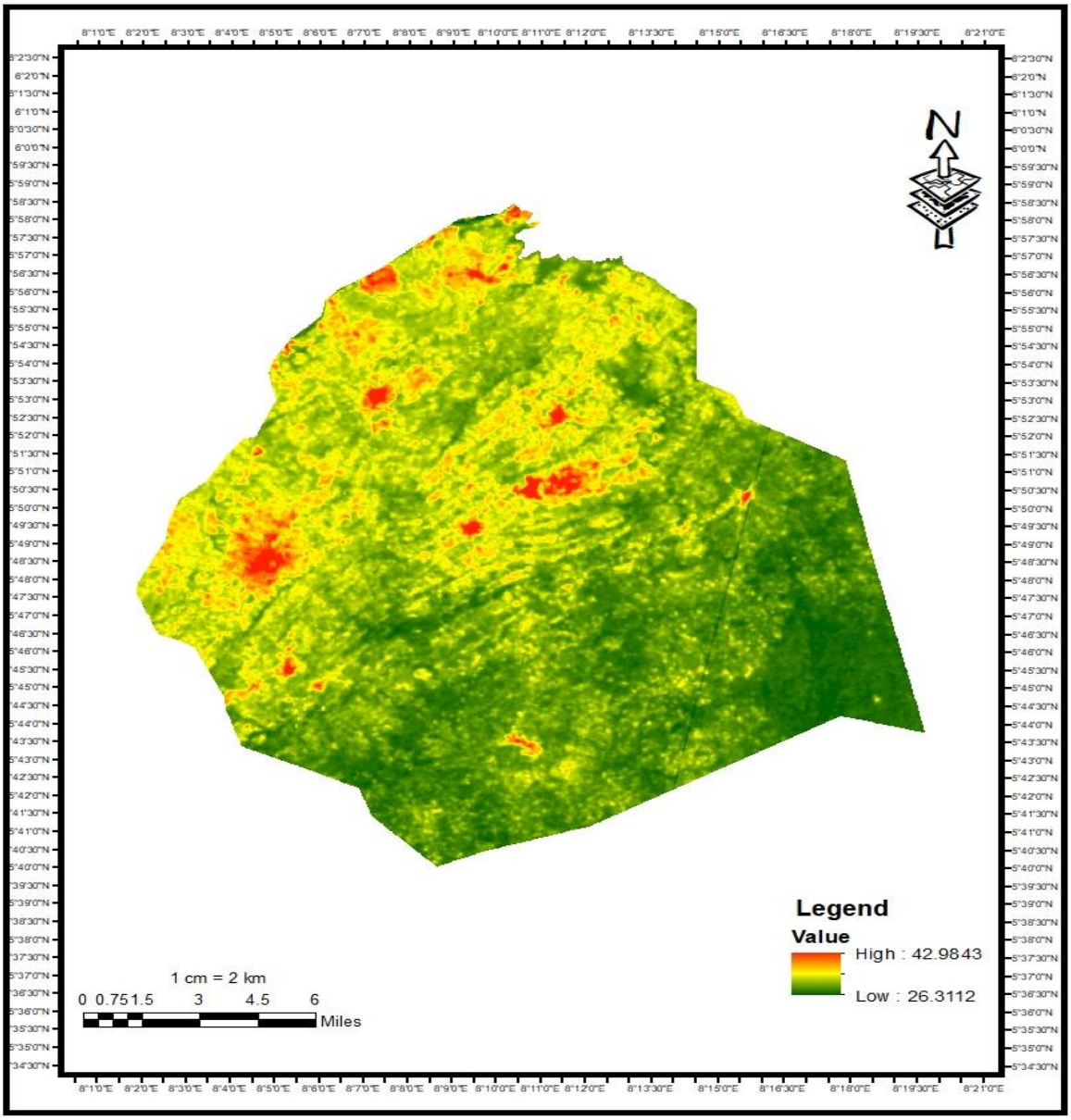


Figure 8. Satellite-derived land surface temperature distribution for Yakurr LGA, 2010.

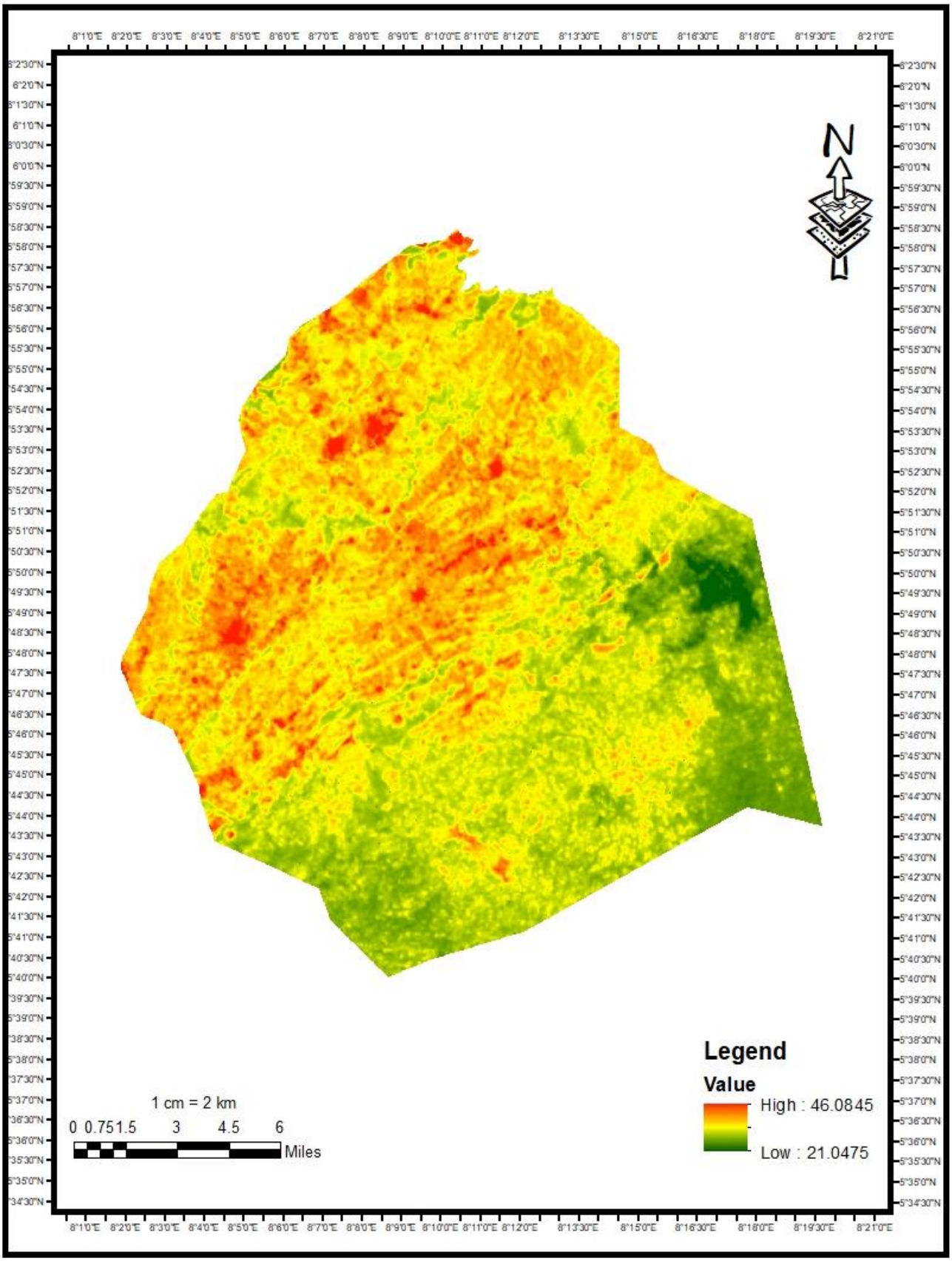


Figure 9. Satellite-derived land surface temperature distribution for Yakurr LGA, 2015.

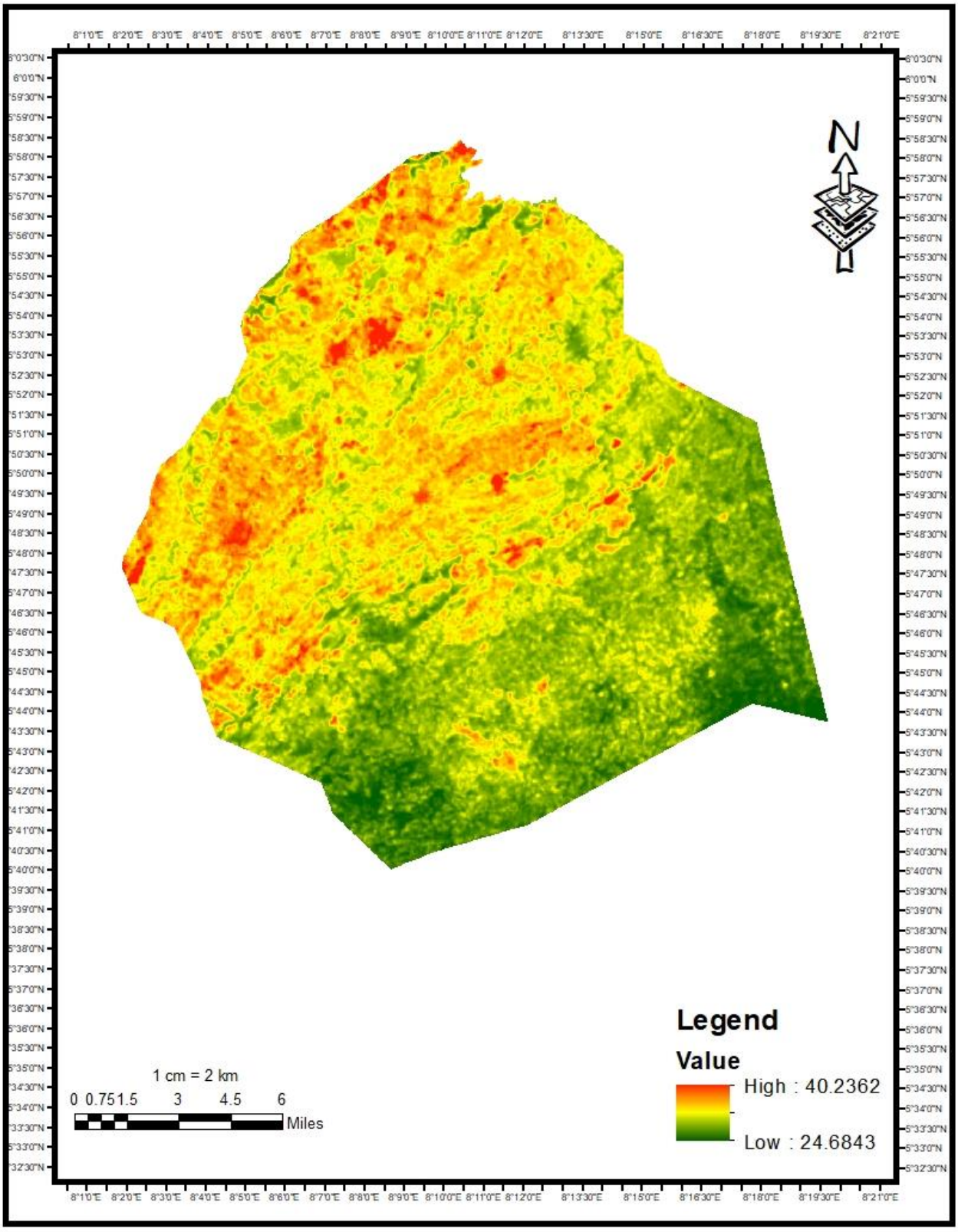


Figure 10. Satellite-derived land surface temperature distribution for Yakurr LGA, 2025.

3.4. Respondent characteristics and perceptions

Survey characteristics are summarized in Table 4. Of the 507 respondents, 278 (54.8%) were male and 229 (45.2%) were female. The age group 31-45 years was the largest at 39.1% and the education level group at 42.2% was at the secondary level. Farming at 267 (52.7%) was the largest occupation. Residing at the locality for a long time was observed in 31.4% of the

respondents who said they had lived there between 11-20 years and 49.9% said more than 20 years. These characteristics are important for interpreting retrospective experiences with the environment but do not eliminate recall bias. Respondents describing conditions of the forest as very or moderately dense made up 51.9% of the assessments around 2010 and 12.6% of the assessments for 2025. Describing conditions of the forest as sparse or not having any forest increased from 48.1% to 87.4% for 2025. Of the respondents, 61.7% and 27.8% described conditions in 2025 as "much hotter" and "slightly hotter" respectively, and 83.6% stated that clearing the forest contributed to warming (Table 5).

As described in Table 5, perceived change is reflected and not a repetitive measurement conducted on the same households in 2010. Also, the descriptions of conditions around 2010 are recorded retrospectively. These perceptions are strong in suggesting worsening conditions of the forest and climate, however, they do not independently verify the changes shown in the satellite data in Tables 1 and 3.

Table 4: Socio-demographic characteristics of respondents.

Characteristic	Category	n (%)
Gender	Male	278 (54.8)
	Female	229 (45.2)
Age (years)	18–30	112 (22.1)
	31–45	198 (39.1)
	46–60	143 (28.2)
	Above 60	54 (10.7)
Education	No formal education	38 (7.5)
	Primary	121 (23.9)
	Secondary	214 (42.2)
	Tertiary	134 (26.4)
Occupation	Farming	267 (52.7)
	Trading	79 (15.6)
	Civil servant	41 (8.1)
	Artisan	56 (11.0)
	Student	37 (7.3)
	Other	27 (5.3)
Length of residence	<5 years	31 (6.1)
	5–10 years	64 (12.6)
	11–20 years	159 (31.4)
	>20 years	253 (49.9)

Note. N = 507. Percentages are retained from the supplied survey tabulations and may not sum to 100% owing to rounding.

Table 5: Respondents' retrospective perceptions of forest condition and temperature-related change.

Indicator	Response	Around 2010 (%)	2025 (%)
Forest condition	Very dense	13.2	1.4
	Moderately dense	38.7	11.2
	Sparse	36.5	44.0
	No forest	11.6	43.4
Perceived temperature trend	Much hotter	56.0	61.7
	Slightly hotter	29.0	27.8
	No change	11.0	8.5
	Cooler	4.0	2.0
Warming attributed to forest clearance	Strongly agree	35.0	40.0
	Agree	42.0	43.6
	Neutral	15.0	10.3
	Disagree	6.0	4.7
	Strongly disagree	2.0	1.4

Note. The columns reproduce the original source labels. The value displayed as "11,0" in the source was normalised typographically to "11.0" without changing its magnitude. Retrospective perceptions are not direct measurements of past conditions.

3.5. Perceived drivers, environmental effects, and adaptation

As shown in Table 6, most of the respondents (85.0%) perceived the expansion of agriculture as a driver of forest cover loss. In second place was illegal logging or timber extraction (76.7%). Other drivers perceived by respondents were fuelwood collection (52.7%), expansion of settlement (23.3%), bush burning (15.6%), mining (7.3%) and others. Because respondents were allowed to suggest multiple drivers of forest loss, percentages in Table 6 should not be interpreted as independently measured proportions of total forest loss. As described in Table 7, the most mentioned impact of the observed changes was increased daytime heat (88.4%), followed by reduction of forest products (76.1%), nighttime cooling (71.6%) and greater number of heat-stress days (67.1%). Respondents also noted other impacts, such as the drying of streams and rivers (63.5%), a change of the normal planting season (52.3%), reduced rainfall (58.0%), and heat-related health issues (58.6%). Among the 267 respondents who listed farming as their primary occupation, 81.3% reported that high temperatures negatively impacted their farming activities. The health impacts and the hydroclimatic changes described in this study are based on self-reports; neither were confirmed by clinical diagnoses or by measurements of rainfall or streamflow.

Adaptations and conservation priorities are reported in Table 8. Preventing heat exposure by staying indoors (72.0%) and planting trees around homes (61.9%) were the most common adapted practices. Modifying farm practices (48.5%) was the next most frequent adaptation. No adaptation was reported by 23.1% of the respondents, while 11.4% relied on mechanical cooling. Most respondents (58.4%) reported forest policies as ineffective, and 22.4% were unable to indicate the status of forest policies. The highest priority was placed on the strengthening of anti-logging policies (81.7%) and adoption of agroforestry (69.8%), community-based forest management (63.1%) and alternative livelihoods (57.4%). 64.3% were willing to participate in afforestation and/or reforestation activities. The information in Tables 6-8 show the public's notion regarding the most critical land use activities, environmental stresses, and preferences toward management of forests. They, however, don't show the effects of the different activities on land surface temperature (LST), rainfall, and household's health condition.

Table 6. Respondent-reported drivers of forest-cover loss.

Reported driver	Respondents (n)	Respondents (%)
Agricultural expansion	431	85.0
Illegal logging/timber	389	76.7
Fuelwood collection	267	52.7
Settlement expansion	118	23.3
Bush burning	79	15.6
Mining	37	7.3

Note. N = 507; multiple responses permitted. The table describes perceived drivers, not quantified contributions to land-cover conversion.

Table 7. Self-reported environmental changes and selected livelihood or health impacts.

Reported change or impact	Reference group (n)	Respondents (%)
Increased daytime heat	507	88.4
Reduced nighttime cooling	507	71.6
Drying up of streams/rivers	507	63.5
Reduced rainfall	507	58.0
Changed planting seasons	507	52.3
More extreme heat days	507	67.1
Farming affected by high temperatures	267	81.3
Household reported heat-related health problems	507	58.6
Forest product availability decreased	507	76.1

Note. The "reference group" represents the reported eligible group, not a confirmed item-specific response denominator. The farming item refers to respondents whose occupation is farming (n = 267). Health impacts are self-reported.

Table 8. Reported household adaptation, policy perceptions, and conservation priorities.

Domain	Response or intervention	Respondents (%)
Household adaptation	Planting trees around homes	61.9
	Changing farming practices (e.g., mulching and irrigation)	48.5
	Staying indoors during hot periods	72.0
	Using fans/air conditioning	23.1

	No strategy adopted	11.4
Policy evaluation	Very effective	3.0
	Somewhat effective	16.2
	Not effective	58.4
	Not aware of any policy	22.4
Priority intervention	Strengthen anti-logging enforcement	81.7
	Promote agroforestry	69.8
	Community-based forest management	63.1
	Alternative livelihood programmes	57.4
Conservation participation	Willing to participate in tree planting	64.3

Note. N = 507. Multiple responses were permitted for relevant items, and the priority interventions listed are those supplied with the original results.

3.6. Factors associated with perceived warming intensity

The multivariable linear regression is reported in Table 9. Of the factors considered in this analysis, perceived loss of forests was found to be the most strongly positively related to perceived warming intensity (B = 0.412; β = 0.298; p < 0.001). Experience of health impact was also positively related to warming perception (B = 0.221; β = 0.161; p < 0.001). Being a farmer (B = 0.187, p = 0.004) and longer duration of residence (B = 0.093, p = 0.024) also showed positive coefficients. The effectiveness of climate policy was negatively related (B = -0.108, p = 0.019) to perceived warming, however, the directional significance of this is uncertain until the original code of the variable is examined. Education was not related to perceived warming (B = -0.031, p = 0.412) in this specification (Table 9).

The coefficients in the regression relate one set of survey perceived characteristics to another set of survey perceived characteristics; it is not a measure of the effect of Forest loss on LST. This distinction is emphasized in the interpretation of Table 9, in relation to Tables 1 and 3.

Table 9. Reported multivariable linear regression for perceived warming intensity.

Predictor	B	SE	95% CI for B	β	t	p
Perceived forest loss	0.412	0.058	0.298 to 0.526	0.298	7.10	<0.001
Farmer status	0.187	0.064	0.061 to 0.313	0.126	2.92	0.004
Length of residence	0.093	0.041	0.012 to 0.174	0.097	2.27	0.024
Education	−0.031	0.038	−0.106 to 0.044	−0.034	−0.82	0.412
Policy effectiveness evaluation	−0.108	0.046	−0.198 to −0.018	−0.102	−2.35	0.019
Health impact experience	0.221	0.059	0.105 to 0.337	0.161	3.75	<0.001

Note. Outcome coded 1–4 (higher scores indicate stronger perceived warming); N = 507. B = unstandardised coefficient; SE = standard error; β = standardised coefficient. Model diagnostics and fit statistics were not included in the supplied results.

Collectively, the Results contain the geographical reference in Figure 1, the dated land-cover maps in Figures 2–4, transition presentation in Figures 5–7, and thermal maps in Figures 8–10. The quantitative evidence appears in Tables 1–3 and the respondent-level summaries and regression in Tables 4–9. All figures have been reproduced from the supplied research files (apart from Figure 1 retained from the earlier study-area results file) rather than digitally reconstructed for the present revision.

3.7. Integrative synthesis of physical and social evidence

Read jointly, Table 1 and Table 3 show that the observation year with the smallest forest extent (2015) also had the highest mean LST; Figures 8–10 visualise the corresponding three thermal surfaces. The reported transition summaries (Table 2; Figures 5–7) are not sufficiently consistent for an independent gross-change explanation. Tables 4–8 document strong experiences of forest deterioration and heat exposure, and Table 9 shows that perceived forest loss is associated with perceived warming within the survey. Thus, the physically measured and socially reported evidence streams offer related but non-equivalent descriptions of landscape change rather than a validated causal chain.

4. DISCUSSION

4.1. Forest depletion, partial recovery and the meaning of mapped change

The most prominent change in land cover was the discontinuous forest trend shown in Table 1. It shows a steep forest loss between 2010 and 2015, with some recovery between 2015 and 2025, resulting in a 28.9% loss of forest cover from the baseline. This process is illustrated in Figure 1. The forest cover loss and gain trend is consistent with an idea that land-cover change in the tropics is the result of disturbance, management and

regrowth, as opposed to the conversion of land cover. However, the regrowth of trees does not guarantee a recovery of ecosystems and improvement in carbon stocks. Recent regional and global mapping has demonstrated that differently resolved products can identify forest cover and tree cover change (Liu et al, 2025).

The reported increases in barren and developed land, as shown in Table 1, are broadly consistent with increased land-use pressure. However, it is not possible to determine the underlying cause of this pressure without validated origin–destination transitions. In this regard, Tables 2, 3 and their accompanying graphs, Figures 5 and 6, together with Figures 7 and 8 provide informative transition labels, and help explain spatial context. However, because some transition marginal totals are inconsistent with class area totals, no product is currently able to determine reliable rates of forest-to-barren or forest-to-developed cover change. This is a critical deficiency that affects the reliability of the conclusion drawn with respect to forest cover change. Olofsson *et al.,* (2014) also highlight this and other related issues and conclude that defensible area estimations and verification of map accuracy are essential for area-based inventories.

Regional studies reinforce both the relevance and complexity of landscape change in Cross River State. Ewona *et al.,*(2025) recorded deforestation in the central part of the State. Remote sensing and community evidence were combined by Mashi *et al.,*(2026) to study forest dynamics and the impacts of changing livelihoods in the Okwangwo Division of Cross River National Park. While these studies don't pertain directly to Yakurr, they reinforce the need to connect land change with the local resource-use systems of a given area, and not presume that pressures documented in surveys have been captured by the satellite data.

The 2010, 2015 and 2025 land cover maps (Figs. 2, 3 and 4) illustrate the benefit of multiple time-slices of the same landscape rather than making inferences from start and end points. The baseline condition remains one of a relatively extensive forest cover (compared to the end conditions) despite partial regeneration occurring after 2015 (Table 1). Similar studies in humid tropical forests show that ecological quality and biodiversity can be adversely impacted by canopy disturbance, selective logging, edges and small, persistent clearings, and that surface greenery can return despite these disturbances being long-term (Vancutsem *et al.,* 2021; Bourgoin *et al.,* 2024; Xu *et al.,* 2026). Thus, the use of the term 'recovery' in the context of this study denotes return to mapped forest class rather than the recovery of mature forest or biodiversity.

As shown in Table 6, respondents named Agricultural expansion as the most important pressure. However, land-cover maps cannot differentiate between subsistence farming, commercial crop production, plantations and fallows. Such distinctions are important because drivers of deforestation are associated with various spatial configurations and thermal responses (West *et al.,* 2025; Singh & Persson, 2026; Smith *et al.,* 2026). It is, therefore, important to map post-deforestation land uses, particularly at the ward level, and in combination with plans for ward-level land use planning (Gupta *et al.,* 2025). The surrounding landscape configuration can also affect the likelihood of future forest loss or gain. Transitions in land use are inventoried in Figures 5-7, but because of conflicting class marginals, they cannot be numerically related to the losses documented in Table 1.

In the study area, the arrangement of forests may be as important as the size of forests in determining thermal mitigation. Outside of the 'formal' forest classes of Africa, Reiner *et al.,* (2023) found the importance of trees in the 'other vegetation' class. In other geographic areas, the relationship between canopy height and temperature may not always be positive (Rahimi *et al.,* 2025). Li *et al.,* (2026) indicated that forest fragmentation, in addition to other environmental factors, may also help to explain thermal variations. The classified forest category in the Yakurr LULC data does not separate shade trees and other forms of vegetation; therefore, the partial forest gain cannot be assumed to have cooled the study area.

4.2. Complex temporal responses to changing temperature and unresolved attribution

The thermal evidence is more complex than simply stating that forest loss is always associated with a temperature increase. As shown in Table 3, the mean LST increased by 2.73 °C from 2010 to 2015. Then, it decreased by 3.35 °C from 2015 to 2025. Figure 8, Figure 9, and Figure 10 show the spatial temperature fields associated with the three summaries. Thus, lower forest cover and higher mean LST occurred at the same time in 2015. However, in 2025, the mean LST was lower than in 2010, but the forest cover was still less than in 2010. Such evidence makes the case for a monotonic relationship between forest cover and temperature and warrants caution about attributing all LST differences to changes in forest cover.

The biophysical literature provides mechanisms for what has been observed and may occur in the future in the study region. For example, forest removal can change albedo and surface energy balance (Zhu *et al.,*2023). Forest loss can have distinct, asymmetric, and contrasting thermal impacts in the tropics (Zhang *et al.,*2024). Changes in processes of forest loss may impact the duration of thermal effects (Li *et al.,*2025). In Africa, the impact of additional vegetation cover on the local

climate depends on other land surface conditions (Ruijsch *et al.,*2024). Forest cover can modify regional and local climate (Rahimi *et al.,*2025).

An important methodological problem is that figures 8-10 show temperatures with year specific limits. Thus, colors depicted in the figures should not be interpreted as directly comparable without a common scale. Several factors, such as satellite overpass timing, seasonality, the state of the atmosphere, soil moisture and the masking of water or cloud contaminated pixels can impact the summaries of annual LST (Table 3). For this reason, this study established an observation level pattern. It would be necessary to have synchronized images and to hold other variables constant, to assess changes within forest related temperature patterns.

Any apparent connection between the forest contraction shown in Table 1 for 2015 and the LST peak shown in Table 3, should be investigated by overlaying co-registered images, temperature summaries for stable versus changed forest pixels and addressing other factors in the atmosphere. These analyses remain recommended extensions rather than unreported completed results.

The highest mean LST in 2015 (Table 3) occurred with the lowest forested-class extent (Table 1). Thermal surfaces in Figures 8-10 illustrate the spatial heterogeneity of the three examples. Decreased mean LST in 2025 with the 2010 forest cover baseline remaining unrecovered suggests other factors, including atmospheric conditions and moisture, the date of the observations, and land cover, must be accounted for. The variation of the forest cover-LST relationship across Africa suggests that the impact of forest restoration may not be the same everywhere (Ruijsch *et al.,*, 2024; Abafogi *et al.,*, 2026). Thermal effects and vegetation also display substantial spatial variability (Ebaju *et al.,*, 2026; Zhao *et al.,*, 2026).

4.3. Perceptions, heat exposure and implications for livelihoods

In the absence of strong evidence for an expansion of the forests, the perception of the community was that conditions were becoming warmer and more dry. In many ways, the social indicators confirmed the remotely sensed data. Half the respondents in the survey identified farming as their main occupation and most of the respondents (long standing) had a command of the landscape. The majority of respondents (survey and interview combined) reported increased temperature and an absence of normal night-time cooling, resulting in additional stress on farming.

These observations need not be interpreted as contradictory. Perceived heat includes personal exposure near fields and homes, shade loss, humidity, the frequency of unpleasant hot periods, and memory over multiple seasons; the satellite-derived LST values in Figures 8-10 show spatially averaged, radiometric surface conditions at the time of the overflights. Reports of poorer nighttime cooling (Table 7) especially, cannot be assessed by daytime LSTs alone. It is important to make this distinction because a surface temperature map does not directly measure occupational thermal burden or clinical outcomes. However, Masuda *et al.,*(2021) provide evidence that deforestation-related warming has been shown to negatively impact labor, and the Yakurr survey does not assess loss of productivity.

As noted earlier, communities recognize multiple combined factors (Table 6), and in Table 9, it is shown that perception of greater forest loss, experience of heat-related health issues and farmer status, and length of residence are associated with the perception of greater warming. These are associations among self-report data, and may, in part, be due to shared perceptions of exposure, i.e. differential exposures. These cannot be used to establish an independent relationship between satellite-based detection of forest change and land surface temperature.

Given the rural livelihood context described and illustrated in Figure 1, designed research that included objective measurements of air temperature and within-household exposure, coupled with crop-yield and social surveys would help distinguish perceived change from actual exposure and impact.

Additionally, the inconsistent mixed forest cover change trends and perceptions of heat should not be seen as contradictory. As shown in Table 5, there is expressed concern about the loss of forests and conditions becoming hotter. Heat, stream flow, and planting season, and health concerns are shown in Table 7, and the large farming population and long residence periods are shown in Table 4. The survey captures what the respondents indicate that they are experiencing, and while it captures trends in the ways that people think about and explain their environment, it does not necessarily capture actual clinical and environmental trends, i.e. air-temperature trends, stream discharge, rainfall, or other diseases. Masuda *et al.,*(2021) provide evidence that heat from deforestation affects productivity of agricultural workers. However, such cause-and-effect relationships should not be directly extrapolated to the situation in Yakurr. Future studies should measure actual environmental conditions, i.e. air temperature and relative humidity.

The positive correlations in Table 9 are with regard perceived warming and not the satellite LST in Figures 8-10. The perceived loss of forest cover may reflect a true experience of an environmental change; however, it may also reflect a shared response bias because the perceived and measured loss of forest cover are in the same survey. Other similar studies in Nigeria and other parts of Africa incorporate vegetation cover and temperature changes (Pepple & Hart, 2024; Tanko &

Bawale, 2025; Keno *et al.,*, 2025). These studies do not necessarily prove or disprove causal relationship between heat and vegetation loss.

4.4. Conservation priorities and planning responses

A focus on livelihoods, as opposed to law enforcement, is signaled by the results. The main forest drivers (Table 6) were agricultural expansion and timber harvest. Most respondents evaluated existing policies as inadequate (Table 8), although they expressed support for a variety of interventions. Of particular relevance to the current analysis are strategies to manage forests, agriculture and livelihoods. These strategies support other findings from recent Cross River research (Mashi *et al.,*, 2026) which emphasized the need for greater participation.

Some households engaged in vegetation-based adaptation (Table 8). Positive side effects of vegetation-based adaptation, such as the provision of shade and ecological services, can alleviate the negative effects of a changing climate. The cooling effect of vegetation may also be significant at the local level (Ruijsch *et al.,*2024). In the context of Cross River, it would be more relevant for studies in this area to look at the survival of trees, canopy structure, and how the trees are integrated into the livelihoods of the local community and how they help the community to adapt to changes, rather than the hectarage of trees planted.

Administrative, Change and Thermal maps (Figures 1, 6-10) provided by this study may be beneficial for future ward-based planning. However, care must be taken not to focus on high LST areas (pixels) due to map color alone, nor to assume the unverified transition matrix (Table 2) reflects a true change prioriody.

Plan-wise, Figure 1 offers a ward framework for future programming, and Figures 2-4 give a hint of where field classifications should be checked. Table 8 shows support for enforcement, agroforestry and community-led protection. Table 6 places livelihoods related forest demand at the core of the reported pressures. Latest Cross River data illustrates the importance of local social and ecological conditions (Ewona *et al.,*2025; Mashi *et al.,*2026). The policy challenge is not just to scale up planted hectares but also to set up credible monitoring of survival of trees, condition of the forest, local heat exposure and participation. Elsewhere in Africa, evidence suggests the need for context-sensitive restoration, rather than generalized claims related to cooling (Ruijsch *et al.,*2024).

4.5. Methodological strengths, uncertainties and research agenda

The main strength of the study lies in integrating three types of evidence: Land cover area statistics (Table 1), thermal summaries and maps (Tables 3; Figures 8-10), and household level experience with multivariable surveys (Tables 4-9). Figure 1 shows the geographic area of interest and Figures 5-7 show the expected temporal change. While the integration helps frame some policy relevant questions, it does not always resolve measurement and/or causality challenges.

First, source metadata and validation are incomplete (e.g. imagery dates, algorithms, classification confusion matrices and temperature retrieval are missing). Second, the inconsistency between Tables 2 and 1 prevents definitive transition-based claims. Third, no comparable meteorological series or pixel level forest LST analyses are reported. Fourth, respondent's retrospective comparisons in Table 5, and reported experiences in Table 7, are subject to recall bias. Fifth, Table 9 is based on a linear model of a four category ordinal response, without reporting model fit and/or diagnostic checks.

An improved research design would entail use of seasonally aligned Landsat imagery, independent and consistent reference samples and adjust uncertainty estimates based on area (Olofsson *et al.,*, 2014). Transitions in forest would then be analyzed in relation to LST anomalies, climatic covariates and other vegetation indices (Liu *et al.,*, 2025; Rahimi *et al.,*, 2025). Field measurements of ambient heat would also be used to support analysis and claims made. Parallel household surveys would be used to support assessments of adaptation and its impacts on livelihoods. In the absence of the recommended improved research design, these suggestions are proposed for future work.

The complete evidence base comprises the context maps (Fig. 1), year-specific LULC maps (Fig. 2-4), the change-pathway display and maps (5-7), thermal maps (8-10), summary and thermal class and survey and model output tables (1-3), and survey and model outputs (4-9). In combination, they inform on the change and its drivers. A strong link among these components is informative, but only verified sensor metadata, classification methods that incorporate uncertainty and combine with cross-tabulation, seasonally comparable LST data, and properly scoped geospatial statistical analyses would support strong claims of forest loss causing an observed change in surface temperature. The methodological research on scene consistency and the local and non-local climate signal underscores the need for this (Tyukavina *et al.,*, 2022; Zhao *et al.,*, 2026).

5.0 CONCLUSIONS

The study found a significant, but non-linear change in the mapped forest extent in Yakurr LGA. The area of forest cover decreased from 37,288 ha in 2010 to 21,856 ha in 2015 and partially recovered to 26,509 ha in 2025, leaving it 28.9% less than in 2010. Mean LST from satellites increased from 30.93 °C in 2010 to 33.66 °C in 2015 and further to 30.31 °C in 2025. These temporally-coincident and non-monotonic changes,

suggest that the observed thermal pattern is likely not due to the change in the forest area alone. The household results, on the other hand, provided a distinct social dimension, with the majority of respondents reporting the deterioration of the forest, increasing heat and livelihood stress. Further, they were in support of forest law enforcement, and community based forest management as well as agroforestry. Perceived forest loss was positively related to the intensity of perceived warming, but the survey regression does not imply a physical relationship between forest loss and LST.

The main policy implication is that policy and plans related to the conservation of forests and climate change adaptation should account for the condition of the forest, as well as the situation of the most vulnerable, rather than focus on changes in the area of forests alone. The most important recommendation is to carry out further research in order to improve the body of evidence on the status of forests and climate in southeastern Nigeria. In the absence of such evidence, this study provides a preliminary, but usefully descriptive analysis.

6.0 RECOMMENDATIONS

The study highlights the need for integration of conservation of forests, sustainable management of land and adaptation to climate change in Yakurr Local Government Area. It revealed a decline in forest cover, Non-monotonic variability in LST and several concerns about environmental degradation. Based on the findings and recommendations of this study are:

Improving the conservation of forests and sustainable management of land is crucial. The loss of 10,779 ha (28.9%) of forest cover between 2010 and 2025, underscores the need to improve the governance of forest protection and management. The Cross River State forestry and planning authorities should enhance the monitoring of the exploitation of forest resources, enforce existing environmental regulations and integrate the conservation of forests in local development plans. Areas under pressure from vegetation should be verified based on changes seen in the satellite images.

Conservation should focus on the protection of the remaining forest ecosystems, and addressing the socio-economic needs of the communities associated with forest resource dependence. Additionally, consideration should be given to enabling more sustainable use of the already cleared lands by promoting, for example, improved agricultural practices and other alternative sources of livelihoods that would reduce the rural population's dependence on forests.

Third, promote participatory forest restoration and management programs. About two-thirds of the respondents support agroforestry, community-based forest management and tree-planting activities. Therefore, community participation should be the basis for the restoration of forest ecosystems through the incorporation of appropriate indigenous tree species and restoration of degraded areas and fragile ecosystems. However, the success of the program should be determined by the improvements of the ecological systems and community participation as opposed to the area under restoration. Participation of government and non-government institutions, together with traditional and local community leaders will ensure program ownership, long-term success and sustainability.

Fourth, address heat risk in local area and spatial plans. There is a clear indication that climate change has affected the local communities, as evidenced by high levels of respondents reporting hotter daytime conditions (88.4%) and challenges related to heat affecting agricultural activities. Planners at all levels should be advocating for integrating climate resilient green and blue infrastructure as part of their recovery and adaptation plans. Sensitive adaptation measures should be based on community vulnerability and their level of exposure to climate related stress, as determined by local climatic conditions. Given that satellite LST does not measure human exposure to heat, adaptation measures should be guided by terrestrial measurements of air temperature and humidity.

Fifth, promote the regular, geospatial monitoring of environment, and integrate it into environmental decision-making.

Evaluate the dynamic of forest cover and changes in land surface temperatures through regularly acquired satellite imagery, Geographic Information Systems and field work. Pay special attention to improving classification accuracy, determine acquisition conditions of satellite images, and resolve inconsistencies in land cover and land use change estimates. A spatially-explicit monitoring framework would facilitate the identification of patterns of vegetation loss and assess the impact of restoration activities, and integration of environmental consideration in local planning.

Finally, undertake longitudinal and spatially-explicit research on forest-temperature relationships.

The trends shown in LST demonstrate that other factors apart from forest cover changes contributed to the temperature increase and decrease shown. Future studies should incorporate various categories of vegetation, combinations of land use (e.g. agriculture and pasture) and transitions, changes in land cover and land use, as well as meteorological variables (e.g. soil moisture and atmospheric conditions). Use of statistical tools to analyze spatial differences in temperature may help understand temperature variations in stable forest, and regenerating and converted vegetation. Combining repeated household surveys and other direct measurements of temperature may provide valuable

insight on heat stress and vulnerability of different households.

Implementation of these measures will move beyond the focus on area-based targets on forests to integrated management of the environment, which integrates biodiversity, ecosystems and environmental services, and draws the participation and stake of the community. It will also improve environmental governance and spatial planning, especially in relation to climate change, in Yakurr and similar areas of southeastern Nigeria.

DECLARATIONS

Ethics Approval and Consent to Participate

The study was conducted in accordance with the applicable ethical standards and research guidelines of Abia State University, Uturu, Nigeria, and relevant principles of the Declaration of Helsinki. All participants were adequately informed about the objectives, procedures and voluntary nature of the research before their participation, and informed consent was obtained from each respondent. Participants were assured of the confidentiality of their responses, anonymity in research reporting and their right to withdraw from the study without any adverse consequences. For participants with limited or no literacy, the consent information was explained in an accessible language, with the assistance of a witness to facilitate understanding and the informed-consent process. All data were collected and handled with due regard for participants' privacy, dignity and confidentiality.

Consent for Publication

Not applicable. The manuscript does not contain personally identifiable information, individual photographs or other materials that could reasonably lead to the identification of any research participant.

Availability of Data and Materials

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request, subject to applicable ethical considerations and confidentiality requirements governing participants' information.

Competing Interests

The authors declare that they have no known financial or non-financial competing interests that could have influenced the conduct, interpretation or reporting of this research.

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Authors' Contributions

Okeudo, G. N.: Conceptualisation, research design, supervision, project administration, critical review and editing of the manuscript.
Onuegbu, F. E.: Data analysis, interpretation of findings, preparation of the original manuscript draft, and manuscript review and revision.

Both authors contributed to the intellectual development of the research, reviewed and approved the final version of the manuscript, and accept responsibility for the integrity and accuracy of the work.

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REFERENCES

- Abafogi, M. A., Kebebew, Z., & Gemeda, D. O. (2026). Impacts of land use/land cover change on normalized difference vegetation index and land surface temperature in southwestern Ethiopia. Environmental Monitoring and Assessment, 198, Article 585. https://doi.org/10.1007/s10661-026-15389-9

- Abera, T. A., Heiskanen, J., Maeda, E. E., *et al.,*(2024). Deforestation amplifies climate change effects on warming and cloud level rise in African montane forests. Nature Communications, 15, Article 6992. https://doi.org/10.1038/s41467-024-51324-7
- Tanko, M. H., & Bawale, A. S. (2025). 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. Kaduna Journal of Geography. https://doi.org/10.47514/kjg.2025.07.01.003
- Bourgoin, C., Ceccherini, G., Girardello, M., *et al.,*(2024). Human degradation of tropical moist forests is greater than previously estimated. Nature, 631, 570–576. https://doi.org/10.1038/s41586-024-07629-0
- Ebaju, G. K., Zhang, F., Yeboah, E., *et al.,*(2026). Urban expansion and its effects on land surface temperature and vegetation in three East African cities. Urban Climate, 67, Article 102966. https://doi.org/10.1016/j.uclim.2026.102966
- Ewona, M. A., Ndifon, S. O., & Jande, J. A. (2025). An assessment of the rate of deforestation in Central Cross River State, Nigeria. Journal of Research in Forestry, Wildlife and Environment, 17(1), 271–302. https://www.ajol.info/index.php/jrfwe/article/view/295817
- Gupta, A., *et al.,*(2025). The effect of dominant land-cover transitions in shaping trajectories of global forest change. Environmental Management, 75, 2826–2840. https://doi.org/10.1007/s00267-025-02245-8
- Keno, H. A., Moisa, M. B., Kuris, B. K., & Chalchissa, F. B. (2025). Monitoring seasonal land surface temperature and land cover dynamics in West Wollega, Ethiopia, using remote sensing technology. Journal of African Earth Sciences, 232, Article 105812. https://doi.org/10.1016/j.jafrearsci.2025.105812
- Li, J., Li, Z.-L., Liu, X., *et al.,*(2025). Contrasting temporal dynamics of land surface temperature responses to different types of forest loss. The Innovation, 6(6), Article 100875. https://doi.org/10.1016/j.xinn.2025.100875
- Li, J., Wu, J., & Ma, J. (2026). Fragmentation outweighs forest cover in shaping land surface temperature across half of global forests. Proceedings of the National Academy of Sciences, 123(40), Article e2615021123. https://doi.org/10.1073/pnas.2615021123
- Liao, Z., Zhang, C., Wang, Y., *et al.,*(2026). Biodiversity regulates the asymmetric influence of forest cover gain and loss on land surface temperature. Communications Earth & Environment, 7, Article 19. https://doi.org/10.1038/s43247-025-03048-9
- Liu, S., Zhang, J., Wang, L., *et al.,*(2025). Mapping previously undetected trees reveals overlooked changes in pan-tropical tree cover. Nature Communications, 16, Article 5561. https://doi.org/10.1038/s41467-025-60662-z
- Mashi, S. A., Nnachi, N. I., Oluyori, R. N., Jenkwe, E. D., & Idris, K. (2026). Forest cover dynamics and socio-ecological drivers in the Okwangwo Division of Cross River National Park, Nigeria (1987–2022). Journal of Sustainable Forestry. https://doi.org/10.1080/10549811.2026.2666519
- Masuda, Y. J., Garg, T., Anggraeni, I., Ebi, K., Krenz, J., Game, E. T., Wolff, N. H., & Spector, J. T. (2021). Warming from tropical deforestation reduces worker productivity in rural communities. Nature Communications, 12, Article 1601. https://doi.org/10.1038/s41467-021-21779-z
- Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. Remote Sensing of Environment, 148, 42–57. https://doi.org/10.1016/j.rse.2014.02.015
- Pepple, G. T., & Hart, L. (2024). Pixel-based land transformation study in parts of Rivers, Abia and Akwa Ibom States, Nigeria. International Journal of Environment and Geoinformatics, 11(4). https://dergipark.org.tr/en/pub/ijegeo/article/1411106
- Rahimi, E., Dong, P., & Jung, C. (2025). Global variations in the relationship between tree canopy height and land surface temperature. Tropical Ecology, 66, 496–506. https://doi.org/10.1007/s42965-025-00392-x
- Reiner, F., Brandt, M., Tong, X., *et al.,*(2023). More than one quarter of Africa's tree cover is found outside areas previously classified as forest. Nature Communications, 14, Article 2258. https://doi.org/10.1038/s41467-023-37880-4
- Ruijsch, J., Teuling, A. J., Duveiller, G., & Hutjes, R. W. A. (2024). The local cooling potential of land restoration in Africa. Communications Earth & Environment, 5, Article 495. https://doi.org/10.1038/s43247-024-01650-x
- Singh, C., & Persson, U. M. (2026). Global patterns of commodity-driven deforestation and associated carbon emissions. Nature Food, 7, 138–151. https://doi.org/10.1038/s43016-026-01305-4
- Smith, C., Baker, J. C. A., Doggart, N. H., *et al.,* (2026). Commodity-driven deforestation doubles local warming from tropical forest loss. Environmental Research Communications, 8(2), Article 025005. https://doi.org/10.1088/2515-7620/ae3944
- Tyukavina, A., Potapov, P., Hansen, M. C., *et al.,*(2022). Global trends of forest loss due to fire from 2001 to 2019. Frontiers in Remote Sensing, 3, Article 825190. https://doi.org/10.3389/frsen.2022.825190

- U.S. Geological Survey. (n.d.). Landsat Collection 2 surface temperature. https://www.usgs.gov/landsat-missions/landsat-collection-2-surface-temperature
- Vancutsem, C., Achard, F., Pekel, J.-F., *et al.,*(2021). Long-term (1990–2019) monitoring of forest cover changes in the humid tropics. Science Advances, 7(10), Article eabe1603. https://doi.org/10.1126/sciadv.abe1603
- Wang, Z., Chu, B., Chen, Z., *et al.,*(2026). Monitoring annual forest carbon stock loss using very high-resolution time series remote sensing images and earth-foundational data. International Journal of Applied Earth Observation and Geoinformation, 149, Article 105320. https://doi.org/10.1016/j.jag.2026.105320
- West, C., Rabeschini, G., Singh, C., *et al.,*(2025). The global deforestation footprint of agriculture and forestry. Nature Reviews Earth & Environment, 6, 325–341. https://doi.org/10.1038/s43017-025-00660-3
- World Resources Institute. (2026). Tropical rainforest loss slowed in 2025, but fire is a growing threat to forests worldwide. Global Forest Review. https://gfr.wri.org/latest-analysis-deforestation-trends
- Xu, Y., Ciais, P., Santoro, M., *et al.,*(2026). Small persistent humid forest clearings drive tropical forest biomass losses. Nature, 649, 375–380. https://doi.org/10.1038/s41586-025-09870-7
- Zhang, Y., Wang, X., Lian, X., Li, S., Li, Y., Chen, C., & Piao, S. (2024). Asymmetric impacts of forest gain and loss on tropical land surface temperature. Nature Geoscience, 17, 426–432. https://doi.org/10.1038/s41561-024-01423-3
- Zhao, Z., *et al.,*(2026). Intercomparison of methods for disentangling local and nonlocal biophysical impacts of land cover changes. Earth's Future, 14(5), Article e2025EF007704. https://doi.org/10.1029/2025EF007704
- Zhu, L., Li, W., Ciais, P., *et al.,*(2023). Comparable biophysical and biogeochemical feedbacks on warming from tropical moist forest degradation. Nature Geoscience, 16, 244–249. https://doi.org/10.1038/s41561-023-01137-y