Land surface dynamics and meteorological forcings modulate land surface temperature characteristics

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A B S T R A C T

This study examines the effect of land cover, vegetation health, climatic forcings, elevation heat loads, and terrain characteristics (LVCET) on land surface temperature (LST) distribution over West Africa (WA). We employ fourteen machine-learning models, which preserve nonlinear relationships, to downscale LST and other predictands while preserving the geographical variability of WA. Our results showed that the random forest model performs best in downscaling predictands. This is important for the sub-region since it has limited access to mainframes to power multiplex machine-learning algorithms. In contrast to the northern regions, the southern regions consistently exhibit healthy vegetation. Also, areas with unhealthy vegetation coincide with hot LST clusters. The positive Normalized Difference Vegetation Index (NDVI) trends in the Sahel underscore rainfall recovery and subsequent Sahelian greening. The southwesterly winds cause the upwelling of cold waters, lowering LST in southern WA and highlighting the cooling influence of water bodies on LST. Identifying regions with elevated LST is paramount for prioritizing greening initiatives, and our study underscores the importance of considering LVCET factors in urban planning. Topographic slope-facing angles, heat loads, and diurnal anisotropic heat all contribute to variations in LST, emphasizing the need for a holistic approach when designing resilient and sustainable landscapes.

1. Introduction

Land surface temperature (LST) is a pivotal environmental variable, that is integral to various earth system processes and has significant implications for climate research, ecosystem functionality, and human well-being (Adeyeri et al., 2022b; Wang et al., 2023). Regardless of the time, climatic or environmental factors, LST dynamics spatially modulate the human population distribution (Jaber, 2020), a vital element of the global ecosystem. Due to their importance in the physical processes of water balance and surface energy, LST dynamics are widely applied in many environmental studies, including those on climate change, evapotranspiration, vegetation and land-use, the hydrological cycle, and urbanization (Adeyeri & Ishola, 2021; Lau et al., 2009; Mai-maitiyiming et al., 2014; Meng et al., 2009; Peng et al., 2016; Raoufi &

Abbreviations: LVCET, Land Cover Vegetation Health, Climatic Forcings, Elevation Heat Loads and Terrain Characteristics; LST, Land Surface Temperature; WA, West Africa; NDVI, Normalized Difference Vegetation Index; SOM, Self-Organized Maps; DAH, Diurnal Anisotropic Heat; LULC, Landuse Landcover; ERAS, Enhanced Global Dataset of the 5th Generation European Reanalysis Product; SST, Sea Surface Temperature; TAS, 2 m Air Temperature; SSR, Downward Shortwave Solar Radiation; MODIS, Moderate Resolution Imaging Spectroradiometer; DEM, Digital Elevation Model; ML, Machine Learning; HL, Heat Load; LANDSAT, Land Remote Sensing Satellite; IGBP, International Geosphere-Biosphere Programme; EM, Expectation-Maximization; BIC, Bayesian Information Criterion; TR, Terrain ruggedness; R², Coefficient of Determination; RMSE, Root Mean Squared Error; RRME, Relative Root Mean Squared Error; MBE, Mean Bias Error; PBIAS, Percentage Bias; U95, Uncertainty at the 95% confidence level.

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Beighley, 2017; Tan et al., 2020; Zou et al., 2020). Thus, comprehension of LST dynamics and their influencing factors is paramount for effective land management, urban planning, and strategies for mitigating climate change (Deng et al., 2018).

Globally, the land surface undergoes constant transformation due to natural factors like vegetation growth, land cover changes, and changes in soil moisture content. Moreover, human activities such as urbanization, deforestation, and agricultural practices significantly alter land surface attributes (Adeyeri et al., 2017; Akomolafe & Rosalzina, 2022; Chen et al., 2022a, 2022b; Herrmann et al., 2020). These dynamics can profoundly impact local and regional climate patterns, energy demands, thermal comfort, and heat exchange between land and atmosphere (Abydou et al., 2012; Adeyeri et al., 2023b; Bokaie et al., 2016).

Additionally, meteorological drivers, including solar radiation, wind speed, and precipitation, intricately shape temporal and spatial LST variations (Adeyeri & Ishola, 2021; Shorabeek et al., 2022; Simo et al., 2019). These drivers interact with land surface features, giving rise to complex feedback mechanisms influencing LST distribution and patterns. A comprehensive grasp of the interplay between land surface changes and meteorological influences is essential for accurately assessing the effects of climate change, land use alterations, and urban development on LST attributes.

Many studies across different world regions have extensively examined alterations in land surface characteristics, meteorological influences, and LST dynamics (Adeyeri et al., 2017, 2023b; Akomolafe & Rosalzina, 2022; Bokaie et al., 2016; Chen et al., 2022b; Deng et al., 2018; Portela et al., 2020; Rafique et al., 2016; Sanogo et al., 2015). For instance, studies in Asia have shown that warmer surface temperature is attributed to increasing atmospheric water vapor, sea surface temperature, declining cloud fraction, and snow area cover (Rani & Mal, 2022; Shawky et al., 2023). Additionally, increasing urbanization significantly contributes to the intensification of local and regional LST in many regions of Europe, Asia, North America and Africa (Adeyeri et al., 2017; Guha et al., 2018; Huszar et al., 2014; Zhou et al., 2022). These investigations have revealed the significant role of urbanization in shaping urban heat islands, the effects of land modifications on various meteorological variables, and the cooling impact of vegetation in mitigating extreme heat events. Most importantly, the effects of these modifications have been catalyzed due to global warming and climate change, leading to more extreme events.

As with other regions worldwide, rising atmospheric greenhouse gas concentrations and land surface dynamics influence temperature changes in West Africa (WA). The region has some of the most extreme climatic conditions, with an expanding population and significant biophysical and social transformations over the past several decades (Herrmann et al., 2020). However, these transformations come with substantial changes to land use land cover (LULC) and LST (Adeyeri et al., 2017, 2023b; Awuh et al., 2019; Bokaie et al., 2016; Herrmann et al., 2020; Ishola et al., 2016b). Additionally, many studies in this region have linked the modifications of LST to LULC and vegetation health (Adeyeri et al., 2017; Awuh et al., 2019; Herrmann et al., 2020; Ishola et al., 2016b). Nevertheless, elevation characteristics can also influence these properties, as has been established in other regions (Aguilar-Lome et al., 2019; Ahmed et al., 2020; Zhou et al., 2025). Many studies (e.g., Mustafa et al., 2021a; Traore et al., 2021) have emphasized a significant relationship between LST and vegetation health. However, other driving factors have not been considered.

LST is projected to increase, and several human activities caused by the rising human population are driving and exacerbating land surface changes (Chen et al., 2022a; Mustafa et al., 2021b). For example, natural surfaces with vegetation maintain a lower LST than bare land because they reflect more incoming solar radiation (Adeyeri et al., 2017). Still, this relationship is constantly being modified by human interventions. Multiple investigations have shown that warming accelerates with elevation (Aguilar-Lome et al., 2019; Ahmed et al., 2020; Oyler et al., 2015; Palazzi et al., 2019; Pepin et al., 2015), leading to more pronounced temperature shifts in high-mountain ecosystems compared to lower-altitude ones. Warming that is reliant on topography has the potential to hasten the transformation of land cover, ecosystems, hydrology, and biodiversity. However, studies attributing warming to topographic features are relatively non-existent in WA.

Additionally, previous WA studies (e.g., Adeyeri et al., 2017; Awuh et al., 2019; Ishola et al., 2016a, 2016b; Mustafa et al., 2021b, 2021a; Traore et al., 2021) have attributed LST changes to LULC changes or other biophysical variables using regressed and coarse datasets without accounting for regridding uncertainties.

Despite these strides, several knowledge gaps and research challenges persist. For example, the joint attribution of LST distribution to terrain characteristics, elevation heat loads, LULC, meteorological forcings and vegetation health has not been explored. Neither has there been an attempt to downscale coarse-resolution drivers while maintaining the nonlinear relationship between them. The intricate interplay among the aforementioned integrated multifactor analysis of LST distribution necessitates interdisciplinary approaches and advanced modelling techniques. Furthermore, the imperative for precise, high-resolution data and reliable remote sensing datasets remains pivotal for robust analyses of LST characteristics. Due to the anticipated influence and varied resolution of LST multivariate drivers, understanding the influence of these drivers on LST has considerable geographical heterogeneity, and acquiring high-precision multivariate driver data remains challenging.

Progress in remote sensing technologies and the availability of high-resolution satellite imagery over recent decades have been invaluable for studying land surface dynamics and their impact on LST (Adeyeri et al., 2017; Akomolafe & Rosalzina, 2022; Bokaie et al., 2016; Chen et al., 2022a). Nevertheless, multivariate driving datasets might have drastically varying spatial resolutions. Even if the grid resolution is consistent, the grids may still be misaligned. To standardize the datasets and convert data from one grid to another, a procedure known as regridding or remapping must be performed. While regridding can improve the quality of the grids, it should be done with caution because it may also alter the statistical characteristics (Rajulapati et al., 2021), especially when downscaling from a lower to a higher resolution. However, most multivariate drivers have a relatively coarse spatial resolution, restricting their use for impact studies. It is thus crucial to downscale these drivers for accurate impact applications.

Several downscaling procedures, including regression fitting (Piles et al., 2010), disaggregation based on physical and theoretical scale change (Merlin et al., 2008), and machine learning (Ke et al., 2016), have been suggested to downscale coarse-resolution data to obtain spatial information with a higher resolution. Due to their assumptions, other approaches, except machine learning, cannot easily sustain and represent the complex relationship between multivariate datasets (Zhang et al., 2017). Moreover, machine learning downscaling approaches have been developed to acquire higher-resolution datasets due to their impressive capacity to simulate the nonlinear connection between auxiliary factors and prediction variables (Liu et al., 2020; Mao et al., 2022; Pelletier et al., 2016). Even though previous studies (e.g., Pan et al., 2018; Yoo et al., 2022) have downscaled LST in different parts of the world, the focus has been on a particular downscaling method; i.e., different downscaling methods have not been evaluated. Also, the relationship of LST with LVGFT has not been investigated. Particularly in WA, this type of study is lacking.

Therefore, this study investigates the influence of land cover, vegetation health, meteorological forcings, and terrain characteristics on the LST distribution in WA.

The specific objectives are to (i) downscale LST and the coarsely integrated multifactor drivers that influence LST dynamics, (ii) evaluate the downscaled predictands for the annual, dry, and wet seasons across the climatic zones of WA, (iii) develop WA vegetation health and LST categorization units based on self-organized clusters, and (iv) establish trends and relationships between LST and its multifactor drivers.
Therefore, we aim to provide a more accurate assessment of land surface temperature dynamics in WA, ensuring a robust evaluation of the driving mechanisms behind LST variation while accounting for the complexity and heterogeneity of the land surface in the region.

2. Study area, data, and methods

2.1. Study area and its associated bioclimatic zones

West Africa (WA) (Fig. 1) is geographically divided into four distinct climatic zones (Abiodun et al., 2012; Adeyeri & Ishola, 2021). The dominant landscape in the north is the Sahara Desert, an expansive semi-arid terrain stretching over 4000 km from the Atlantic Ocean to the Lake Chad area. The Sahel region stretches southward from the Sahara, characterized by scrub vegetation and a rainfall regime ranging from less than 250 mm in its arid north to approximately 750 mm in its more humid south. Farther south is the Savannah zone, a blend of towering trees and expansive savannah grasslands, where the average annual rainfall typically falls within the range of 750 to 1250 mm (Akinsanola et al., 2018). Farther south is the Savannah zone, a blend of towering trees and expansive savannah grasslands, where the average annual rainfall typically falls within the range of 750 to 1250 mm (Akinsanola et al., 2018). The Guinea Coast tropical forests continue southward along the Atlantic coast, a lush expanse that extends inland for approximately 160 to 240 km. This region experiences a notably higher average annual rainfall, typically from 1250 to 1500 mm (Akinsanola et al., 2018). Most of the Sahel region and the transitional vegetation zones to its south are drained by either the Niger River system or the Lake Chad Basin. Notable geographical features along the Atlantic coastal regions include the Mauritanian-Senegalese Basin, drained by the Sénégal River, the Forta Djalgon and Guinea Highlands, the coastal plains of the Volta River and Niger River, and the upland territories of Nigeria’s Jos Plateau and the Cameroon Highlands. The annual rainfall cycle in this region is governed primarily by the Inter-Tropical Convergence Zone (ITCZ), where the convergence of moist southwest-erly monsoon and dry northeasterly harmattan winds plays a pivotal role. In the context of this study, the period from June to August corresponds to the wet season, while December to February represents the dry season. Comprehensive details regarding each climatic zone’s ecological characteristics, biodiversity, and distinctive features within WA are presented in the Supplementary File, Section 1.

2.2. Data

The monthly Enhanced Global Dataset of the 5th Generation European Reanalysis Product (ERA5) and multisource remote sensing data are used in this study. The ERA5 datasets (Hersbach et al., 2020) include sea surface temperature (SST), zonal and meridional winds, 2-m air temperature (TAS), and downward shortwave solar radiation (SSR), all at 0.25° (https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset). The ERA5 dataset spans 1950 to the present, incorporating observations from satellites, weather stations, ships, and other sources, and utilizes advanced data assimilation methods to generate consistent and reliable estimates of atmospheric conditions. The remote sensing data are based on the Moderate Resolution Imaging Spectroradiometer (MODIS) datasets (http://ladsweb.nascom.nasa.gov/), comprising the 500 m resolution MOD12Q1 for LULC, the monthly aggregated eight days 500 m resolution MOD09A1 NDVI (an indicator of vegetation health), and the monthly aggregated eight-day 1 km resolution MOD11C1 LST. The MOD12Q1 International Geosphere-Biosphere Programme (IGBP) Type 1 land-cover classification scheme defines seventeen land cover types, including eleven classes of natural vegetation, three classes of developed and mosaicked land, and three classes of non-vegetated land. The digital elevation model (DEM) data are derived using 500 m resolution hydrological data based on the SHuttle Elevation Derivatives at Multiple Scales (https://www.hydrosheds.org/products). The validation data are based on the upscaled 500 m resolution (originally 30 m) LANDSAT 7 and 8 datasets (https://www.usgs.gov/landsat-missions/landsat-data-access), and the study period spans from 2003 through 2022.

![Map of the study area showing different climate zones. The polygons are country boundaries, and the background colors indicate the elevation (m).](image-url)
2.3.1. **Machine learning downscaling models**

Due to the various resolutions of the driving datasets and the spatial heterogeneity of WA, one of our objectives is to downscale the multivariate drivers to a standard 500 m resolution using fourteen different machine-learning models (Table 1). The fourteen machine-learning models are chosen for a holistic evaluation of the best downscaling method since each model varies in operation and tuning. Therefore, we need to select the best downscaling model to better understand LST characteristics while maintaining the nonlinear relationship with other drivers. The details of these models are summarized in Table 1 and further elaborated in the Supplementary File, Section 2.1.

NDVI, DEM, terrain ruggedness, slope, aspect, and LST are employed to establish the relationships between the auxiliary variables. Other auxiliary variables include SST, zonal and meridional winds, TAS, and SSR. The training subsample for fitting the ML models constitutes 70 % of the data, with the remaining 30 % reserved for testing. The hyperparameters of the models are fine-tuned using the Grid Search approach, which involves defining a grid of hyperparameter values to systematically explore and evaluate the model’s performance for every possible combination. Additionally, we compare the downscaled-MODIS LST and independent LST data generated by LANDSAT to ascertain the robustness of the ML approach.

Fig. 2 presents a schematic representation of the two-step procedure employed in the downscaling process. Initially, all first predictors share a uniform resolution, while predictand ‘one’ has a different resolution. As a result, predictors ‘one’ are used to downscale predictand ‘one,’ aligning its spatial resolution with that of predictors ‘one.’ We evaluate the fourteen ML models during this stage, ultimately selecting the most suitable model for the downscaling process. After achieving resolution alignment while preserving spatial heterogeneity, we combine the aligned data from predictors and predictand ‘one’ and utilize them as predictors ‘two’ for downscaling predictands ‘two’. Once again, we assess the performance of fourteen ML models and select the best model for the downscaling process at this stage.

2.3.2. **Self-organizing maps, Gaussian mixture models, and classifications**

Self-organizing maps (SOMs) are a machine learning technique that employs unsupervised learning to cluster and visualize data. They are neural networks that organize and represent high-dimensional data in a lower-dimensional environment, often in a two-dimensional grid of nodes or neurons (Kohonen, 2013). SOMs learn to categorize data based on similarity while maintaining the topological links between the input data points. By repeatedly altering the neuron’s weight, SOMs arrange comparable data points near one another on the grid to form clusters or regions. This permits the visualization of complicated data distributions, the identification of patterns, and the discovery of data point linkages.

Furthermore, the SOM nodes are subjected to parameter estimation using expectation-maximization (EM) algorithms (Meng & van Dyk, 1997) of the Gaussian mixture models with different covariance structures (Scrucca et al., 2016). This is significant since it organizes the SOM nodes into distinct groups. The Bayesian information criterion (BIC) is utilized to select the optimal EM method for the best estimation. Hence, the EM algorithm with the least BIC is adopted for SOM node clustering. Based on the SOM and EM estimation, LST is classified into cool, normal, warm, slightly hot, moderately hot, very hot, and extremely hot. In contrast, NDVI is classified into extremely healthy, very healthy, slightly healthy, slightly unhealthy, moderately unhealthy, very unhealthy, and extremely unhealthy. Section 2.2 of the Supplementary File describes the detailed operation of the SOM and EM.

Furthermore, the 500 m resolution IGBP MCD12Q1 land cover is reclassified into nine distinct classes based on their similarity interval.

2.3.3. **Heat load**

Heat load (HL) is derived from the DEM and latitude to characterize a southwest-facing slope as having higher temperatures than a southeast-facing slope, although they receive the same amount of solar energy (McCune & Keon, 2002). This approach folds the DEM aspect such that the highest (lowest) values are in the southwest (northeast). HL values vary from 0 (coldest) to 1 (warmest).

2.3.4. **Terrain ruggedness**

Terrain ruggedness (TR) represents topographic heterogeneity numerically (Riley et al., 1999). Surfaces with a TR between 0 and 80 are classified as level terrain, between 81 and 116 as nearly level, between 117 and 161 as slightly rugged, between 162 and 239 as moderately rugged, between 240 and 497 as moderately rugged, between 498 and 958 as highly rugged, and greater than 959 as extremely rugged.

2.3.5. **Diurnal anisotropic heat**

Diurnal anisotropic heat (DAH) quantifies the combined characteristics of temperature and topographic solar radiation (Cristea et al., 2017). For a given quantity of received solar radiation, the afternoon
temperature is greater on steep southwest-facing slopes (highest DAH) than on steep east-facing slopes (lowest DAH). Sections 2.6–2.8 of the Supplementary File describe the detailed operation of HL, TR, and DAH.

2.4. Model evaluation

Various quantitative statistical metrics are frequently utilized to evaluate the efficacy of ML models in downscaling predictands. These metrics offer valuable insights into various facets of the model’s performance. Below are the metrics used in this study.

2.4.1. Coefficient of determination ($R^2$)

This quantifies how much the estimated values align with the reference data, where values approaching 1 signify models of higher effectiveness.

2.4.2. Root mean square error (RMSE)

This assesses the average magnitude of the discrepancies between the predicted values generated by a model and the reference data. A lower RMSE signifies superior prediction performance, corresponding to diminished errors.

2.4.3. Relative RMSE (RRMSE)

This is calculated as:

$$RRMSE = \frac{\sqrt{\sum_{i=1}^{n} (\hat{H}_{im} - H_{ic})^2}}{\sum_{i=1}^{n} H_{ic}} \times 100 = \frac{RMSE}{\sum_{i=1}^{n} H_{ic}} \times 100$$  (1)

where, $\hat{H}_{im}$ and $H_{ic}$ are the measured and observed data, respectively, at time step $i$ for a number of steps $n$.

According to Despotovic et al. (2015), model precision is deemed excellent when $RRMSE < 10\%$, good when $10\% < RRMSE < 20\%$, fair when $20\% < RRMSE < 30\%$, and poor if $RRMSE > 30\%$.

2.4.4. Mean bias error (MBE)

This is used to quantify the average discrepancy between the predicted values generated by a model and the corresponding reference data. Ideally, the MBE should approach zero, signifying unbiased predictions.

2.4.5. Percentage BIAS (PBIAS)

This quantifies the average probability of the model’s predictions deviating from the reference data. A PBIAS value of 0 signifies precise model simulation.

2.4.6. Uncertainty at the 95 % confidence level (U95)

This offers valuable insights into the deviation and uncertainty associated with the model. Higher U95 values indicate increased uncertainty associated with the predictions made by the model. U95 is given as (Despotovic et al., 2015):

$$U_{95} = 1.96[SD^2 + RMSE^2]^{1/2}$$  (2)

where, 1.96 is the coverage factor confidence level at 95 %, and SD is the standard deviation of the discrepancy between computed and observed data.

A detailed interpretation of the model evaluation is given in Supplementary File, Section 2.9.

2.4.7. Model rank

Since error metrics are sensitive to differences in precision, it is vital to have a combined metric to account for the different statistical properties of an ideal model rank. To create a universal ranking algorithm Adeyeri et al., 2020b; Dieng et al., 2022), Eqs. (3) and (4) are used to integrate the performance measures while giving each measure an equal weight, given as (Adeyeri et al., 2022b):

$$T_{ij} = \frac{T_{ij} - \min(T_{ij})}{\max(T_{ij}) - \min(T_{ij})}$$  (3)
where, $T_{ij}$ is the error in space and time of metric $j$ and particular model $i$. The total relative error $T_{tot}$ is calculated by adding all metrics $m$. The best-performing model should have a total relative score close to 0; therefore, $R^2$ is inverted for the min() and max() functions (Adeyeri et al., 2022b). The best-performing model is ranked 1st.

Collectively assessing these statistical metrics provides a comprehensive understanding of the performance of each machine learning model in downscaling predictands. This approach provides valuable insights for overall evaluation of the models. The ensemble method of statistical metrics further reveals the overall efficacy and reliability of the models.

### 2.5. Correlation, partial correlation, variable of importance, and trends

The degree of association quantifies the strength of the relationship between two variables, independently of any potential influence from a third variable. However, in cases where the influence of a third variable or multiple other variables must be considered, partial correlation becomes necessary (Adeyeri et al., 2022b). It measures the correlation between two variables while controlling for the effects of the third variable or other additional variables. This investigates the relationship between the two variables of interest while examining the potential confounding effects of other variables (Adeyeri et al., 2022b; Ndehe-dehe et al., 2023a). Due to the mutuality of LST, the partial correlation is used to examine the relationship between the multivariate drivers (e.g., climate forcings) and LST. These climate forcings include sea surface temperature, air temperature, shortwave radiation, and wind speed and direction.

The partial correlation is given as follows:

$$
\rho_{UVW} = \frac{\rho_{UV} - \rho_{UW}\rho_{VW}}{\sqrt{(1 - \rho_{UV}^2)(1 - \rho_{VW}^2)}}
$$

For a set of $n$ controlled climate forcing variables, $W$ is $W = \{W_1, W_2, ..., W_n\}$.

At the 95%, 99%, and 99.9% confidence levels, the Student’s $t$-test is utilized to investigate statistically significant partial correlations.

Given the interdependence of these variables, we further investigate the causal relationship between the predictands and the response of LST. Various methodologies exist to assess such relationships, with the permutation of importance being the most widely employed method, leveraging the capabilities of the random forest algorithm (Breiman, 2001; Debeer & Strobl, 2020). However, it is important to note that the traditional permutation of importance approach may not be suitable for highly correlated variables, as it cannot differentiate between the conditional and marginal influences of each variable (Adeyeri et al., 2022b, 2023b; Strobl et al., 2008).

Therefore, we used the conditional permutation importance method in this study to assess the partial importance of the multivariate drivers of LST. We refer the reader to Adeyeri et al. (2023a) and Strobl et al. (2008) for a more comprehensive understanding of this methodology. We utilized the Mann-Kendall statistics (Adeyeri et al., 2022b, 2023b; Kendall, 1948; Mann, 1945) to estimate the spatial trend and the trends’ magnitude is based on the Theil-Sen slope (Adeyeri et al., 2020b, 2022a; Sen, 1968; Theil, 1992). The details of this method are presented in the Supplementary File, Section 3.

### 2.6. Validation

Abuja City, Nigeria, is adopted as a test site to ascertain the robustness and dependability of the downscaled variables. LST from LANDSAT images is processed and compared with MODIS-downscaled LST regarding bias, trend, and uncertainties. This validation spans the annual, dry, and wet seasons. The procedure for calculating LST from LANDSAT has been documented in many studies (Adeyeri et al., 2017; Chen et al., 2022a; Ige et al., 2017; Ishola et al., 2016a; Pan et al., 2018).

### 3. Results

#### 3.1. Performance of machine learning models for downscaling predictands

The spatial distribution of the downscaled downward shortwave solar radiation (SSR) during the dry season reveals some disparities in the SSR representation by the ML models (Fig. 3). For instance, not all models observe the low SSR in northern Niger. Most importantly, the linear model, principal component analysis, and independent component regression models do not observe the reference spatial patterns. Notably, these models cannot replicate extreme SSR values. Nonetheless, there is a general similarity in the spatial patterns of the downscaled SSR from other models. As a result, the relationships between the ML models and the downscaled SSR are further explored with scatter plots (Fig. 4). Random forest is the best-performing model (ranked 1st), with an $R^2$ of 0.89, an RMSE of 7.23 %, and a U95 of 151.42 W/m$^2$. In contrast, the worst-performing model is the linear model (ranked 14th), with an $R^2$ of 0.04, an RMSE of 21.89 %, and a U95 of 458.36 W/m$^2$.

We further examine the performance of these models in the wet season (Supplementary File Figs. S1 and S2). As in the dry season, the models represent the spatial SSR signals differently. However, there is a slight improvement in the spatial patterns for the linear model, principal component analysis, and independent component regression models compared to the dry season. The random forest model retains the best rank, with an $R^2$ of 0.89, an RMSE of 10.23 %, and a U95 of 195.42 W/m$^2$, while the worst-performing model is the linear model, with an $R^2$ of 0.08, an RMSE of 31.24 %, and a U95 of 596.47 W/m$^2$. Based on model performance, the random forest downscaled predictands are used in the subsequent sections to establish LST dynamics.

#### 3.2. Validation of downscaled land surface temperature

To assess the effectiveness of the random forest downscaled products, as discussed in the previous section, we conduct tests at a specific location, Abuja, the capital city of Nigeria (Fig. 5a). We compare LST data from LANDSAT and the downscaled MODIS data across different timescales, including the annual, dry, and seasonal periods. As illustrated in Fig. 5b–d, the downscaled MODIS LST closely resembles most LANDSAT LST patterns during the annual, dry, and wet seasons. However, some uncertainty is observed, particularly in the wet season, where the uncertainties appear to be more widespread. This observation aligns with previous performance assessments of random forest downsampling in the previous section. In general, the bias ranges between $-1.48$ °C and 0.63 °C. This low uncertainty range underscores the robustness of the random forest algorithm in capturing essential LST patterns.

#### 3.3. Trends and evolution of LST and NDVI

To further substantiate the precision of the downscaled LST data, a comparative analysis is conducted by examining the decadal trends between the LANDSAT and downscaled-MODIS LST datasets (see Appendix Fig. A1). In the annual season (Fig. A1a and d), the LST trends exhibit a 2 to 2 °C/decade range. Notably, regions characterized by built-up areas within the central districts display more prominent positive trends. During the wet season, positive trends are more prevalent in the northeast, while negative trends dominate the west. In the dry season, positive trends persist in the central districts, and a noticeable shift from negative to positive LST trends is observed in various areas of the east. Remarkably, these discernible patterns are consistent across the LANDSAT and downscaled-MODIS LST datasets. This observation
emphasizes that the random forest algorithm successfully downscales the variable and effectively preserves the underlying trend. Across all seasons, the LST trend observed at the Abuja test site generally ranges from \(-2.8\) to \(2\) °C/decade.

After establishing the robustness of the random forest downscaling algorithm, as detailed in the preceding sections, we ascertain the NDVI (Fig. 6a–c) and downscaled LST (Fig. 6d–f) trends across WA. Notable patterns emerge in the NDVI trends, revealing significant negative trends during the annual and wet seasons, particularly within the Savannah zone encompassing Nigeria, Benin, and Togo. In contrast, the Savannah regions of Cote d’Ivoire exhibit significant positive NDVI trends during the annual and dry seasons, diverging from the wet season’s trend. The Guinea Coast displays varied NDVI trend characteristics. For instance, coastal Nigeria exhibits negative trends, whereas coastal Liberia displays positive trends across all seasons. The general NDVI trend magnitude in WA ranges from \(-0.2\) to \(0.2\) /decade.

Regarding LST trends, the Sahara and Sahelian zones display mixed trends (Fig. 6d–f). While Niger and Mali share similar ecological characteristics, Niger records predominantly negative LST trends during the dry season, in contrast to Mali’s primarily positive trends. Conversely, the Guinea Coast exhibits consistent positive LST trends throughout all seasons. The overall intensity of LST trends across WA ranges from \(-4.4\) to \(2.5\) °C/decade. Furthermore, assessing the temporal evolution of LST and NDVI across different ecological zones in WA reveals a generally positive trend in NDVI and LST within the Guinea Coast region throughout all seasons (Fig. A2a). Notably, the year 2014 (2007) witnesses the highest (lowest) NDVI values, while the year 2020 (2004) marks the highest (lowest) LST values during the annual season.

Similarly, in the Savannah region (Fig. A2b), the year 2003 (2015) displays the highest (lowest) NDVI values, while 2021 (2012) registers the highest (lowest) LST values. In the Sahelian region (Fig. A2c), the year 2022 (2004) observes the highest (lowest) NDVI values, with 2021 (2012) recording the highest (lowest) LST values.

3.4. Vegetation and LST classification

After analysis of the LST and NDVI trends, it becomes vital to categorize their representations into identifiable features that share common properties. Using competitive neuronal learning, we utilize self-organized maps to identify common features across varied input combinations. Through initialization, competition, collaboration, adaptation mechanisms of self-organization, and parameter estimation using EM algorithms, we successfully classify NDVI and LST into seven distinct components (Fig. 7). This classification enhances the understanding of these variables and their underlying patterns. The annual distribution of vegetation health reveals consistent healthy vegetation in most southern regions (Fig. 7a and d). However, the vegetation is unhealthy in the north. The distribution of LST (Fig. 7b and f) reveals that areas with unhealthy vegetation are synonymous with the hot LST classification. Like the LST distribution, the SSR records maximum values in the Sahara, corresponding to very hot LST (Fig. 7b and c). Due to the vegetation cover described in Fig. 7a, less SSR reaches the surface (Fig. 7c) in areas with healthy vegetation, resulting in lower LST (Fig. 7b and f). However, the direct implication for air temperature (TAS, Fig. 7g) is that more radiation is reflected as upward longwave radiation, heating the overlying air and forming low-level clouds.

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Fig. 3. Spatial distribution of machine learning models in downscaling SSR to 500 m during the dry season. “Raw” indicates the coarse data, and “NN” means neural network.
reflected longwave radiation, lower TAS accompanies most areas with lower LST. In addition, elevated areas have substantially lower TAS (Figs. 1 and 7g). A triangular plot (Fig. A3) demonstrates the robust relationship between LST and vegetation cover. Higher LST values match lower values of vegetation cover, which translate to barren land. In comparison, lower LST values match higher values of vegetation cover in the forest, wetlands, and savannah land cover classes.

3.5. Relationship between terrain characteristics, vegetation health, land cover classification, and other climate drivers

Further, we examine the relationship between terrain characteristics, heat load, vegetation health, and LST. Fig. 8a reveals that most areas in WA are on level terrain. However, WA topography ranges from level to extremely rugged terrain depending on the area’s elevation. Rugged terrain is associated with a high heat load (Fig. 8c). The diurnal anisotropic heat (DAH) is also higher on steep southwest-facing slopes in
rugged terrain than on steep east-facing slopes for a comparable quantity of received solar energy (Fig. 8d). The analysis of vegetation health and LST is shown using a linear relationship (Fig. 9). The results show that an increase in LST lowers vegetation health for most LULC classes. At the 95 % confidence level, a strong negative correlation ranging from 0.75 (forest) to 0.98 (shrubland) is observed between LST and vegetation health in seven of the LULC classes. However, the magnitude depends on the LULC category and season. For waterbodies, LST values are lower than 30 °C while vegetation health ranges from 0 to 0.9, establishing no significant relationship between both variables at a 95 % confidence level. However, this underlines the cooling effect of water bodies on surface temperature.

We further examine the relationship between LST and LVCET over WA and different climatic zones (Figs. S3–S5). LST and NDVI show a consistent linear relationship across all regional zones, with significant variability between Guinea and Savannah. The correlation coefficient in the Guinea Coast (−0.75) is lower compared to the Savannah (−0.88) and the whole of WA (−0.92). The relationship between LST and terrain-dependent variables also shows variability at regional levels, with a negative LST-elevation correlation in the Guinea zone and Guinea Coast and a positive correlation over Savannah and the whole of WA.

Bivariate analysis (Fig. 10) shows the inter-seasonal relationship.
among the surface variables in WA. Relatively low LST and sparse vegetation characterized much of the Sahel in the dry months compared to warmer surface temperatures in the wet months (Fig. 10a and b). In contrast, greener vegetation cover in the dry months dominates the Guinea and Savannah zones. However, a cooler surface temperature is observed in the latter compared to the former. Over all regions, a higher surface temperature is observed in the wet season.

Additionally, surface roughness influences LST. Lower LST values in wet months over the Guinea zone are associated with high terrain ruggedness. In contrast, warmer surface temperatures in the wet months
in the Sahel are associated with low terrain ruggedness (Fig. 10f).

We further examined the inter-seasonal variability of LST and its relationship with other climate drivers over WA in dry and wet months (Fig. 11). During dry months, we observe heightened warming in the Savannah and Sahel regions (Fig. 11a). Conversely, much of the Sahara exhibits a distinct cooling pattern in surface temperatures, which can be attributed to the transport of dust aerosols. Notably, dust aerosols, originating from the Saharan Desert and propelled by northeasterly

Fig. 10. Bivariate analysis between different surface variables: (a) land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) during the dry season, (b) LST and NDVI during the wet season, (c) LST and heat load (HL) during the dry season, (d) LST and HL during the wet season, (e) LST and terrain ruggedness (TR) during the dry season, (f) LST and TR during the wet season.

Fig. 11. Inter-seasonal variability of (i) sea surface temperature (over the ocean with black contours), LST over land, and wind fields in white vectors, and (ii) downward solar radiation (SSR) during the (a) dry and (b) wet seasons.
winds, play a dominant role in the Saharan region. This leads to cooler LST by attenuating a significant portion of the incoming solar radiation and reducing the amount of SSR that reaches the Earth’s surface. In addition, we observe lower LST in the Guinea region during this period. However, in Guinea, the mechanism differs due to the prevalence of southwesterly winds over northeasterly winds. In the wet season (Fig. 11b), we note that SSR is minimal in the Sahel and increases in intensity northward or southward. The highest LST is observed in the northern Saharan region, where SSR reaches its maximum.

Fig. 12 illustrates correlation and partial correlation plots for land and atmospheric variables, including SST, LST, SSR, wind direction, and wind speed, across WA and its distinct climatic zones. For instance, we find that LST exhibits a positive correlation with SSR (50 %) and wind direction (52 %) while having a negative correlation with wind speed (–62 %) across the entire West African region (Fig. 12d, upper diagonal), all at the 99.9 % confidence level. However, when considering partial correlation (lower diagonal) within the same region, we observe a significant positive correlation only between LST and SSR (88 %) and SST (82 %). Within specific climatic zones, LST displays a notable positive partial correlation with SSR (95 %) in both Guinea and Savannah, but this relationship is nonsignificant in the Sahel (39 %). This disparity could result from the different vegetation features in the various regions. For example, forests and broad-leaved trees characterize Guinea and the Savannah (Fig. 8b), which may reduce the overall SSR reaching the surface compared to the Sahel, where sparse grasslands dominate.

Similarly, LST exhibits a more pronounced negative relationship with wind direction in the Sahel (–56 %), indicating the influence of northeasterly winds and associated dust entrainment. While distinct relationships exist between various climate drivers and LST, it is imperative to further discern the predominant climate driver that influences LST the most across different climatic regions. It becomes evident that SST and SSR exert the strongest influence on LST in the Guinea Coast and Savannah regions (Fig. 13a and b). This observation reinforces the significant correlation among LST, SST, and SSR, as illustrated in Fig. 12. Conversely, SSR and WD emerge as the dominant variables influencing LST dynamics in the Sahel and Saharan regions (Fig. 13c and d). These relationships underscore the pivotal roles played by SSR and WD in shaping LST patterns, as corroborated by the findings in Fig. 11. Furthermore, NDVI emerges as the primary modulator of LST across the entire WA region (Fig. 13e). Overall, these findings underpin the varying degrees of influence that distinct climate drivers exert on LST in different climatic regions of WA.

4. Discussion

Land surface temperature is paramount in environmental research and scientific investigations. Its significance resonates across multiple disciplines and has far-reaching implications, making it a pivotal variable in studies of climate change assessment (Simó et al., 2019), ecosystem functionality (Vargas-Hernández et al., 2023), urban heat islands (Adeyeri et al., 2017), the hydrological cycle (Zhou et al., 2023), vegetation dynamics (Bindajam et al., 2020; Zou et al., 2020), human health implications (Adeyeri et al., 2023b; O’Malley & Kikumoto, 2021), climate modeling, and water resources management (Adeyeri et al., 2022b; Masitoh & Rusyd, 2019; Mustafa et al., 2021a). Therefore, a comprehensive understanding of LST dynamics and the influencing factors is paramount, especially in this climate change era (Deng et al., 2018). Particularly, this study advances the understanding of land surface temperature dynamics in WA by downscaling LST and its drivers, considering the influence of multiple factors, including land cover, vegetation health, meteorological forcings, and terrain characteristics. The key findings are discussed below.

![Fig. 12. Correlation and partial correlation of land surface temperature (LST) and downward solar radiation (SSR), sea surface temperature (SST), wind direction (WD), and wind speed (WS). The upper diagonal to the variable is the correlation values, and the lower diagonal to the variable is the partial correlation values; *, **, and *** represent significant correlations, and partial correlations at P values of 0.001, 0.01, and 0.05, respectively.](image-url)
4.1. Evaluation, trends, and evolution

The model performance analysis reveals that the random forest method exhibits superior performance across different time scales for downsampling predictands. This observation accentuates the effectiveness of the random forest's ensemble learning approach in seamlessly amalgamating multiple classifiers (Mao et al., 2022), thereby adeptly capturing the intricate nonlinear associations between predictors and predictands (Schonlau & Zou, 2020) over WA. However, the poor performance of the linear model can be attributed to its linear fitting assumptions (Zhao et al., 2017). In general, the performance of the random forest model shows a slight improvement during the dry season compared to the wet season. The effectiveness of downscaled products using the random forest approach is further assessed in Abuja, Nigeria, by comparing LANDSAT and downscaled-MODIS LST data. This reveals that the downscaled-MODIS LST closely mimics most LANDSAT LST patterns at different timescales. However, some uncertainty is observed, particularly in the wet season. The range of uncertainty is relatively low, ranging from −1.48 °C to 0.63 °C, indicating the robustness of the random forest algorithm in capturing essential LST patterns. While it is commonly believed that random forest models are less accurate in prediction than gradient-boosted trees, our investigation does not confirm this assertion. This outcome may be attributed to the tuning parameters of gradient-boosted trees (Schonlau & Zou, 2020). Nonetheless, realizing optimal parameters that result in a minimized out-of-bag error is vital in model selection and parameter adjustment. Notably, in the random forest algorithm, the subset size of predictor variables plays a crucial role in controlling the final depth of the trees (Schonlau & Zou, 2020).

Consequently, the fine-tuned hyperparameters identify the model exhibiting the highest testing accuracy. Generally, parameter tuning in statistical learning models involves a grid search, an exhaustive exploration within a defined subspace of hyperparameter values specified by the user.

While machine learning algorithms are promising for downsampling from low to high resolution, they also have drawbacks. These include challenges associated with data availability and quality, difficulties in generalizing unseen data or different spatiotemporal contexts, substantial computational requirements that can hinder scalability, and assumptions that may introduce biases based on the training data. Nevertheless, random forests have proven to be dependable in downsampling variables in other areas of the world (Aria et al., 2021; Mao et al., 2022; Pelletier et al., 2016; Schonlau & Zou, 2020; Shi & Horvath, 2006; Zhao et al., 2019).

Given that the simple random forest model fares best in both seasons in WA, future downsampling research over WA could adopt the random forest ML algorithm. This is important for the region since it lacks access to mainframes, which could power more multiplex machine-learning algorithms. Also, random forests necessitate substantial memory storage for preserving data from several hundred unique trees (Aria et al., 2021).

Comparative analysis between LANDSAT and downscaled-MODIS LST datasets demonstrates the precision of the downscaled LST data, with consistent patterns of LST trends observed across different seasons. Positive LST trends are observed in built-up areas during the annual and dry seasons, indicating urban heat island effects (Adeyeri et al., 2017). In the wet season, positive LST trends are more prevalent in the north east, while negative trends dominate the west. These variations in LST trends can be attributed to different meteorological properties and land cover characteristics (Akolafale & Rosalzina, 2022; Bindajam et al., 2020; Cai et al., 2018).

NDVI trends show significant negative trends during the annual and wet seasons, particularly in the Savanna zone. The Guinea Coast shows varied NDVI trends, highlighting the influence of meteorological properties like sea surface temperature and wind systems (Koranteng & Mcglade, 2001). The Sahara and Sahelian zones show mixed trends, with Niger and Mali showing predominantly negative LST trends during the dry season. The temporal evolution of LST and NDVI across different climatic zones reveals generally positive trends. The increasing NDVI trend in the Sahel and Sahara zones may be attributed to a phenomenon known as "desert greening" (Paasata et al., 2020) and rainfall recovery in the Sahel after long drought episodes (Adeyeri et al., 2022a). Generally, the seasonal changes in the LST and NDVI trends confirm the modulating effects of climate dynamics on these variables.

Fig. 13. Ranking of LST-modulating variables for (a) Guinea Coast, (b) Savanna, (c) Sahel, (d) Sahara, and (e) West Africa.
4.2. Vegetation, LST, and elevation characteristics

There are discrepancies in the annual distribution of vegetation health, with more healthy vegetation in the south and less healthy vegetation in the north. These discrepancies can be attributed to the migration of the Inter-Tropical Convergence Zone (ITCZ), which regulates the rainfall regime in WA, accounting for the intra-annual rainfall distribution and extreme wet and dry conditions (Abiodun et al., 2012). Notably, the wet southwesternly monsoon winds bring moisture from the Guinea Coast up north to the Savannah and Sahel regions (Abiodun et al., 2012; Akinsanola et al., 2018). Rainfall abundance, especially on the Guinea Coast and Savannah, contribute to the healthy vegetation in these regions. Conversely, the dry northeastern trade winds from the Sahara Desert do not support moisture buildup; less water is available for plant use, resulting in sparse and unhealthy vegetation. Compared to LST, areas with unhealthy vegetation are synonymous with the hot LST classification. The healthier the vegetation, the cooler the environment (Adeyeri et al., 2017; Schall et al., 2023; Ullah et al., 2023). Identifying locations with high LST and declining vegetation health could facilitate prioritizing sites for afforestation, reforestation, and sustainable agricultural practices.

Also, vegetation cover substantially influences the magnitude of SSR that reaches the Earth’s surface. Regions characterized by robust vegetation have greater vegetative coverage, resulting in less SSR penetration to the Earth’s surface. However, the direct implication of this on air temperature is that more radiation is reflected as upward longwave radiation, heating the overlying air and forming low-level clouds (Danso et al., 2020). Besides the reflected longwave radiation, most areas with lower LST have lower TAS.

Moreover, increased convective activity and cloudiness in the wet season reduce the surface energy budget over southern WA (Matthew et al., 2020). In particular, from Guinea to Sahel zones, low-level clouds resulting from the influx of cold air from the Guinea Gulf (see the southwesterly winds, Fig. 11) could attenuate up to 50% of the downwelling shortwave radiation in the wet months (Danso et al., 2020). As established by Koranteng and McGlade (2001), a short cold season in December-January (minor upwelling), a long warm season in February-June, a long cold season in July-September (major upwelling), and a short warm season in October-November characterize the coastal hydrography of the Gulf of Guinea. We establish a lower sea surface temperature in the wet season. This agrees with Koranteng and McGlade (2001), who reported that SST is lower during the major upwelling season. The upwelling of cold water from the deep ocean, convected inland by strong southwesterly trade winds, contributes to lower LST. Low LST and SSR are prominent where the southwesterly trade winds dominate. We establish that SSR and SST modulate LST the most over a considerably large proportion of WA, but this may vary across seasons and space depending on the sun’s elevation angle (He et al., 2019; Zhao et al., 2019).

Further analysis of the region’s terrain shows that rugged terrain is associated with a high heat load. This implies that southwest-facing slopes of rugged terrain have higher temperatures than the southeast-facing slope, although they receive the same amount of solar radiation (McCune, 2007). Nevertheless, the heat load caused by elevation is independent of the land cover. While LULC influences the LST distribution (Figs. 8b and 77) (Adeyeri et al., 2017; Akomolafe & Rosazlina, 2022; Ghosh et al., 2022; Ige et al., 2017; Ishola et al., 2016b), a high heat load and diurnal anisotropic heat could translate to a comparatively high LST (Ile et al., 2019), depending on the slope-facing angle.

Furthermore, land biophysical characteristics can modulate the relationship between LST and vegetation indices (Chen et al., 2022b; Ishola et al., 2016b; Li et al., 2011; Shorabeh et al., 2022). For example, an increase in LST lowers vegetation health for most LULC classes. This is corroborated in several past reports (e.g., Adeyeri et al., 2017; Akomolafe & Rosazlina, 2022; Schwaab et al., 2021), where, the LST – vegetation health relationship is typically negative in tropical environments. However, the magnitude depends on the LULC category and season. For instance, the wet season has a higher moisture content than the dry season, exhibiting a more significant negative correlation (Guha et al., 2020). Moreover, the negative correlation between vegetation health and LST clusters over water bodies is challenging to explain in WA. Previous studies have identified similar abnormal patterns over urban LST and vegetation clusters (Cai et al., 2018; Masitho & Rusydi, 2019; Sun et al., 2021). However, this may result from impoundments, riparian changes, human activities, and rainfall variability, influencing the temperature regimes of freshwater ecosystems by altering water energy flows (Adeyeri et al., 2020a; Bois et al., 2023). In addition, plants on a riverbank and the volume of water in a stream also influence the LST distribution on water bodies (Adeyeri et al., 2020a). Nonetheless, a more accurate relationship can be explained over water bodies where vegetation health clusters are less than −0.06 (Cai et al., 2018).

Generally, LST hotspots indicate that various LULC classifications and terrain features exhibit distinct LST characteristics. Such an LST characterization based on many auxiliary variables gives insight into how land surface composition controls the regional dynamics of LST. The relationship between LST, NDVI, and other environmental-based indicators may vary across different regions (Madanian et al., 2018; Rafique et al., 2016). The disparities in the LST–NDVI relationship over different climatic zones in WA emphasize the role of regional-specific features and how they modulate the LST–NDVI relationship in different regions. For example, rainfall is higher predominantly in the Guinea regions (Akinsanola et al., 2018; Sanogo et al., 2015), which affects the LST–NDVI relationship (Fayech & Tarbouni, 2021). Consequently, the distinct differences (spatial and temporal) in the inter-regional NDVI values can be attributed to rainfall systems (Martin et al., 2006). While NDVI variability may be attributed to climatic drivers, the increasing LST over the Savannah is credited to reduced vegetation cover, impeding evaporative cooling (Adeyeri & Ishola, 2021). The effects of land cover types on surface temperature also depend on elevation, with higher warming effects at higher elevations (Aguilar-Lome et al., 2019). Areas around the Jos Plateau (northern Nigeria) and Bagazane Plateau (northern Niger) are associated with higher elevation and warming. Heat load shows a more pronounced effect over the Guinea and Savannah zones in the wet months at lower LST. The highest LST in the dry months is dominated by evapotranspiration (Adeyeri & Ishola, 2021; Schrot et al., 2016).

5. Implications for city planning

Understanding and mitigating the urban heat island phenomenon relies on accurately assessing LST and its associated drivers. Urban areas are known to exhibit higher LST compared to adjacent rural regions, attributed primarily to the presence of impermeable surfaces, reduced vegetation cover, and emissions from buildings and vehicles (Adeyeri et al., 2017; Ige et al., 2017; Ishola et al., 2016b; Portela et al., 2020). LST is influenced by many factors, including soil type, topography, surface biophysical properties (Ishola et al., 2016b), vegetation cover (Adeyeri et al., 2017), and water availability (Bindajam et al., 2020).

Hence, transforming natural land surfaces into tar and concrete, an integral component of construction and development initiatives, increases heat absorption. In contrast to other natural surfaces, the impervious surfaces in urban areas exhibit a higher propensity for releasing accumulated heat energy into the atmosphere. Furthermore, it is worth noting that the natural surfaces possess a greater capacity for moisture absorption, whereas impervious surfaces tend to facilitate elevated rates of moisture evaporation. Consequently, it has been observed in several studies that urban areas tend to experience higher temperatures compared to the surrounding rural regions (Adeyeri et al., 2017; Madanian et al., 2018; Tyagi & Sahoo, 2022).

However, based on our findings, we have identified several potential quantitative actions to cushion the effect of high LST.
5.1. Green spaces and urban forestry

Green spaces, such as parks, gardens, and urban forests, play a crucial role in enhancing the quality of life for urban residents. They provide numerous benefits, including improved air quality. Our observations reveal a negative correlation between vegetation density and LST. Specifically, areas exhibiting higher vegetation density exhibit lower LST values. Hence, we recommend prioritizing establishing and maintaining green spaces, parks, and urban forestry to mitigate the adverse effects of high LST. Urban planners can establish precise objectives to augment green spaces within urban areas. For instance, a proposed objective could be to achieve a 20% augmentation in the aggregate expanse of green spaces within the northwestern region of Abuja over the next five-year period. This initiative may encompass the implementation of an annual tree plantation program, wherein a predetermined quantity of trees is planted, or the transformation of designated regions into recreational parks.

5.2. Cool roof technologies

Cool roofs are designed to reflect more sunlight and absorb less heat than traditional roofs, reducing the heat transferred into buildings. In regions exhibiting positive LST trends and high SSR, and where the implementation of urban forestry poses challenges, such as certain regions in Niger and Mali (refer to Figs. 1, 6 and 7), we suggest the adoption of cool roof technologies. Additionally, the government can enforce policies mandating the incorporation of cool roof technologies in new building. Also, incentives should be offered to encourage retrofitting roofs in existing buildings. For instance, a proposed policy may entail the implementation of cool roof technologies in 50% of newly constructed buildings in Niger and Mali by the year 2025.

5.3. Strategic location of facilities

We identify clusters of high LST and areas with positive LST trends (Figs. 6 and 7). Therefore, we suggest that critical facilities, such as schools and hospitals, be situated in areas distant from regions characterized by high temperatures. This strategic placement would effectively mitigate the potential health hazards associated with heat-related ailments resulting from thermal stress (Adeyeri et al., 2023b). Policymakers can utilize the downscaled LST data we have provided or adopt our proposed methodology to generate cost-effective LST data with a satisfactory spatio-temporal resolution to effectively identify specific zones and establish comprehensive guidelines for strategically placing new facilities. As a guiding principle, policies may include avoiding construction of new educational institutions or medical facilities in regions where the average LST exceeds a predetermined threshold.

5.4. Energy-efficient cooling systems

We underscore the increased cooling demands in areas with high LST. Dwellers in areas with elevated LST may have greater cooling demands to offset elevated surface temperatures to attain thermal comfort (Adeyeri et al., 2023b). The reliance on electricity-dependent cooling systems leads to a rise in power consumption and electrical grid loads. An uncoordinated urban design may present a considerable challenge for many cooling systems as they struggle to meet the growing energy demands of users suffering from thermal stress. The anticipated consequences include the likelihood of overheating and subsequent system malfunctioning (Adeyeri et al., 2023b). Hence, policymakers should encourage the adoption of energy-efficient cooling systems to mitigate electricity consumption. This could encompass establishing energy-efficiency standards for cooling systems or providing incentives to promote their adoption and utilization. Also, future energy designs must carefully consider the impact of LST and the resulting amplification of thermal stress as a result of climate change.

5.5. Water resource management

LST and topography have notable impacts on the hydrological cycle. In level terrain, higher LST (Figs. 5b and 7a) elevates the temperature of the overlying air (Fig. 5g), intensifying evaporative demands (Adeyeri & Ishola, 2021; Schroth et al., 2016). This leads to higher water requirements and subsequently induces water stress. These conditions have the potential to initiate multivariate drought events and rapid propagation of extreme events across various hydrological sub-systems (Adeyeri et al., 2023a; Ndehedehe et al., 2023b, 2023a), thereby inducing stringent urban governance, as well as imbalanced water resource management, control, and distribution. Urban planners can use the information derived from the LST and topography impacts on hydrology to improve water resource management. This could involve implementing water-saving measures and improving the efficiency of water distribution in areas with high LST or areas with a high heat load and diurnal anisotropic heat resulting from the elevation slope-facing angle.

Therefore, a profound understanding of LST dynamics and its associated variables can assist urban planners and policymakers in making well-informed land use, infrastructure development, and overall sustainability decisions.

6. Conclusion

This study provides valuable insights into land surface temperature dynamics in West Africa by elucidating the intricate interplay between LST and its multivariate drivers, e.g., land cover, vegetation health, meteorological influences, and terrain characteristics. Machine-learning approaches, particularly the random forest model, effectively downscale LST and its associated drivers, requiring fewer computational resources. The study also highlights the modulating effects of climate dynamics on LST and NDVI trends, emphasizing the importance of considering terrain characteristics, vegetation health, land use, and land cover categories in LST distribution.

Even though climate is anticipated to continue to change, LST plays a significant role in urban planning by influencing decisions about urban heat island reduction, microclimate variability, energy consumption, human health, water management, and air quality. Understanding and successfully managing LST hotspots can contribute to developing resilient, sustainable, and livable cities. In addition, urban planners and policymakers should consider future land use plans that preserve a significant share of public space, green space, and water bodies in places with high LST clusters. Structures erected on southwest-facing slopes should have adequate cooling resources to protect inhabitants from thermal stress, especially during heat waves.

Future research can further explore the role of climate teleconnections in modulating LST across different LULC categories, contributing to a deeper understanding of this complex phenomenon.

Data availability statement

The MODIS data used are available through the Earth Observational System Data and Operations System at http://ladsweb.nascom.nasa.gov/

The ERA5 datasets are available through the European centre for Medium-Range Weather Forecasts (ECMWF) and are publicly available on https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dat

LANDSAT 7 and 8 datasets are publicly available on https://www.usgs.gov/landsat-missions/landsat-data-access

CRediT authorship contribution statement

Oluwafemi E. Adeyeri: Conceptualization, Software, Methodology, Resources, Investigation, Writing – original draft, Writing – review &
Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Supplementary materials


Appendix

Fig. A1. Decadal LST trends at the validation site for downscaled MODIS (a), (b), (c) and Landsat (d), (e), (f) during the annual, wet, and dry seasons, respectively, between 2003 and 2022.
Fig. A2. Evolution of LST and NDVI for the different ecological zones between 2003 and 2022.

Fig. A3. Red-eye triangular plot of LST and vegetation for different LULC classes.

References


