Analyzing the Impact of Land Cover Changes on Spatio-Temporal Temperature Dynamics in the Kara Region of Togo

M’Ponkrou Takin1, Myint Myint Shwe2, Abraham Okrah3, Emmanuel Yeboah4,5, Hashimu Zuberi4, Kwamivi Nyonuosoro Segbeaya1, Tanko Amamata Abubakar7, George Darko4, Genesis Magara3, Thet Mar Soe3, Ali Hasan Jaffry4, and Isaac Sarfo9

ABSTRACT

This comprehensive study delves into the intricate interplay between temperature trends and land cover dynamics in the Kara region, offering robust insights into the evolving climate and environmental patterns. Employing the Mann-Kendall trend test, our analysis reveals a statistically significant and consistent warming trend over the study period. The observed low p-values, positive Tau values, and upward-sloping regression lines emphasize the urgent need for proactive measures to address the climate-related challenges faced by the region. Simultaneously, a meticulous correlation analysis explores the relationships between land surface temperature (LST) and key land metrics—farms, barelands, built-ups, forests, and water bodies. Farmlands exhibit a noteworthy and statistically significant negative correlation of $-0.74$ with LST ($p < 0.05$), indicating a cooling influence and supported by a substantial 43.8% predictive power. Conversely, barelands and built-ups demonstrate strong positive correlations of 0.89 and 0.78, respectively, with LST both statistically significant at the 95% confidence level ($p < 0.05$), emphasizing their considerable warming impact. Forests and water bodies, with moderate negative correlations of $-0.65$ and $-0.54$, maintain statistical significance ($p < 0.05$), indicating their role in temperature moderation, supported by 8.5% and 13% significance. The inclusion of Sen's slope values further enriches the analysis, providing quantitative insights into the rate of temperature change. The positive slope values underscore the increasing trend in temperatures over each respective decade. The observed statistical significances, Tau values, and Sen's slope values accentuate the importance of these relationships for effective land management and environmental planning. Recognizing the cooling influence of farmlands suggests their potential use in strategic urban planning to mitigate temperature increases. Conversely, the warming impact of barelands and built-ups emphasizes the need for sustainable urban development practices to counteract rising temperatures in urbanized regions. Additionally, the cooling influence of forests and water bodies underscores their crucial role in temperature moderation.

Keywords: ArcGIS, Land Cover Changes, Mann-Kendall, Temperature.

1. Introduction

Climate change is an unequivocal global reality (Adu-Prah et al., 2017; Dore, 2005) with profound impacts on ecosystems, communities, and economies (Näschen et al., 2019; Stern & Cooper, 2011). The Kara region, nestled within the broader context of climate change, has experienced temperature variations and evolving land cover patterns (Akodéwou et al., 2020; Koubodana et al., 2019).
These changes pose both challenges and opportunities for sustainable development in the region. Understanding the historical context of these shifts is essential for formulating effective strategies that address the impacts on local livelihoods, biodiversity, and ecosystem health. Moreover, a deeper understanding of the region’s environmental history will shed light on the potential driving forces behind observed changes.

A comprehensive review of existing literature (Fonji & Taff, 2014; Kleemann et al., 2017; Koubodana et al., 2019; Näschén et al., 2019; Okrah et al., 2023) provides valuable insights into the broader context of climate change and land dynamics. Studies conducted globally have explored the impacts of climate change on various regions, showcasing the interconnected nature of temperature changes and land transformations. However, specific analyses focused on the Kara region are limited. This study seeks to build on the collective knowledge derived from global and regional literature, applying advanced statistical analyses to discern patterns that are unique to the Kara context. By synthesizing existing knowledge, the research aims to contribute to the growing body of literature on climate-land dynamics.

The Kara region represents a unique environmental setting characterized by diverse ecosystems, including expansive forests and extensive agricultural lands (Akodewou et al., 2020; Koglo et al., 2019). In recent decades, global climate change has triggered discernible shifts in temperature dynamics and land use/land cover (LULC) changes across the world (Doe et al., 2018; Yaslam Bawahidi, 2005). The Kara region, with its distinctive climatic and topographic features, has not been immune to these changes. This study seeks to delve into the multifaceted dynamics of temperature trends and LULC alterations in the Kara region, aiming to unravel the nuanced interconnections between these environmental variables.

The significance of this study extends beyond academic exploration. As the Kara region grapples with ongoing environmental changes (Kombate et al., 2022; Koubodana et al., 2019), the findings of this research are poised to offer practical insights for local communities, policymakers, and environmental practitioners. The implications of understanding the intricate relationships between temperature trends and land cover alterations are far-reaching. This knowledge can influence decisions related to sustainable agriculture, conservation practices, and community resilience initiatives. By bridging the gap between scientific research and practical applications, the study aims to empower stakeholders with the tools needed for informed decision-making. The primary objective is to explore shifts in temperature parameters within the Kara region, encompassing both average and extreme values. By analyzing historical temperature data, we aim to identify patterns indicative of climate change in the region. Another key objective is to identify land use/land cover types exhibiting the highest sensitivity to temperature fluctuations. By discerning which land cover types are most responsive to temperature changes, we can inform targeted conservation and land management strategies. The study seeks to gauge the consequences of land use/land cover alterations on the trends of Land Surface Temperature (LST) and Surface Air Temperature (SAT). Understanding these consequences provides valuable insights into the complex relationships between land cover changes and temperature dynamics.

In the research methodology, a robust interdisciplinary approach was adopted, combining advanced statistical analyses to capture the complexity of temperature-land cover dynamics in the Kara region. The Mann-Kendall test and Sen’s slope analysis (Okrah et al., 2023) provide a solid statistical foundation for assessing trends in temperature parameters, including both average and extreme values. Additionally, we correlate mean Land Surface Temperature (LST) values with annual rates of land cover change, employing a deterministic factor and F-change analysis. This multifaceted methodology ensures a comprehensive exploration of the intricate interplay between climate and land dynamics (Alberini et al., 2005; Asamoah & Ansah-Mensah, 2020; Mensah et al., 2020).

This research aims to investigate the impact of land use on climate change and explore the connection between spatiotemporal land cover changes and land surface temperature at the local level in Kara. Specifically: (1) to discern shifts in temperature parameters, encompassing both average and extreme temperature values, within the Kara region; (2) to pinpoint the LULC type that exhibits the highest sensitivity to temperature fluctuations; (3) to gauge the consequences of LULC alterations on the trends of LST and SAT. This study holds both scientific and practical relevance for the Kara region. By bridging the gap between temperature dynamics and land cover changes, the research strives to offer actionable insights that can inform sustainable development practices, adaptive strategies, and policy decisions tailored to the unique challenges and opportunities presented by the Kara environment. The study aims to contribute not only to the academic understanding of climate-land dynamics but also to the practical knowledge needed for effective environmental management in the region.
2. MATERIALS AND METHODOLOGY

2.1. Study Area Description

The Kara Region, situated in the northern part of Togo (Fig. 1), is characterized by its diverse landscape, which is not only shaped by its geography but also by the changes in land use and land cover (LULC) that have occurred over the years (Akdéwou et al., 2020; Kleemann et al., 2017; Koubodana et al., 2019). This region features a mix of vast plains, rolling hills, and plateaus alongside a dynamic LULC pattern that has seen the expansion of urban areas, agricultural activities, and deforestation. These changes have contributed to the creation of microclimates and urban heat islands, influencing local climate patterns and, notably, land surface temperatures (LST).

The region’s geography includes woodlands, grasslands, and thriving agricultural areas, and its climate is tropical, with distinct wet and dry seasons (Koubodana et al., 2019). The Kara Region is not immune to the broader global issue of climate change. Its changing LULC is marked by processes like urbanization and deforestation and significantly impacts local temperatures. These changes in land cover and land use have given rise to variations in temperature parameters, affecting both average and extreme temperature values across different districts within the Kara Region.

Efforts to investigate the relationship between LULC changes and temperature are pivotal in understanding the region’s climatic dynamics (Kleemann et al., 2017; Tahiru et al., 2020). Furthermore, recognizing the interplay between urbanization, agricultural expansion, and deforestation on local climate patterns and temperatures is essential for the development of strategies that can mitigate the adverse effects of these processes. This multifaceted exploration of LULC changes and their impact on temperature provides valuable insights for local decision-makers in Kara, enabling them to plan and manage land use more effectively in the face of ongoing climate change.

2.2. Data Source and Analysis

2.2.1. Land Use/Land Cover Change Data

This study utilized remote sensing techniques to gather and process data pertaining to changes in Land Use and Land Cover (LULC), referring to works such as those by Mensah et al. (2020), Fonji and Taff (2014), Näschen et al. (2019), and Tahiru et al. (2020) for guidance. However, a notable drawback associated with remote sensing is its susceptibility to challenges in data acquisition and information retrieval when faced with cloud cover (Okrah et al., 2023). The presence of cloud cover can obscure distinct phenomena, leading to potential confusion when similar features are detected by the sensor. Nevertheless, remote sensing has proven to be an exceptionally effective tool for monitoring and detecting changes in both aquatic environments (Mason & Schmetz, 1992; Nott & Price, 1999; Ysalam Bawahidi, 2005) and terrestrial landscapes (Kleemann et al., 2017; Mensah et al., 2020; Näschen et al., 2019). For instance, a previous investigation (Koglo et al., 2019; Kombate et al., 2022; Koubodana et al., 2019) utilized remote sensing techniques to evaluate the impact of Land Use and Land Cover Change (LULCC) on surface temperature in Togo. Furthermore, remote sensing data...
has proven to be a valuable resource for researchers studying LULC changes, facilitating resource inventory, land use characterization, and the identification, tracking, and quantification of shifting landscape patterns (Adu-Prah et al., 2017; Gou et al., 2020; Quaye-Ballard et al., 2020).

The Landsat images employed in this research were acquired from the United States Geological Survey (USGS) through the Earth Explorer website. More precisely, satellite images from Landsat 4-5, 7, 2, and 8 for the years 1990, 2000, 2010, and 2020 (Table I) were procured and employed to extract information related to land cover. These identical Landsat images were also utilized to retrieve data on Land Surface Temperature (LST) for the respective years under investigation.

The Kara subregion encounters challenges in accessing spatiotemporal data for scientific research, as noted in previous studies (Asamoah & Ansah-Mensah, 2020; Koubodana et al., 2019). To overcome this limitation, researchers often resort to reanalysis and satellite datasets. In our investigation, surface temperature data was obtained from the fifth generation of the European Reanalysis (ERA-5), which provides an improved horizontal resolution of 9 kilometres and hourly temporal resolution compared to earlier products like ERA-Interim.

To capture temperature information for our specified study location, we utilized the latitude and longitude coordinates from ERA5-Land. Our analysis covered mean temperature trends from 1990 to 2020, with the original, hourly data aggregated into daily and monthly averages (Okrah et al., 2023; Quaye-Ballard et al., 2020) for further scrutiny.

To visualize the spatiotemporal distribution of temperature, we generated time series plots depicting the monthly progression of temperature values within our designated study site. The temperature data obtained from ERA-5 was initially recorded in Kelvin but was subsequently converted to Celsius for our study using appropriate formulas. Leveraging satellite data and reanalysis products allowed us to examine temperature trends across an extensive spatial and temporal range, providing valuable insights into our study area.

2.2.2. Land Cover Analysis

We utilized ArcGIS 10.8 for an extensive analysis of both land cover and land surface. To identify diverse land cover types, we employed a composite band analysis method. The land cover analysis was conducted using the supervised classification method (Nielsen, 2014; Tahiru et al., 2020). Before initiating the land cover analysis, we employed ArcMap 10.8 to rectify issues associated with cloud cover in the imagery. Specifically, for the Landsat 7 image from the year 2000, we addressed scan lines on the bands using GIS software before proceeding with the supervised classification for that particular imagery.

2.2.3. Accuracy Assessment

To assess the reliability of the classified images, we performed a feasibility evaluation involving accuracy assessments to establish an acceptable margin of error within the images (Näschen et al., 2019). The precision of the categorized images was assessed through the utilization of Kappa coefficient statistics (K). The software was used to delineate the area for all categorical land covers, and this data was exported in Excel format for subsequent calculations of the Kappa coefficient.

A K > 0.80 indicates a strong agreement for the evaluated class, whereas a K value falling within the range of 0.40 to 0.80 signifies a satisfactory level of agreement. Conversely, a K < 0.40 suggests a less acceptable level of agreement (Kombate et al., 2022). The calculation of the Kappa coefficient (K) was done using the following formula:

$$K = \frac{N \sum_{y=1}^{p} T_{mn} - \sum_{y=1}^{p} (X_{b+y} \cdot X_{s+y})}{N^2 - \sum_{y=1}^{p} (X_{b+y} \cdot X_{s+y})}$$

where;

- \(N\) = total count of observations within the matrix,
- \(p\) = the count of rows in the matrix,
- \(y\) = the count of columns in the matrix,
- \(T_{mn}\) = the count of observations in row \(p\) and column \(y\), respectively.
$T_{y+1} =$ total counts for row y,
$T_{p+} =$ total counts for column p.

### 2.2.4. LST Analysis

Land Surface Temperature (LST) data for the Kara region was extracted from the identical Landsat images used in the land cover analysis, covering the years 1990, 2000, 2010, and 2020. The choice of spectral bands for LST extraction depended on the specific Landsat image being analyzed. For Landsat 4-5, spectral band 7 was utilized to compute surface temperature, and bands 8 and 11 were employed for calculating the Normalized Difference Vegetation Index (NDVI).

The process of LST calculation followed these steps:

1) Step 1 involves calculating the radiance values, which are necessary for converting pixel values (DN) into physical units.

$$T_{\lambda} = N_{L}Q_{Cal} + M_{L}$$  \hspace{1cm} (2)

where:

- $T_{\lambda} =$ Radiance,
- $M_{L} =$ Top Spectral radiance Watts,
- $N_{L} =$ Radiance multiplicative band (No.),
- $Q_{Cal} =$ Quantized and calibrated standard.

2) Step 2: The level of brightness was considered by using the following formula:

$$BT = \frac{m_{2}}{\ln \left( \frac{m_{1}}{T_{\lambda}} - 1 \right)} - 273.15$$  \hspace{1cm} (3)

where:

- $BT =$ Atmosphere brightness temperature (at top),
- $T_{\lambda} =$ Spectral radiance Watts/m² rad μm (at top),
- $m_{1} =$ $m_{1}$ band specific, constant band (No.),
- $m_{2} =$ $m_{2}$ band specific, constant band (No.).

3) Step 3 involved calculating the NDVI (measure of green vegetation) in the studied areas. This was done by subtracting the reflectance values in the near-infrared (NIR) band from the reflectance values in the red band and then dividing the result by their sum.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$  \hspace{1cm} (4)

where:

- $RED =$ DN value from the RED band,
- $NIR =$ DN values from the near-infrared band include data from Band 7 and the red band (Band 8) for Landsat 4-5, and Band 8 and the red band (Band 11) for Landsat 8.

4) Step 4: Proportional Vegetation (PV) was calculated as:

$$PV = \left[ \frac{NDVI - NDVI_{mn}}{NDVI_{mx} + NDVI_{mn}} \right]^{2}$$  \hspace{1cm} (5)

where:

- $NDVI =$ DN values from NDVI image,
- $NDVI_{mn} =$ minimum value from INDVI image,
- $NDVI_{mx} =$ maximum value from INDVI image,

5) Step 5: Land surface Temperature in Degree Celsius is calculated by the following equation:

$$LST = KT + V \left( \frac{BT}{14388(h)} \right)$$  \hspace{1cm} (6)

where:

- $KT =$ Top of atmosphere brightness temperature,
- $V =$ Wavelength of emitted radiance,
- $h =$ Surface Emissivity.
2.2.5. Change Detection Analysis

To evaluate the scope and trends of land cover transformations in the Kara region from 1990 to 2020, we employed a change detection methodology (Afrifa-Yamoah, 2015; Jaiswal et al., 1999; Yaslam Bawahidi, 2005). Additionally, we computed the annual rates of change for the specific periods of 1990–2000, 2000–2010, and 2010–2020 to quantify the magnitude of alterations during these time spans. Heat maps were also generated for the years 1990, 2000, 2010, and 2020 and subsequently compared to the classified land cover images. An evaluation was conducted to understand the influence of land use.

2.3. ERA-5 Temperature Analysis

In the initial phase of the Surface Air Temperature (SAT) analysis, we conducted normality tests to understand the characteristics of the datasets in accordance with the methodology. To achieve this, we subjected the SAT data to normality tests, utilizing both the Kolmogorov-Smirnov (K-S) and Shapiro-Wilk (W) tests. The choice of these tests was informed by their suitability and widespread application in assessing the degree to which sample data conforms to a normal distribution (Okrah et al., 2023; Quaye-Ballard et al., 2020). These tests were selected due to their appropriateness and common usage in normality testing, as well as their complementary nature. The null hypothesis for these tests assumes that the sample distribution is normal and the test scores are compared to scores from a normal distribution with the same mean and standard deviation.

The following is the formula used for the Shapiro-Wilk test:

$$\sum_{i=1}^{p} n_{yi}y_{i}^{2}$$

$$\sum_{i=1}^{p} (y_{i} - \bar{y})^{2}$$

The provided equation indicates that $y_{i}$ denotes the ordered sample value, with $n$ representing a constant derived from the means, variances, and covariance of the ordered statistics. The variables $p$ and $\sigma$ represent the number of observations and the sample mean, respectively. Alongside the statistical tests, a visual analysis was carried out to depict the long-term variability of both annual and monthly temperatures. The examination of the slope coefficient aimed to discern whether the data displayed a positive or negative trend.

2.3.1. Trend Analysis

To determine the prevailing trend in the dataset, we employed the Mann-Kendall (MK) trend test, a commonly used non-parametric method for identifying monotonic trends in climate data (Koglo et al., 2019; Mekonnen et al., 2018; Mensah et al., 2020). The null hypothesis ($H_0$) in this test assumes the absence of any trend in the dataset. A positive or negative outcome from the MK test indicates an upward or downward trend, respectively, and this trend direction was further verified through Sen’s slope estimator test. Sen’s slope estimator enables us to quantify the magnitude of the trend, essentially assessing the average annual temperature change (rate of change).

Furthermore, we employed ground validation methods and statistical inferences to assess the influence of Land Use and Land Cover (LULC) changes on Land Surface Temperature (LST). The comparison of means for land cover change and LST was done using the Z-test, while ANOVA was utilized to validate and examine their correlation. These analytical methods were applied to enhance our comprehension of the relationship between LULC changes and LST, as well as Land Cover Changes (LULC) on temperature within the study districts.

2.3.2. Land Metric Analysis

Methods for image classification (Buyantuyev & Wu, 2010; Dash et al., 2007; Kudo, 1991; Okrah et al., 2023; Yaslam Bawahidi, 2005), including supervised or unsupervised classification, were utilized to categorize the land cover data into distinct classes. During this phase, each pixel or area was assigned to a specific land cover type. Depending on the study’s objectives, pertinent land metrics such as area, the percentage of land cover types, fragmentation indices, edge density, or diversity indices were computed using the Percentage of Landscape (PLAND).

$$PLAND = 100 \times \sum_{x=a_{p}}^{v} a_{x} / R$$

Here, $v$ represents the number of patches in the landscape for class $x$; $a_{p}$ is the area of patch $i$; and $R$ denotes the total landscape area, reflecting the proportion of the total area occupied by a particular land-use type. These metrics aid in comprehending the spatial arrangement and structure of land cover types in the research area. The percentage of landscape land metric indicates the proportion or relative contribution of a specific land cover class or feature in the overall landscape. It offers valuable insights into the spatial distribution and dominance of various land cover types within a specified region. This metric is commonly applied in environmental studies, land use planning, and landscape ecology to evaluate and grasp the composition and structure of landscapes.
2.3.3. Correlation Analysis of Land Metric and LST

Correlation coefficients (R) were calculated to assess the relationship between land metrics and Land Surface Temperature (LST) values for various land cover classes. This examination aids in identifying potential connections between land cover types and patterns of Land Surface Temperature (LST).

\[
R = \frac{\sum (p_i - \mu)(y_i - \delta)}{\sqrt{\sum (p_i - \mu)^2 \sum (y_i - \delta)^2}}
\]

where:
- \( R \) = Correlation coefficient,
- \( p_i \) = Values of the x-variable in the sample,
- \( \mu \) = Average values of the x-variable,
- \( y_i \) = Values of the y-variable in the sample,
- \( \delta \) = Average values of the y-variable.

3. Results and Discussion

3.1. Land Cover

3.1.1. Land Use/Land Cover Change

The classified Land Use and Land Cover (LULC) maps, which depict both built-up areas and non-built-up regions such as forests in the respective districts, served as the foundation for evaluating LULC changes that transpired between 1990, 2000, 2010, and 2020, as visualized in Fig. 2.

Significantly, the year 2010 exhibited the lowest overall accuracy and kappa coefficient, with recorded values of 92.02% and 0.5, respectively, in contrast to the adjacent years. This finding suggests some inconsistency in the Land Use and Land Cover (LULC) classification during that specific period. The LULC images highlighted a notable increase in built-up areas within the districts from 1990 to 2020 (Table II), particularly witnessing substantial expansion between 2010 and 2020 (Fig. 2). Conversely, there was a noticeable decline in forested areas within the district (Tables II and III). This reduction in forest cover can be attributed to the increasing prevalence of built-up areas (Kleemann et al., 2017; Koubodana et al., 2019), primarily fuelled by urbanization and intensified agricultural activities. These alterations in land use often result from the growing demands for housing, food production, and employment opportunities in the Kara region and its surrounding areas.

In the research conducted by Kombate et al. (2022), it is noteworthy that vegetated areas have been cleared to accommodate housing and various social amenities. This transformation is primarily...
driven by the increasing demands associated with the growth of urban populations in developing cities. The accelerated urbanization, illustrated by a substantial increase of 57.38% as depicted in Fig. 2 and detailed in Table IV, can be attributed to the rapid population growth experienced in several urban regions in Togo during the same timeframe from 2010 to 2020.

### TABLE II: Land Use Land Cover Change Analysis from 1990–2000 within the Kara Region

<table>
<thead>
<tr>
<th>Class names</th>
<th>LULC 1990</th>
<th>LULC 2000</th>
<th>LULC 1990–2000</th>
<th>Area change (km²)</th>
<th>Cover change (%)</th>
<th>Annual rate of change (km²/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Waterbody</td>
<td>0.29</td>
<td>0.01</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Forest</td>
<td>2107.58</td>
<td>97.64</td>
<td>2043.23</td>
<td>94.66</td>
<td>–64.35</td>
<td>–6.43</td>
</tr>
<tr>
<td>Built-up areas</td>
<td>50.58</td>
<td>2.34</td>
<td>115.2</td>
<td>5.34</td>
<td>64.62</td>
<td>6.46</td>
</tr>
<tr>
<td>Total</td>
<td>2158.43</td>
<td>100.00</td>
<td>2158.43</td>
<td>100.00</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TABLE III: Land Use Land Cover Change Analysis from 2000–2010 within the Kara Region

<table>
<thead>
<tr>
<th>Class names</th>
<th>LULC 2000</th>
<th>LULC 2010</th>
<th>LULC 2000–2010</th>
<th>Area change (km²)</th>
<th>Cover change (%)</th>
<th>Annual rate of change (km²/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>2043.23</td>
<td>1711.77</td>
<td>–331.46</td>
<td>–38.72</td>
<td>–842.23</td>
<td>–3.87</td>
</tr>
<tr>
<td>Built-up areas</td>
<td>115.2</td>
<td>446.66</td>
<td>331.46</td>
<td>15.66</td>
<td>842.23</td>
<td>3.87</td>
</tr>
<tr>
<td>Total</td>
<td>2158.43</td>
<td>2158.43</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### TABLE IV: Land Use Land Cover Change Analysis from 2000–2010 within the Kara Region

<table>
<thead>
<tr>
<th>Class names</th>
<th>LULC 2010</th>
<th>LULC 2020</th>
<th>LULC 2010–2020</th>
<th>Area change (km²)</th>
<th>Cover change (%)</th>
<th>Annual rate of change (km²/year)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>1711.77</td>
<td>869.47</td>
<td>–842.23</td>
<td>–38.72</td>
<td>842.23</td>
<td>3.87</td>
</tr>
<tr>
<td>Built-up areas</td>
<td>446.66</td>
<td>1288.96</td>
<td>842.32</td>
<td>38.72</td>
<td>842.32</td>
<td>3.87</td>
</tr>
<tr>
<td>Total</td>
<td>2158.43</td>
<td>2158.43</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The rapid population growth in the Kara region of Togo can be attributed to the significant influx of expatriates from nearby towns on the Burkina Faso border, drawn to the area for business purposes. This influx has resulted in an increase in housing stocks and urbanization. Since 2000, the population of the districts has experienced a considerable surge, accompanied by a corresponding growth in housing stock and urban development. Migration, particularly interregional migration linked to agriculture and related activities, has played a pivotal role in this population growth, forming the economic backbone of the region.

However, the heightened population density has exerted pressure on essential social infrastructure, including schools, water, health facilities, and sanitation (Akindewu et al., 2020; Folega et al., 2014). To meet the demands of the growing population, vegetation is cleared for housing and other social amenity purposes, contributing to an increased rate of deforestation in forest reserves for timber production and agricultural activities (Fonji & Taff, 2014; Kleemann et al., 2017; Tahiru et al., 2020).

3.1.2. Land Surface Temperature (LST)

The study revealed an increase in the mean LST across the Kara Region from 1990–2020 (Fig. 3 and Table V).

3.2. SAT and LST Variability and the LULCC Correlations with Associated Urbanization

3.2.1. LST and the LULC Change Correlation with Associated Urbanization

The Kara region has experienced a notable increase in Land Surface Temperature (LST), accompanied by significant land cover changes attributable to urbanization (Figs. 2 and 3). Previously vegetated areas in most parts of the region have been replaced by built-up structures constructed with asphalt,
TABLE V: Maximum, Minimum, and Mean LST for 1990–2020 within the Kara Region

<table>
<thead>
<tr>
<th>Year</th>
<th>Temperature (°C) (Maximum)</th>
<th>Temperature (°C) (Minimum)</th>
<th>Temperature (°C) (Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>26.67</td>
<td>17.02</td>
<td>19.45</td>
</tr>
<tr>
<td>2000</td>
<td>42.98</td>
<td>19.10</td>
<td>23.16</td>
</tr>
<tr>
<td>2010</td>
<td>28.2</td>
<td>14.8</td>
<td>21.7</td>
</tr>
<tr>
<td>2020</td>
<td>39.55</td>
<td>17.27</td>
<td>23.42</td>
</tr>
</tbody>
</table>

concrete, bricks, and stones. These developed areas contribute to the warming of the surrounding environment by absorbing and radiating heat (Alberini et al., 2005; Mensah et al., 2020; Nielsen, 2014).

To delve deeper into the relationship between land cover changes and LST, the mean values of LST for 1990, 2000, 2010, and 2020 were correlated with their corresponding percentage annual rate of change in land cover. The analysis yielded a deterministic factor of $R = 0.81$ and a significant F-change of 0.013 at a 95% confidence interval. These findings align with previous studies (Doe et al., 2018; Mensah et al., 2020; Okrah et al., 2023) that have observed an increase in mean LST in areas characterized by the proliferation of built-up surfaces.

3.2.2. Normality Test Results for SAT

In this test, the probability was taken at a 95% confidence level. $H_0$ was not accepted at $p$ (significance) < 0.05 but was accepted at $p > 0.05$. This indicates that the data followed a normal distribution and could be used for trend analysis.

3.2.3. Trends and Variability in Mean Annual SAT

As depicted in Fig. 4, the annual minimum and maximum temperatures in the Kara region exhibited a robust and statistically significant positive trend. Linear regression trend lines were employed to visually represent the evidence of temperature variability and the discernible trend within the dataset.

3.2.4. The Mann-Kendall Trend Test

The Mann-Kendall trend test results for the minimum (Fig. 4a), maximum (Fig. 4b), and mean temperatures (Fig. 5) in the Kara region indicate statistically significant increasing trends for all three-temperature metrics. The $p$-values associated with each test are notably small, providing strong evidence against the null hypothesis of no trend (see Table VI).

The Tau values, which gauge the strength and direction of the trend, provide additional support for the statistical significance of the observed trends. Specifically, for minimum temperature (Min. T), Tau
3.2.5. Statistical Interpretations of the Correlations Between Land Cover Types and LST

The correlation analysis between land metrics—farmlands, barelands, built-ups, forests, and water bodies—and Land Surface Temperature (LST) has revealed statistically significant relationships, providing key insights into the strength and direction of these associations. Farmlands exhibit a robust and statistically significant negative correlation of $-0.74$ with LST ($p < 0.05$), indicating that regions with higher farmland coverage experience lower temperatures (Dash et al., 2007; Yaslam Bawahidi, 2005). This negative correlation is both scientifically and statistically meaningful. Approximately 43.8% of the variation in LST can be confidently attributed to changes in farmland coverage.

Conversely, barelands and built-ups show strong positive correlations of 0.89 and 0.78, respectively, with LST, and both are statistically significant at the 95% confidence level ($p < 0.05$). These results underscore the substantial impact of barelands and built-up areas on elevated temperatures (Akedewou et al., 2020; Doe et al., 2018; Mason & Schmetz, 1992). The robust statistical significance...
reinforces the reliability of these positive correlations, emphasizing the heat-absorbing nature of exposed soil and impervious surfaces in urbanized regions. Barelands and built-ups contribute to 18.2% and 16.5% of the variation in LST, respectively, highlighting their significant role in shaping local temperature patterns.

For forests and water bodies, with moderate negative correlations of $-0.65$ and $-0.54$, respectively, both demonstrate statistical significance ($p < 0.05$). The negative correlations, indicative of a cooling influence (Buyantuyev & Wu, 2010; Dash et al., 2007; Okrah et al., 2023), are supported by statistical evidence. Changes in forest cover and water body extent contribute to 8.5% and 13% of the variation in LST, respectively. The statistical significance of these correlations reinforces the importance of vegetation and water bodies in moderating local temperature dynamics.

The inclusion of statistical significance enhances the credibility of the observed relationships, emphasizing not only their scientific relevance but also their practical importance for land management and environmental planning. The percentages further quantify the contribution of each land cover type to the variability in Land Surface Temperature.

3.3. Effects of Increasing Temperatures in the Kara Area

The escalating temperatures in the region carry significant implications for the livelihoods of the residents. The noteworthy temperature increase suggests the potential to disrupt rainfall patterns through processes like evapotranspiration (Akom et al., 2020; Buyantuyev & Wu, 2010; Fonji & Taff, 2014), leading to water scarcity manifested in the drying-up of rivers and deficient soil moisture. This poses a major challenge for agriculture in the area, particularly as farmers heavily rely on rain-fed farming (Asamoah & Ansah-Mensah, 2020; Koglo et al., 2019).

The heightened Land Surface Temperature (LST) and Surface Air Temperature (SAT) in the region can be partially attributed to anthropogenic activities. These activities include deforestation for charcoal production and timber, clearing of vegetation for farming, population pressure on the environment, urbanization, sand mining, and urban heating. These human-induced factors contribute to the observed changes in temperature patterns and have wider implications for the local environment and community well-being.

Moreover, the ongoing increase in Land Surface Temperature (LST) and Surface Air Temperature (SAT) could contribute to the persistent occurrence of respiratory diseases in densely populated areas of the region. The warming trend fosters the proliferation of agricultural pests and diseases (Adu-Prah et al., 2017; Afrifa-Yamoah, 2015; Mason & Schmetz, 1992), thereby heightening risks for crop yields. Additionally, a higher frequency of extreme events, such as droughts, floods, and heatwaves, is likely to cause substantial damage to crop production.

Residents in the region may face continued uncertainty regarding temperature variations in the coming years. Consequently, it is imperative to conduct a thorough assessment of anticipated mean and extreme climate events under climate change and their associated consequences (Akom et al., 2020; Buyantuyev & Wu, 2010; Fonji & Taff, 2014). This should be an integral part of initiatives aimed at promoting agricultural development and mitigating the impact of high-temperature-related infections in the Kara districts.

3.4. Further Analysis of Conservation Efforts in the Kara Area

The integrated analysis, combining Mann-Kendall trend analysis, correlation analysis, and PLANd (Proportion of Landscape) analysis, offers a comprehensive understanding of the relationships between various land metrics (farmlands, barelands, built-ups, forests, and water bodies) and Land Surface Temperature (LST) in the Kara area.

The study’s findings indicate a strong interconnection between Land Use Land Cover Change (LULCC), Land Surface Temperature (LST), and Surface Air Temperature (SAT) in the Kara region. The analysis reveals a deterministic factor $R = 0.81$, with a significant F-change of 0.013 at a 95% confidence interval, suggesting that the increase in LST and SAT is linked to substantial changes in land cover from 1990 to 2020. Notably, the Kara region experienced significant land cover changes, accompanied by a corresponding rise in LST and SAT. Rapid urbanization was identified as a key factor, leading to the conversion of a significant portion of green vegetated surfaces into non-transpiring and less evaporative built-up environments.

The non-linear relationship between land cover changes and LST underscores the importance of considering the specific context when analyzing this connection. Further analysis could inform conservation efforts in the Kara area, emphasizing the urgency of protecting remaining forested areas and implementing reforestation initiatives.

Conservation strategies should prioritize sustainable land use practices, including green infrastructure and sustainable agriculture techniques (Fonji & Taff, 2014; Okrah et al., 2023; Yaslam Bawahidi,
to mitigate the impact of urbanization and agricultural expansion on the environment. Reforestation efforts can contribute to restoring forest cover, improving the local climate, and providing essential ecosystem services.

The study’s findings also have important implications for conservation efforts, suggesting that strategies to reduce urban sprawl and promote sustainable agriculture can mitigate the negative impacts of land cover changes on temperature. Focusing on preserving forest cover is crucial for mitigating the effects of temperature on biodiversity and ecosystem services.

Further analysis can identify specific conservation strategies tailored to the unique needs of the Kara area, fostering a holistic approach to land use planning and management. This approach should account for the intricate interrelationships between human activities, land cover changes, and climate.

4. Conclusion and Recommendation

In conclusion, our comprehensive statistical analysis of temperature dynamics and land use/land cover (LULC) effects in the Kara region reveals significant shifts supported by robust statistical measures. The Mann-Kendall test underscores the statistical significance of changes in both average and extreme temperature values \(p < 0.05\), and Sen’s slope values quantify the rate of these changes \((0.0333\) for minimum, \(0.0217\) for maximum, and \(0.03\) for mean temperatures). The identification of LULC types with high sensitivity to temperature fluctuations is validated by p-values and trend analyses, enhancing the credibility of our conclusions. Additionally, our study correlates mean values of Land Surface Temperature (LST) for 1990, 2000, 2010, and 2020 with their corresponding percentage annual rate of change in land cover. This analysis yields a deterministic factor \((R)\) of \(0.81\) and a significant F-change of \(0.013\) at a 95% confidence interval. The deterministic factor underscores the strong correlation between LST and land cover changes, while the significant F-change value emphasizes the reliability of this correlation. These statistical values, in conjunction with Sen’s slope values, provide a comprehensive understanding of the temperature-land cover dynamics in the Kara region, forming the basis for data-driven recommendations for sustainable development and climate resilience.

Author Contributions

MT: Conceptualization, data curation, methodology, writing-original draft preparation, visualization, reviewing and editing. MMS: Conceptualization, data curation, methodology, writing-original draft preparation, resources, investigation, reviewing and editing. AO: Conceptualization, project administration, data curation, methodology, visualization, writing-original draft preparation. HZ: Conceptualization, Methodology, visualization, reviewing and editing. EY: Data curation, visualization, supervision, reviewing and editing. TAA: Conceptualization, data curation, investigation, reviewing and editing. GD: Conceptualization, methodology, reviewing and editing. GM: Data curation, methodology, writing-original draft preparation. TMS: Data curation, visualization, reviewing and editing. AHJ: Data curation, visualization, reviewing and editing. IS: Data curation, supervision, validating, reviewing and editing.

Data Statement

Data is available on request.

Conflict of Interest

The authors confirm that they are free from any known financial conflicts of interest or close personal ties that could have influenced the research presented in this study.

References


