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Spatio-Temporal Land Cover Analysis and the Impact of Land Cover Variability Indices on Land Surface Temperature in Greater Accra, Ghana Using Multi-Temporal Landsat Data

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Abstract

Urbanization, as a result of anthropogenic activities, reduces the vegetated and green spaces and thereby increases the impervious surfaces in cities. This in turn increases the surface temperature of cities when compared to the rural regions resulting in the formation of urban heat island. Especially, in under-developed countries, it is very crucial to obtain timely and accurate information on the urban trend and its development due to the higher increasing rate of population growth and lack of infrastructural facilities and regulations to mitigate the adverse consequences of urbanization. The current study analyzes the urban development of Greater Accra, Ghana using Landsat 7 dataset acquired in 2002, 2013, and 2020. Further, the influence of urban growth on the land surface temperature (LST) and land cover variability (LCV) indices including NDVI (Normalized Difference Vegetation Index), NDBI (Normalized Difference Built-Up Index), and NDWI (Normalized Difference Water Index) is identified during the study periods. Results suggest that the area of built-up quadrupled between 2002 and 2020 in the study region. Shannon's entropy-based analysis suggests that the urban development in the region is heterogeneous or dispersive in nature. Further, the regression analysis highlights a strong positive relation between LST and NDBI (0.755) and a negative relation is found associated between LST and NDVI (0.4417) and LST and NDWI (0.76). Results of the study could be useful to design sustainable urban socio-economic and environmental planning policies in the study region.

Keywords

Land Surface Temperature, Urbanization, Land Cover Variability Indices,

Landsat 7 ETM, Greater Accra

1. Introduction

Rapid increase in population, industrialization and economic growth had led to increased urbanization globally. The current global population is estimated to be 7.9 billion, half of which is already living in cities [1]. It is estimated that by 2050 two-thirds of the world's population would be living in urban areas. It is to be noted that world's cities occupy only 3% of the earth's surface. However, these cities account for around 60% - 80% of the global energy consumption and are responsible for 75% of carbon emissions [2]. Rapid urbanization especially in developing nations exerts pressure on freshwater supplies, efficient management of solid waste and the living environment of the people [3]. It is forecasted that almost 90% of urban development would happen in Asia and Africa in the next 30 years [4].

Unplanned and uncontrolled urbanization, especially in low-income countries, results in a growing number of slum dwellers, inadequate infrastructure facilities including clean water and sanitation systems, proper transportation accessibility and efficient waste management system [5]. United Nation's Sustainable Development Goal (SDG) 11 targets are to achieve sustainable cities and communities thereby making cities and human settlements safe, resilient, and sustainable. It is proven that the urban areas that suffer the greatest temperature rises leading to the formation of urban heat islands (UHI) are amplified by human anthropogenic activities [6]. Thus, the knowledge of land surface temperature (LST) and its spatio-temporal influence on the landuse/land cover (LULC) changes within a city is crucial to studying the interaction between urban climate and human-environment [7]. In low-income countries including Africa, urban growth during the last two decades was the highest with 3.5% increase per year. Especially, the current urban settlement patterns in West Africa are the result of various environmental, historical, and socio-political factors. In the West African coastal regions, in particular, settlements are sprawled around the main urban areas and their immediate hinterland. This fast coastal urban expansion is particularly visible from Abidjan (Côte d'Ivoire) to Lagos (Nigeria). In this coastal corridor population density is the highest in the West African region. The Gulf of Guinea countries is in fact the most urbanized in the region, with settlements occupying between 1% (Benin) and 2% (Nigeria) of their national territory [8].

Natural increase in population is estimated to be the major factor responsible for the increase in urban populations in many African countries compared to the migration of people from rural to urban centers [9]. Compared to the West African average, Ghana has a higher proportion of urban dwellers, with 51% of the Ghanaian population living in urban centers as of 2015 [10] and this proportion is expected to reach 70% by 2050 [11]. The urban population of Ghana is however highly concentrated in bigger cities regions, such as Accra, Kumasi, and Tamale [12]. The current study has been dedicated to the Greater Accra Region, known as the most densely occupied region of the country. Following the existing studies that had already analyzed the LULC change in West African metropolitan regions [13] [14] the current study focuses on identifying the influence of land cover variability (LCV) indices on the LST as the latter is understood to be a good indicator of greenhouse effect as well as of the state of crops and vegetation [15].

Due to the availability of high-resolution multi-temporal satellite images and sophisticated GIS based spatial analysis techniques, the study of impact of LULC changes on the thermal environment is widely carried out globally [16] [17] [18]. [19] established that increase in urban settlements between 1989 and 2015 in Nakuru County, Kenya increased the LST of the region. Further, the regression-based analysis highlighted that the urban development of the region had strong positive relationship with Normalized Difference Built-Up Index (NDBI) and negative relation with Normalized Difference Vegetation Index (NDVI) during the study periods. The impact of LULC changes on LST of Chattogram Metropolitan Area of southeastern Bangladesh between 1990 and 2018 was studied by [20]. The study highlighted that urbanization in the region increased at a rate of 2.25% per year and the average LST increased by 5.66˚C during the study periods. The authors identified that the expansion of built-up areas was the major contributing factor for the increasing LST in the region, which resulted in the formation of UHI in 15 thana of the study region. Further, the spatial and temporal changes in the LULC changes and its impacts on LST of two Indian cities of Surat and Bharuch were studied by [21]. Results of their study revealed that between 2008 and 2016 both the cities experienced extensive growth in built-up area with significant reduction in green space, which led to the increase in LST of the study regions. These kinds of studies would help urban planners, policy regulators and land management professionals to identify the potential hotspots of drastic urban development that must be controlled and planned to avoid further environmental degradation thereby incorporating appropriate urban planning practices in the region.

However, not many studies focusing on assessing the impact of LULC change on the LCV indices leading to change in climatic conditions in African cities are reported. This is crucial for coastal cities like Accra as it has been proven that the rise in temperature of cities would lead to various natural hazards including heat related droughts, floods, intense rainfall apart from the human discomfort due to excess thermal environment [22] [23]. In this context, the objectives of the current study are to analyze the urbanization of Greater Accra region, Ghana through multi-temporal Landsat 7 ETM data of 2002, 2013 and 2020 and identify the pattern of urban development based on Shannon's entropy analysis between 2002 and 2020. The study further aims to identify the influence of urban development of the study region on the LCV indices including NDBI, NDVI, and NDWI (Normalized Difference Water Index) through spatial regression analysis technique in 2002, 2013, and 2020.

2. Study Area

The Greater Accra Region (**Figure 1**) is the smallest of the 10 administrative regions in terms of area, occupying a total land surface of 3696 km^2 or 1.4% of the total land area of Ghana. In terms of population, however, it is the most populated region, with a population of 5,455,692 in 2021, accounting for 17.69% of Ghana's total population [24]. The region has therefore the highest population density in the country. It has a coastline of approximately 130 km, stretching from Kokrobite in the west to Ada in the east.

The region is relatively dry since it falls within the dry coastal equatorial climatic zone with temperatures ranging between 20˚C and 30˚C and annual rainfall ranging from 635 mm along the coast to 1140 mm in the northern parts. There are two rainfall peaks notably in June and October. The rains are mostly intensive short storms that normally cause floods in most parts of the region [25]. The biggest urban center of Greater Accra Region is the Greater Accra Metropolitan Area, which has evolved from a group of coastal fishing villages to become the economic hub of Ghana, providing 25% of the national GDP and

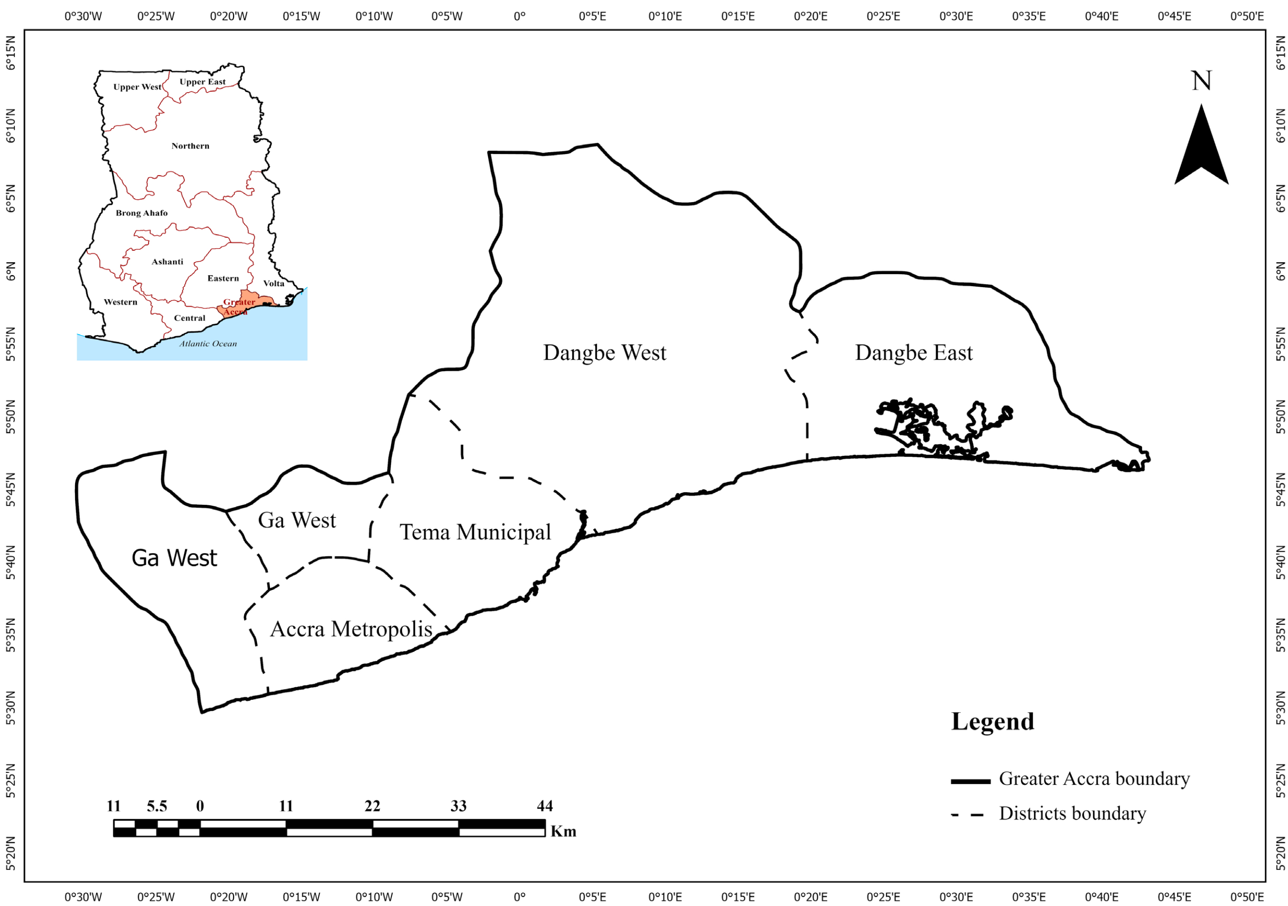

Figure 1. Map of the study region.

attracting people from all over the country and other parts of the world [26].

3. Data and Methods

In the current study, to estimate the influence of LCV indices (NDVI, NDBI, NDWI) on LST and to analyze the urban growth pattern of the study region, the following dataset are used.

1) Land cover maps of 2002, 2013 and 2020 are derived using 15 m resolution (Multispectral PAN merged) satellite images of Landsat 7 ETM acquired during 26 December 2002, 6 January 2013, and 26 January 2020 respectively (https://earthexplorer.usgs.gov/).

2) Band 6 of Landsat 7 ETM (100 m resolution) of 2002, 2013 and 2020 are used to derive the LST maps of the study region.

3) Bands 3, 4 and 5 with 15 m resolution (Multispectral PAN merged) are used in the estimation of LCV indices (NDVI, NDBI and NDWI) of the study region during the study periods.

4) Urban maps prepared from the land cover maps are used in the identification of urban sprawl patterns of 2002, 2013 and 2020 in the study region.

5) Google Earth along with field information is used in the validation of land cover maps of the study region.

3.1. Influence of Land Cover Variability Indices on the LST

The influence of LCV indices (NDVI, NDBI and NDWI) on LST is analyzed (**Figure 2**) in the study area for the years 2002, 2013 and 2020 and are discussed in section 3.1.1 - 3.1.4. Section 3.2 explains the identification of urban pattern of the study region between 2002 and 2020.

3.1.1. Land Cover Maps

Support Vector Machine (SVM) of supervised classification technique is implemented to prepare the land cover maps of the study region in 2002, 2013 and 2020. SVM technique [27] classifies the study region into four land cover categories including built-up, vegetation, waterbody and openland.

3.1.2. Validation

Validation is an important process through which users understand the accuracy of the land cover maps prepared through classification technique [28] [29]. Error Matrix or Contingency Table is the most commonly adopted technique to validate the land cover maps through overall accuracy (OA) and kappa co-efficient (k) value. In the current study, the accuracy of the land cover maps of the study region are expressed in terms of OA and k.

3.1.3. Estimation of Land Surface Temperature

The estimation of LST through Landsat 7 ETM [30] is based on Equations (1), (2) and (3).

Conversion of Digital Number (DN) to Radiance

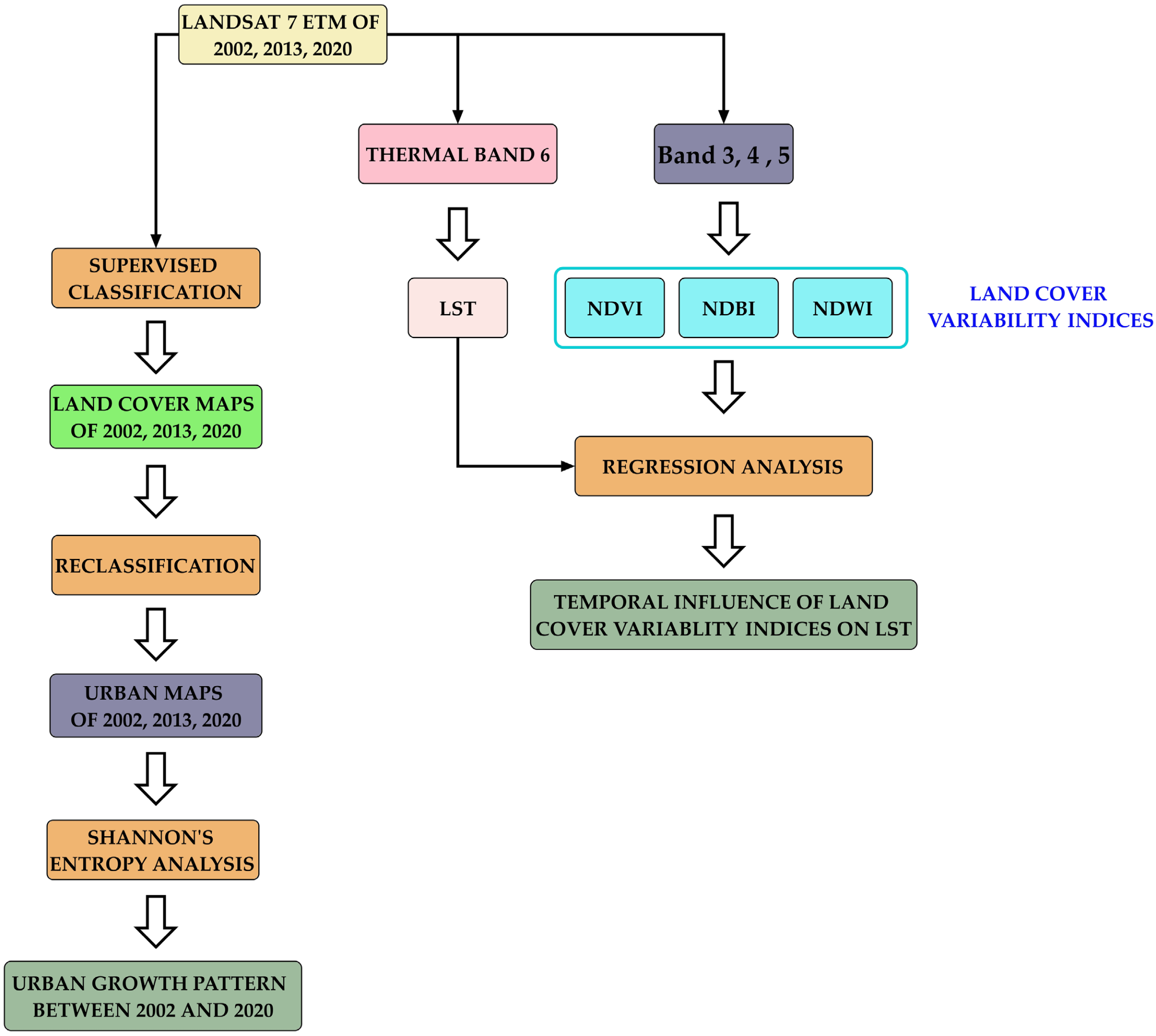

Figure 2. Methodology implemented in the study region.

$$L_{\lambda} = \frac{L_{\mathrm{MAX}\lambda} - L_{\mathrm{MIN}\lambda}}{Q_{\mathrm{CALMAX}} - Q_{\mathrm{CALMIN}}} * \left(Q_{\mathrm{CAL}} - Q_{\mathrm{CALMIN}}\right) + L_{\mathrm{MIN}\lambda} \tag{1}$$

where, L_{λ} is the spectral radiance in watts/m^2*srad*μm.

Q_{CAL} is the quantized calibrated pixel value in DN.

Q_{CALMAX} is the maximum quantized calibrated pixel value corresponding to $L_{\mathrm{MAX}\lambda}$ in DN ($Q_{\mathrm{CALMAX}} = 255$).

Q_{CALMIN} is the minimum quantized calibrated pixel value corresponding to $L_{\mathrm{MIN}\lambda}$ in DN.

$L_{\mathrm{MAX}\lambda}$ is the spectral radiance scaled to Q_{CALMAX} in watts/m^2 *srad* μm.

$L_{\mathrm{MIN}\lambda}$ is the spectral radiance scaled to Q_{CALMIN} in watts/m^2 *srad* μm.

Conversion of Radiance to Brightness Temperature

$$B_T = \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}} + 1\right)} \tag{2}$$

where, B_T is the brightness temperature in Kelvin.

K_1 and K_2 are the calibration constants and are given as 666.09 Watts/(m^2.srad.μm) and 1282.71 kelvin respectively. The B_T estimated represents the LST which could also be expressed in degree Celsius (˚C) as per Equation (3).

$$B_T\left(^{\circ}\mathrm{C}\right) = B_T\left(\mathrm{kelvin}\right) - 273.15 \tag{3}$$

3.1.4. Estimation of Land Cover Variability Indices

The LCV indices including NDVI, NDBI and NDWI of the study region are estimated based on Equations (4)-(6). NDVI is the commonly used index to measure the vegetation greenness of a region [31]. It quantifies the vegetation present in a region by measuring the difference between near-infrared and red bands of Landsat data.

$$\mathrm{NDVI} = \frac{\mathrm{Band\ 4} - \mathrm{Band\ 3}}{\mathrm{Band\ 4} + \mathrm{Band\ 3}} \tag{4}$$

where, Band 4 and band 3 are the near infrared (NIR) and red bands of Landsat 7 ETM data.

NDBI estimation helps in extracting the built-up regions in the study area [32] and is the measure of difference between shortwave infrared and near-infrared bands. NDBI is calculated as per Equation (5).

$$\mathrm{NDBI} = \frac{\mathrm{Band\ 5} - \mathrm{Band\ 4}}{\mathrm{Band\ 5} + \mathrm{Band\ 4}} \tag{5}$$

Here, band 5 corresponds to the shortwave infrared band of Landsat 7 satellite data.

$$\mathrm{NDWI} = \frac{\mathrm{Band\ 2} - \mathrm{Band\ 4}}{\mathrm{Band\ 2} + \mathrm{Band\ 4}} \tag{6}$$

NDWI (given in Equation (6)) delineates the open water features present in the study region based on the visible green light (Band 2) and near-infrared bands [33].

3.1.5. Temporal Variation of Influence of Land Cover Variability Indices on the Land Surface Temperature

The influence of LCV indices (NDVI, NDBI and NDWI) on LST greatly depends upon the temporal changes of land cover and the season during which the Landsat data are acquired [34]. In the current study, regression analysis technique was adopted to analyze the influence of LCV indices (prepared as discussed in section 3.1.4) on the LST maps and (estimated based on section 3.1.3) for the years 2002, 2013, and 2020.

NDVI is the most commonly used index to measure the vegetation density and it varies between −1 and +1. Higher the value of NDVI, denser is the vegetation present in the region. NDBI index is used to analyze the built-up area of a given region. NDBI values with higher positive values highlight the presence of built-up or openland in a region. Generally, NDWI value is greater than 0.5 for waterbodies [35].

3.2. Urban Growth Analysis through Shannon's Entropy Analysis

To identify the urban sprawl pattern of the study region, normalized Shannon's entropy method is implemented making use of the urban maps of 2002, 2013 and 2020 [36]. The study region is divided into five distance-based zones (0 - 5 km, 5 - 25 km, 25 - 50 km, 50 - 75 km, and 75 - 100 km) based on the administrative center. Based on the urban development in each of these five zones, the normalized entropy (H_N) is calculated as shown in Equation (7).

$$H_N = \frac{1}{n}\sum_{i=1}^{n} p(x_i) * \log\left\{\frac{1}{p(x_i)}\right\} \tag{7}$$

where, n is the number of zones and in the current study, $n = 5$. $p(x)$ is the probability of built-up in each zone. H_N values range between 0 and $\log_e(n)$. H_N value closer to 0 indicate a compact or homogeneous type of urban sprawl. The urban sprawl of a region could be identified as dispersive or heterogeneous when H_N values are closer to $\log_e(n)$ value.

4. Results and Discussions

The results of the current study are described in the following sections (4.1 - 4.5).

4.1. Land Cover Mapping

The land cover maps of the study region prepared as described in section 3.1 are shown in **Figure 3**. The validation results of the land cover maps highlight an OA of 93.01%, 85.87% and 86.01% with k values of 0.90, 0.8337 and 0.836 for the years 2002, 2013 and 2020 respectively. The land cover maps show significant increase in the built-up area and decrease in openland between 2002 and 2020. The study region covers an area of 3696 km^2 of which 244.19 km^2 (6.6%), 644.85 km^2 (17.45%) and 970.5 km^2 (26.16%) are observed to be built-up in 2002, 2013 and 2020 respectively. There is a considerable decrease in the openland from 2176.36 km^2 in 2002 to 1988.88 km^2 in 2020 accounting to 58.88% and 53.81% in the study region (**Figure 4**). The study region had a population of 3 million in the year 2002 which increased to 5.5 million in 2020 and is expected to reach 13.1 million by 2030 [24]. This increase in the population in the region along with the higher migration rate of people to the region in search of employment opportunities and better lifestyle could have quadrupled the built-up regions from 2002 to 2020 and reduced the vegetation areas to half from 2002 (1131.84 km^2) to 2020 (633.99 km^2). These results align with a similar land cover analysis of the Greater Accra Metropolitan Area by [12] using Landsat Images from 1991, 2000, 2009 and 2015. In this Metropolitan Area which is the most densely urbanized part of the Greater Accra Region their results revealed that built-up area increased by 277% between 1991 and 2015 while it has quadrupled in our case. Their 2025 projected land-use map also shows a quite similar pattern of urban expansion than in ours. The population and economic growth are major

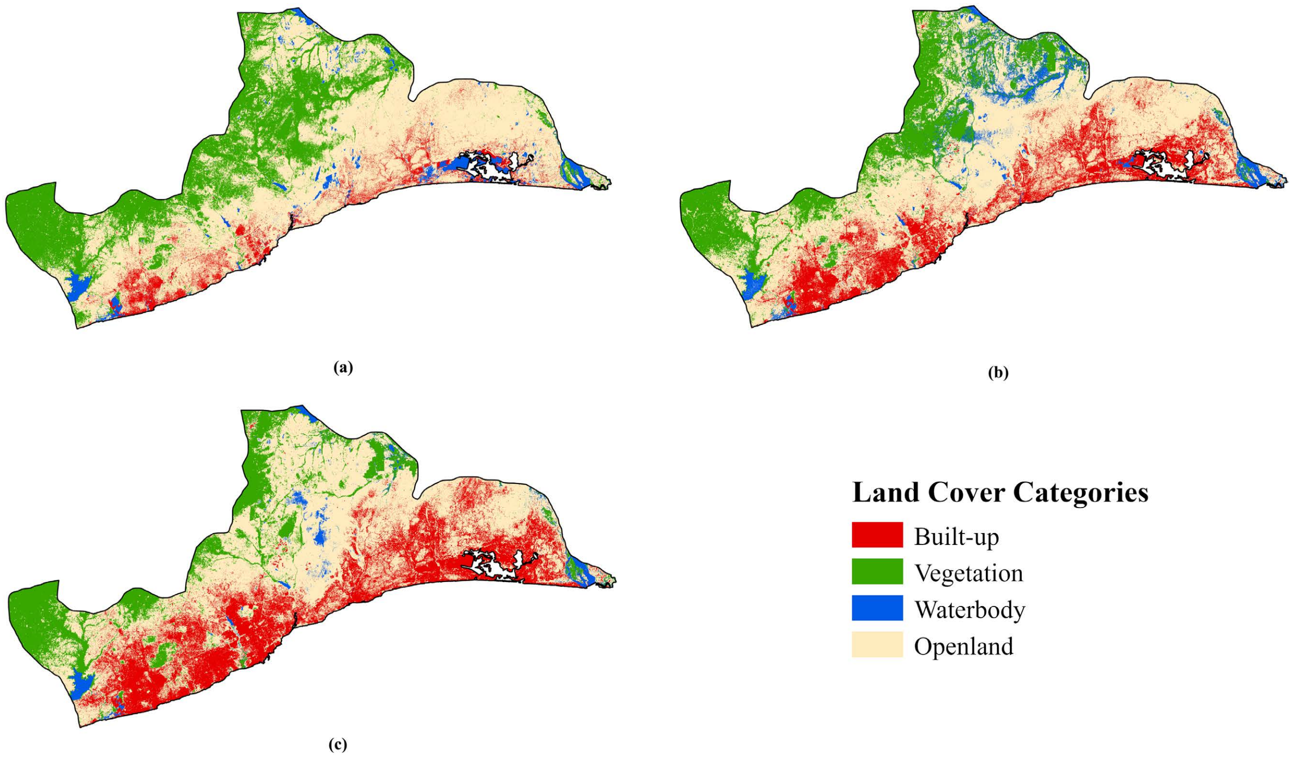

Figure 3. Land Cover Maps prepared through SVM technique in the study region.

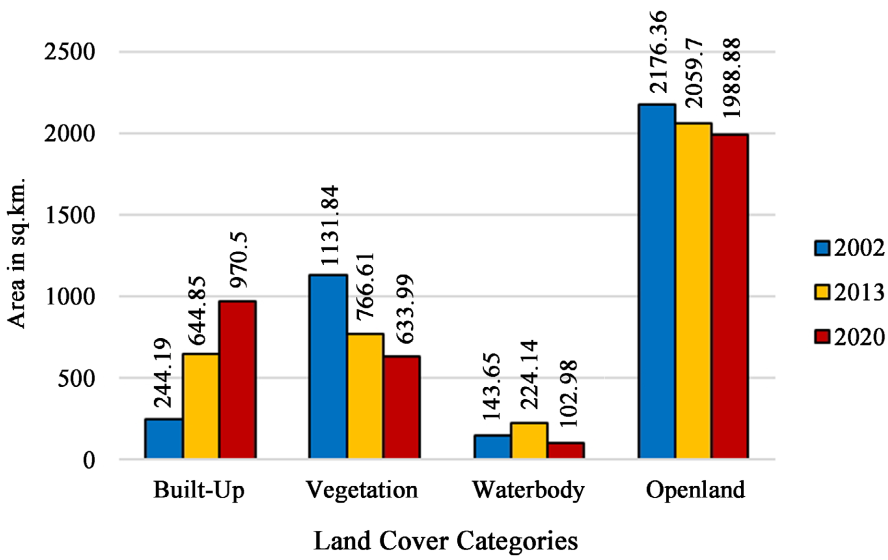

Figure 4. Statistics of the land cover maps of the study region during 2002, 2013 and 2020.

factors of these changes in the land cover [10]. In fact, massive investment has been made in the housing sector in recent years [12] due to the increasing demand by expatriates, repatriates Ghanaians living abroad and the rising middle class. It's mainly an uncontrolled private land use development led by the capital market. [37] has also shown that this private land use development is made possible by traditional chiefs who hold customary land in trust for their communities. These land that are originally used as common good by members of the communities for agricultural purposes are nowadays being sold to private developers as land ownership and acquisition have become very competitive.

4.2. Land Surface Temperature Mapping

The LST maps of the study region estimated through band 6 of Landsat 7 ETM data as described in section 3.2 are shown in Figure 5. The LST of the study region increased considerably between 2002 and 2020 which is evident from the increase in the mean LST value of 10.01˚C in 2002 to 11.24˚C in 2013 and 11.49˚C in 2020. Table 1 highlights that in 2002, 75% of the study region had an observed LST of between 25˚C - 30˚C while higher LST category (greater than 35˚C) occupied less than 1% of the study region. However, in the year 2013, 1448.4 km^2 corresponding to 39% of the study region is observed to have LST between 25˚C and 30˚C, whereas around 58% of the study region (2132.39 km^2) is estimated to have higher LST category (30˚C - 35˚C). It is to be noted that in the year 2020, 69% of the study region had observed LST of 30˚C - 35˚C and 1% in the highest LST category (greater than 35˚C). This could be because of the presence of conventional man-made materials used in the urban environment including roads, pavements, roofing materials and absence of vegetation and waterbodies in the openland. Built-up and openland categories tend to have higher LST values as they emit and absorb higher solar radiations when compared to vegetation or water body land cover categories. The results of this analysis indicate that increase in built-up area by quadruple could have increased the mean

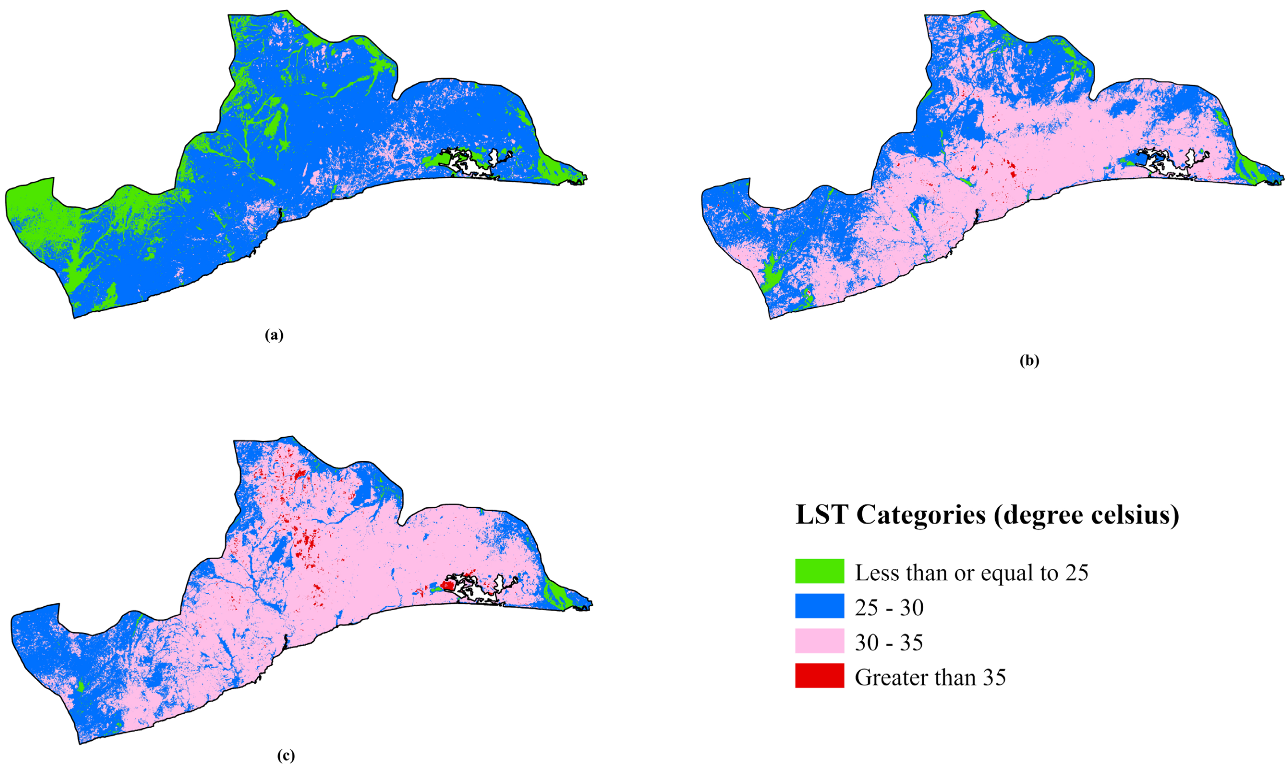

Figure 5. LST maps estimated during 2002, 2013 and 2020 in the study region.

LST by 1.48˚C between 2002 and 2020 in the study region.

Impact of Land Cover Change on Land Surface Temperature

The influence of temporal variations of land cover on LST of the study region in 2002, 2013 and 2020 is shown in Figure 6. It could be seen that the minimum and maximum LST of the study region during 2002 are 14.63˚C and 48.92˚C respectively. However, the mean LST of built-up land cover category in 2002 is higher (28.32˚C) than that of other land cover categories. Similarly, in the years 2013 and 2020, the mean LST of the built-up category (31.38˚C in 2013 and 31.51˚C in 2020) is found to be higher when compared to the LST of vegetation, waterbody and openland categories of the study region.

Next to the built-up category, openland exhibits the higher value of LST in the study region. The mean LST of the openland category is observed to be 28.04˚C in 2002 which increased to 30.92˚C in 2013 and 31.40˚C in 2020 (Figure 6). In the study region, waterbody category is observed to have comparatively lesser LST values during the study periods (24.11˚C in 2002, 27.67˚C in 2013 and 28.29˚C in 2020). Hence, the results of the analysis highlight the fact that built-up and openland categories exhibit higher LST values in the study region than the vegetation and waterbody categories. This substantiates the fact that

Table 1. LST values of Greater Accra during the study periods.

LST categories	Area (sq.km) under each LST category in		
	2002	2013	2020
Less than 25˚C	729.31	104.21	39.46
25˚C - 30˚C	2776.39	1448.40	1057.61
30˚C - 35˚C	191.01	2132.39	2552.06
Greater than 35˚C	0.29	12.02	47.89

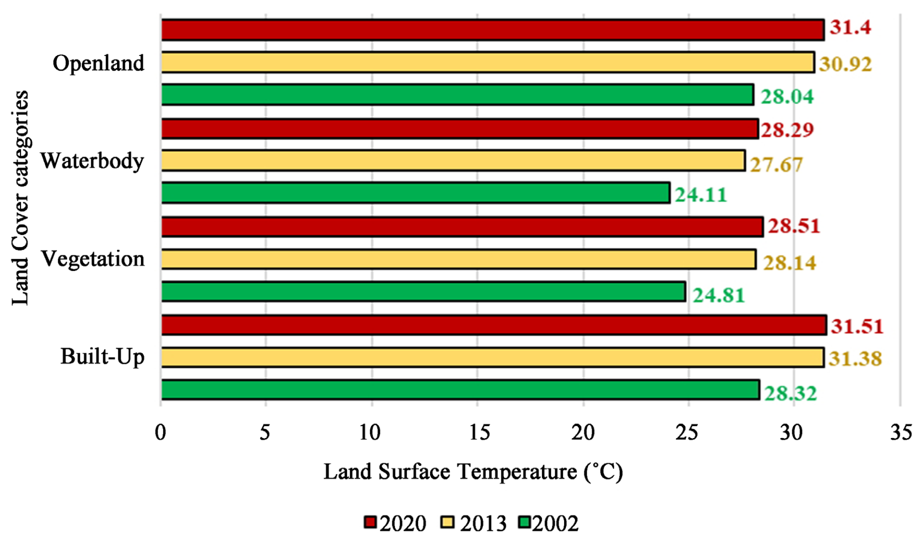

Figure 6. Influence of land cover change on the LST of the study region.

when the study region undergoes urbanization, non-built up land cover categories (vegetation, waterbody) are being cleared and are converted to openland and built-up categories. Since, built-up areas are characteristics of artificial human made materials and openland are devoid of green space, they had exhibited higher LST in the study region in 2002, 2013 and 2020.

Existing statistics of LST clearly confirmed, for tropical cities, that more urbanized areas resulted in higher values of LST and also the LST is increasing over the years as the vegetation areas are decreasing. [38] for example showed with a study on the smaller scale of the city of Accra that the most urbanized and industrial enclaves of Accra like Kwedonu, Accra central, Teshie and Spintex recorded very high temperature values mostly 35˚C and above for the year between 2005 and 2017, whereas lower temperatures were recorded at places with dense vegetation covers like Achimota Ecological Forest, GIMPA and around the University of Ghana.

A comparative study by [39] on Accra, the capital city, and Kumasi, a city of the Ashanti Region, also reveals temperature ranges that are generally lower for Kumasi than for and the most densely built Accra.

4.3. Correlation between Land Surface Temperature and land Cover Variability Indices

The relationship between LST and land cover variability indices attracts more and more scientists [40] [41]. Different types land use and land cover react differently under LST analysis making LST vary widely in urban environment [41] [42] [43], especially in larger urban region like the one under analysis in the current study. As the land use and land cover types evolve through land conversion process, time is an important factor in LST monitoring. Existing studies have also considered seasonal changes as sun elevation and sun azimuth are changed with seasons but this wasn't necessary for Accra, Ghana.

The LCV indices (NDVI, NDBI and NDWI) maps of the study region prepared as explained in section 3.1 are shown in **Figure 7**. The temporal variations in the influence of NDBI, NDWI and NDVI on LST between 2002 and 2020 are analyzed (**Figure 8**). From **Figure 8**, it is evident that NDBI has a positive relation with LST, while the vegetation and the waterbody indices (NDVI and NDWI) are reported to have negative relation with LST. The positive relation between LST and NDBI is more evident in 2020 than in 2002 as revealed in the R^2 value which was reported to be 0.52 in 2002 and 0.76 in 2020. Further, the negative relation between LST and NDVI, NDWI is stronger in 2020 (R^2_LST and NDVI: 0.44; R^2_LST and NDWI: 0.76) than in 2002 (R^2_LST and NDVI: 0.37; R^2_LST and NDWI: 0.52). This indicates the fact that with increase in built-up and openland the LST of the study region also increases. However, increase in vegetation and waterbody decreases the LST between 2002 and 2020 in the study region.

These results have proven has proven a strong correlation between the expansion of built-up areas and of openland as suspected. It's is therefore urgent to

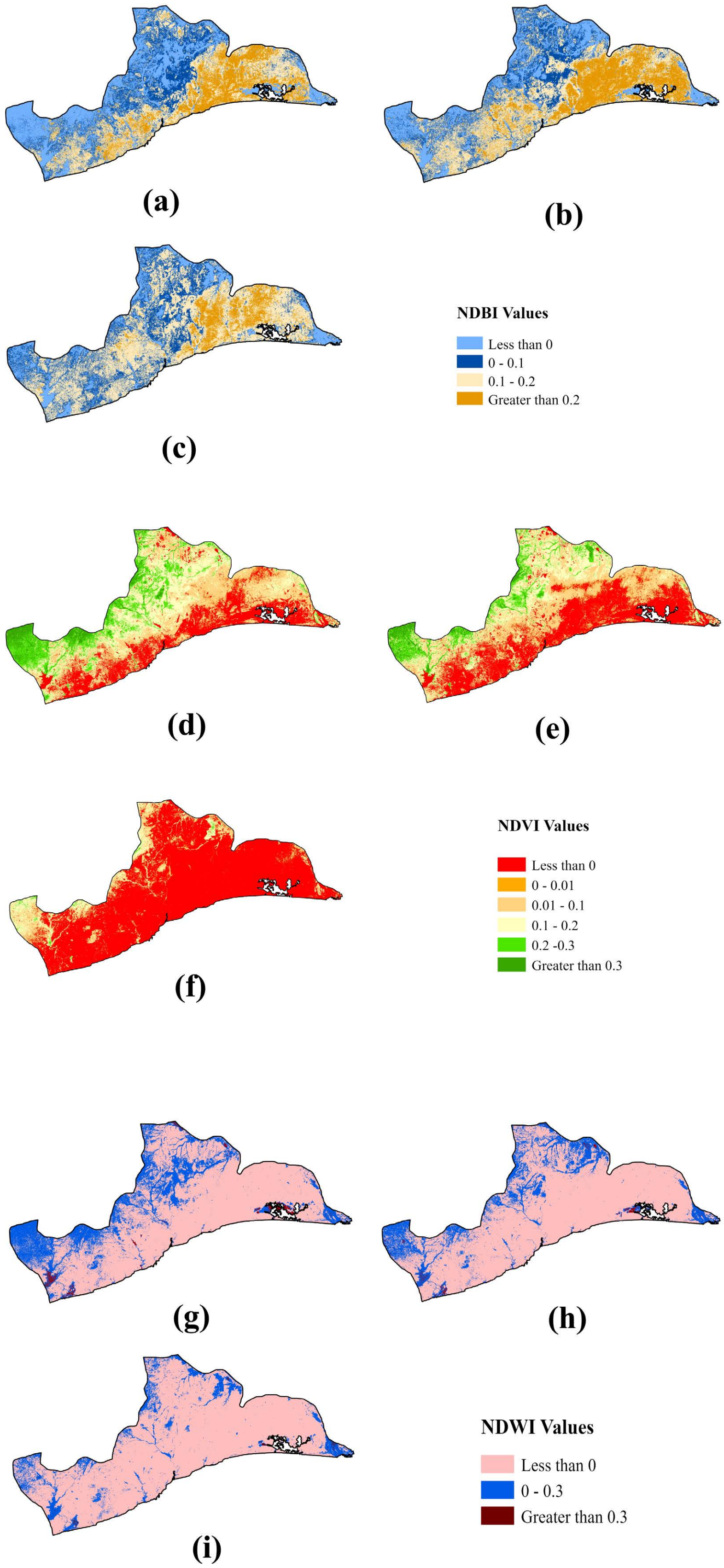

Figure 7. Land cover variability indices maps of the study region.

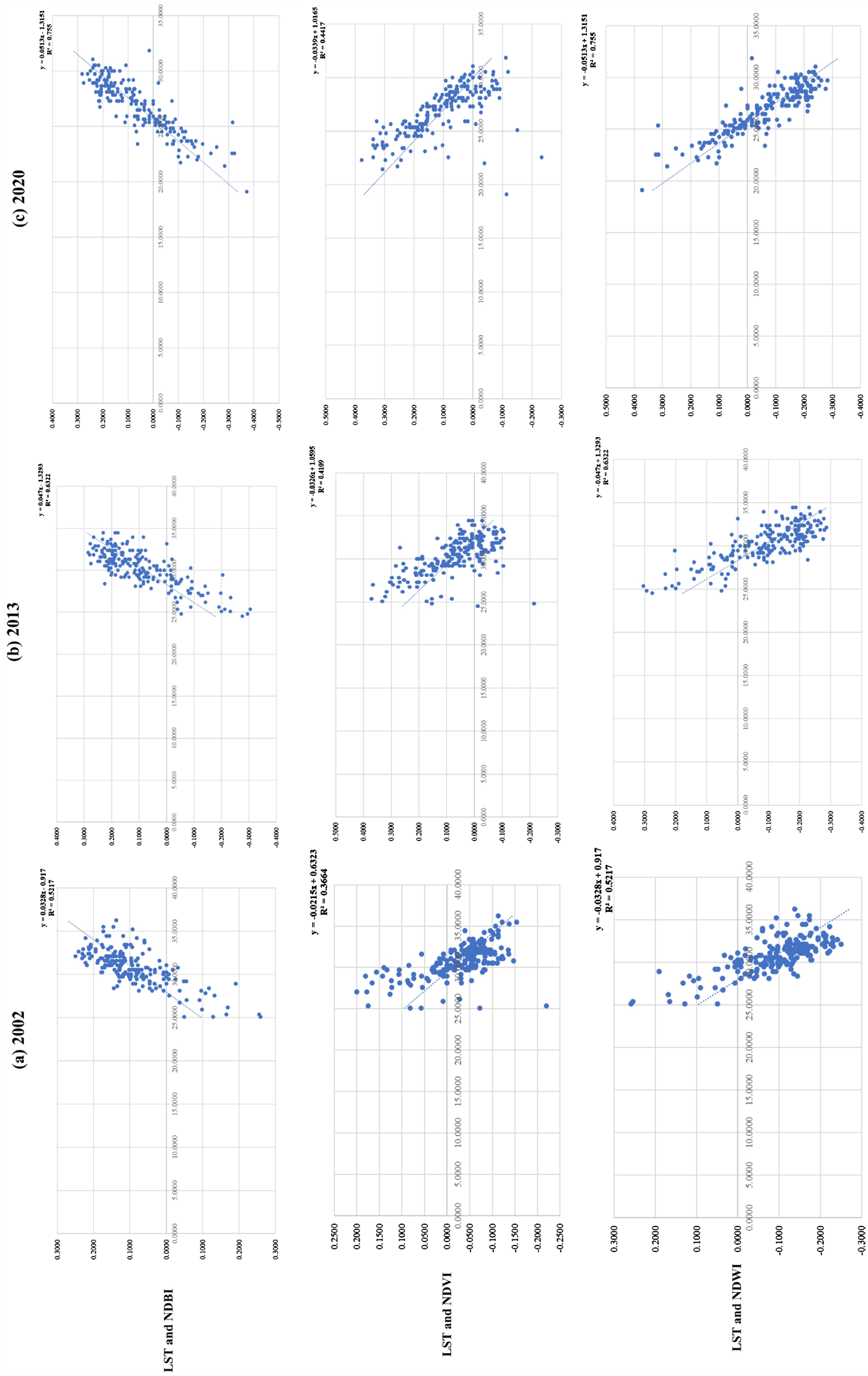

Figure 8. Temporal variations in the influence of land cover variabilities on the LST of the study region between 2002 and 2020.

take action in the framework of urban planning. The challenges lie in the duality of customary and modern land management systems but also in the approaches for urban planning and transformation. The discussions around the master plan of the Greater Accra region need to be taken forward in order for the public hand to ensure a better steering of the spatial development. Intra-city smaller and punctual landscaping projects might also have some effects on urban comfort.

4.4. Analysis of Growth Pattern of Built-Up through Shannon's Entropy

From Figure 3, it is seen that the built-up areas are increasing in the study region from 2002 to 2020. The study region is divided into five distance-based zones from the administrative center (Figure 9). The entropy values of built-up of 2002, 2013 and 2020 are found to be 0.8193, 1.5355 and 1.7035 respectively. The maximum entropy value with five zones is 1.6094 ($\log_e 5$). The entropy values keep increasing from 2002 to 2020 indicating that the urbanization is dispersive in nature in the study region. It could be seen that the zone 5 - 25 km away from the administrative center has the maximum urbanization of during the study periods 2010, 2013 and 2020 accounting to 51%, 43% and 46% respectively.

5. Conclusion

In the current study, the landuse/land cover changes of Greater Accra, Ghana in 2002, 2013 and 2020 were analyzed through multi-temporal Landsat 7 ETM satellite images. Results revealed that the area of built-up in the region in 2002 was observed to be 244.19 km^2 which quadrupled to 970.5 km^2 in 2020. Further, based on Shannon's entropy, the normalized entropy values for the study region were found to be 0.82, 1.54, and 1.7 in 2002, 2013 and 2020. This indicated that the region was undergoing dispersed or heterogeneous type of urban development.

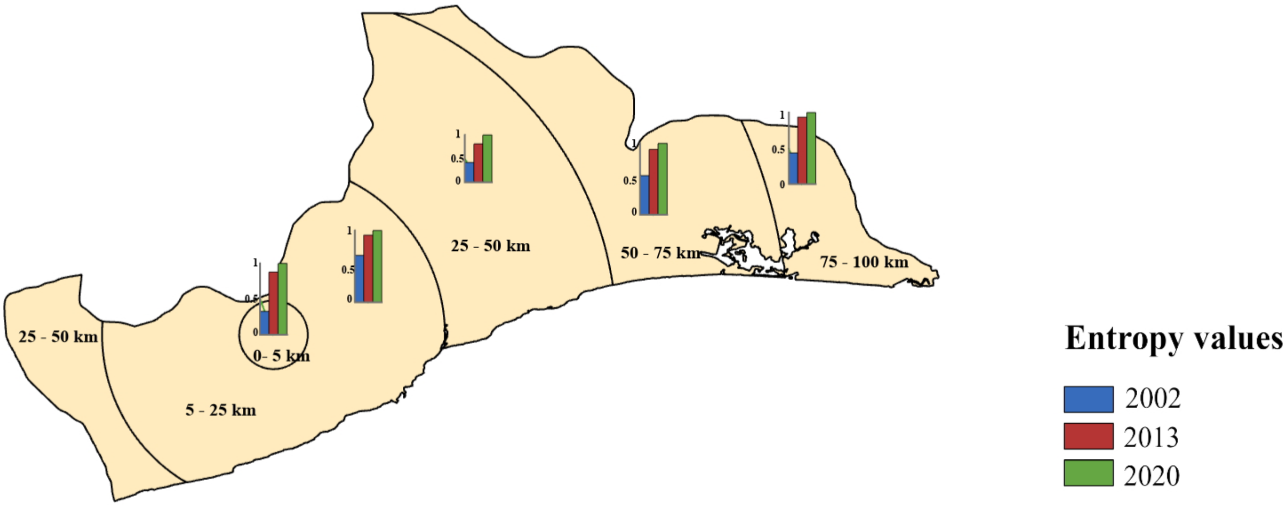

Figure 9. Entropy values of urbanization of the study region based for five distance buffer zones from the administrative center of the study region.

Land Surface Temperature (LST) maps of the study region prepared from the thermal band of the Landsat 7 ETM revealed that the average LST value of built-up was higher than the vegetation, waterbody and openland categories in 2002, 2013 and 2020. Further, regression analysis was carried out to find the relation between LST and the land cover variability indices including NDBI (Normalized Difference Built-Up Index), NDVI (Normalized Difference Vegetation Index) and NDWI (Normalized Difference Water Index) in the study region between 2002 and 2020. Based on the regression results, it was identified that LST exhibited a strong positive relation with NDBI whereas a negative relation was found associated between LST and NDVI, LST and NDWI. The results of this study are crucial information for urban planning that is supposed to provide urban comfort and protect the environment as well as the economic activities through the area and functions allocation. Courageous and urgent actions are needed to mitigate the adverse effects of climate change in the region.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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