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Nexus between Land Surface Temperature and Normalized Difference Vegetation Index in the Bole District in Ghana

Abigail Asare, Cynthia B. Boye and Peter E. Baffoe

University of Mines and Technology Tarkwa, Ghana

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ABSTRACT

Land surface temperature (LST) is the skin temperature of the ground which influences interactions between land surface and atmosphere through processes that play a key role in climate change at the local and global scales. Normalized difference vegetation index (NDVI) is most commonly used vegetation index to observe greenery globally. Accurate understanding of LST and NDVI at the local and regional levels is helpful to evaluate land surface and atmospheric exchange processes. This study analyzes the relationship between LST and NDVI in the Bole District in the Savannah region of Ghana using Landsat 7 ETM+ images for 2010 and 2020. ArcGIS software was used to process, classified the images using Maximum likelihood classifier, and to produce Land use land cover change (LULC) maps. Bands 3 and 4 were used determined NDVI, as well as the land surface emissivity. LST was determined from band 6 by converting the Digital Numbers to Top of Atmosphere radiance and then to reflectance in order to correct for satellite brightness with land surface emissivity as input. The results show that NDVI values vary with seasons, with less vegetation in the dry season and moderate vegetation in the wet season. From the LULC, LST and NDVI maps, areas with lower LST and higher NDVI values had more vegetation, while areas with medium and high LST and lower NDVI values were barren land or settlements. A strong positive correlation was found between NDVI and LST, except for the 2020 image, which had a weak correlation with LST. More vegetation was recorded in 2020 compared to 2010, possibly due to the government's tree planting campaign. Further research on LST and NDVI is recommended for the district to ascertain the findings of this study and to aid future environmental planning and to promote ecological comfort for sustainable development.

Keywords: NDVI, LST, LULC, Dry Season and Wet season

INTRODUCTION

Land surface temperature (LST) is the radiative temperature of the outer surface of the earth which is an important climate variable within the earth's climate system (Tariq *et al*., 2022). LST influences the interactions between the land surface and atmosphere through processes which play a key role in climate change at the local and global scales. These interactions, including exchange of energy and water between the land surface and atmosphere, affects the rate and timing of plant growth (Li *et al*., 2013; Osborne *et al*., 2007). Energy and water exchanges between the land surface and atmosphere also control surface water balance in soil that is absorbed by roots of plants. This in turn influences local climate as moist air retains heat longer than dry air (Betts et al., 1996).

Accurate understanding of LST at the global or regional levels helps to evaluate land surface and atmospheric exchange processes in models, which is beneficial for agricultural, ecological and meteorological processes on the earth surface. LST also allows for the calculation of latent heat flux, also known as evapo- transpiration, as well as sensible heat flux, which is connected to the transmission of heat between the terrestrial surface and the atmospheric boundary layer. LST is affected by seasons (Wet and Dry), land use land cover change (LULC) patterns and vegetation (Kafy et al., 2021; Gohain et al, 2020). The surface temperature of a region is connected to the reflective power of its surface features and the diffusion of electromagnetic energy emitted by the sun

(Almeido and Teodoro, 2016). Non-vegetative LULC types are known to absorb more heat energy compared with vegetative types; thus, LST of some localities turn to be inversely proportional to vegetation proportion in those regions.

Normalized Difference Vegetation Index (NDVI), on the other hand, is the most commonly used vegetation index to observe greenery globally (Oppong, 2021). The two indices (LST and NDVI) play an important role in the environment and their impacts include climate change, hydrological and agricultural processes, land use and land cover changes. In addition, the nexus between LST and NDVI has been used to confirm the hypothesis that human alteration of a region can influence the local climate (He and Silliman, 2019; Pielke et al., 2016) and hence the need to conduct studies in order to monitor and promote sustainability of the land ecology in different regions.

The Bole district is located in the savannah region in the northern part of Ghana with the Bole town as its capital. Over the years, the population of the Bole district keeps increasing thereby causing changes on the land use and land cover due to farming activities and indiscriminate felling of trees.

Urbanization accelerates the ecological stress by warming the local environment. Presently, many urban areas worldwide, are experiencing considerable land conversion from vegetative to non-vegetative classes which has resulted in the creation of heat zones. The Bole district, just like many other Districts in Ghana, is also facing similar environmental changes.

Remote sensing techniques are effective for detecting land use/land cover change and its consequences. Remotely sensed data has emerged as the primary data source for LST and NDVI estimation at various levels as it provides data with a high geographical and temporal resolution for thousands of locations simultaneously (Kuenzer et al., 2011; Palafox-Juárez et al., 2021).

Existing research on LST and NDVI such as Guha and Govil (2020), concluded that LST and NDVI are strongly negatively correlated (−0.51) with vegetation surface, moderately positive with water bodies (0.45), and weakly positively correlated with built-up area and bare land. Also, Ghobadi et al. (2014) and Guha et al. (2019) observed a negative LST-NDVI relationship in their studies. In Shanghai City, Yue et al. (2007) showed a negative LST-NDVI relationship as it varied on different LULC types. Sun and Kafatos (2007), stated that LST-NDVI correlation was positive in winter and vice versa during summer. Aduah et al. (2012), mapped LST and land cover to detect urban heat island effect at Tarkwa in the western region of Ghana, but made no attempt to consider the correlation between LST and NDVI. Annan *et al.* (2021) compared LST between two cities in Ghana using Landsat 8 imagery. Alademomi et al. (2020), in their study assessed the relationship among LST, NDVI and enhanced vegetation index (EVI) with land cover changes in the Lagos Lagoon environment. Stem and Kumi-Boateng (2020), and Devendran and Bannon (2015), also studied about urban heat island and land cover respectively. To the best of our knowledge, no studies on the relationship between LST and NDVI have been carried out for the Bole district of Ghana. Furthermore, in Ghana only few studies have considered the seasonal variations (dry and wet) in LST. This study therefore seeks to analyze the variation between LST and NDVI for both wet and dry seasons in the study area, and to explore how these changes provide information to support management of land use and environmental planning to promote sustainable development and improve the local climate of the savannah region.

BACKGROUND OF THE STUDY AREA

Bole town serves as the capital of the Bole district, situated in the Savannah Region of Ghana. The land area of the district is approximately, 4800 km^2 and it is located between latitudes 8° 30' and 9° 0' North and longitudes 1° 30' and 2° 30' West (Figure 1). The district is bounded by the Sawla, Tuna and Kalba district and the West Gonja district on the north, Kintampo North and Gonja Central on the east; Kintampo South and Banda on the south and southwest respectively, and the district shares common boundary with La Cote D'voire on the west. The district has a low-lying undulating topographic surface with elevation ranging from 180 to 366 m above mean sea level. The main drainage system for the district is surface water. Surface water resources in the district include a number of small streams, the Black Volta, 38 dugouts, and 6 dams that are used for irrigation of homes, farms, and subsistence needs (Anon., 2011).

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The district experiences irregular, unimodal rainfall that varies from 800 to 1200 mm annually. The rainy season begins in May and ends in October. Most of the land is guinea savannah, with a few short trees and grasses. The vegetation is dense to the south, where it borders the Brong-Ahafo Region, but it becomes thiner as it gets closer to the Sawla, Tuna, and Kalba district on the north (see Figure1.1). According to the Ghana statistical Service Report (2021), between 2010 and 2021 the Bole District experienced a population increase from 61,593 to 115,800 with an annual growth rate of 6% in 2021, which is about three times the national annual population growth rate in Ghana. The average population density of the district is 18.6 persons per square kilometer with 51.7% of the population being males and 48.3% females. Between 2010 and 2021, the urban areas of the district increase from 21% to about 34%. Agriculture is the district's main economic activity, employing more over 75% of the workforce (Anon., 2014).

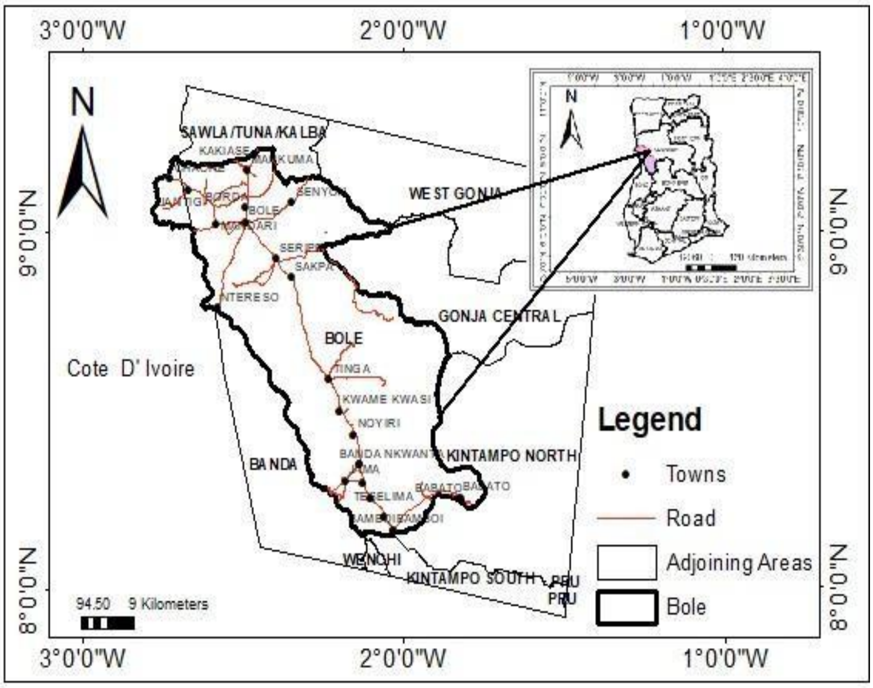

Figure 1.1 A Map of the Study Area

MATERIALS AND METHODS USED

The materials and methods were used are described in the sections below.

Data Used

This study employed secondary datasets. These include; Landsat images (Table 2.1) downloaded from the USGS Earth Explorer website. Topographic dataset of Ghana which was obtained from the Survey and Mapping Division of the Lands Commission of Ghana was also used (See Table 2.1).

The thermal, red, and near-infrared bands of the different Landsat images were utilized for the study.

Table 2.1 Satellite Data Acquisition

Year and Season	Space Craft ID	Sensor ID	Acquisition Date	Path	Row
April, 2010 Wet	LandSat 7	ETM	04-18-2010	195	054
December, 2010 Dry	LandSat 7	ETM	12-14-2010	195	054

April, 2020 Wet	LandSat 7	ETM	04-29-2020	195	054
December, 2020 Dry	LandSat 7	ETM	12-25-2020	195	054

Methods Used

The methods used to achieve the objectives of the study as described in the flowchart in Figure 2.1.

LST and NDVI Maps

The Red and Near Infra-Red bands (NIR) of both 2010 and 2020 Landsat imagery were used to estimate the NDVI of the study area. The bands were converted from the Digital Number (DN) to Top of Atmosphere (TOA) radiance and then to reflectance, using the respective equations to correct for the satellite brightness and then the composite images were created for both years (pre-processing of Landsat images). Equation (1) shows the conversion of Digital Number (DNs) to at –Sensor Spectral Radiance (Lλ) for Landsat ETM+ data.

$$\mathbf{L}_{\lambda} = \frac{(\boldsymbol{LMAX}_{\lambda} - \boldsymbol{LMIN}_{\lambda})}{(\boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MAX} - \boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MIN})} \times (\boldsymbol{Q}_{\boldsymbol{CAL}} - \boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MIN}) + \boldsymbol{LMIN}_{\lambda} \qquad (1)$$

Where $\mathbf{L}_{\lambda}$ is the Top of Atmosphere (TOA) spectral radiance (Wm^2 sr1 mm1), $\boldsymbol{Q}_{\boldsymbol{CAL}}$ is the quantized calibrated pixel value in DN, $\boldsymbol{LMIN}_{\lambda}$is the spectral radiance scaled to $\boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MIN}$, and $\boldsymbol{LMAX}_{\lambda}$ is the spectral radiance scaled to $\boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MAX}$. $\boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MIN}$ and $\boldsymbol{Q}_{\boldsymbol{CAL}}\,\boldsymbol{MAX}$ are the minimum and maximum quantized calibrated pixel values in DN, respectively (Guha and Govil ,2020).

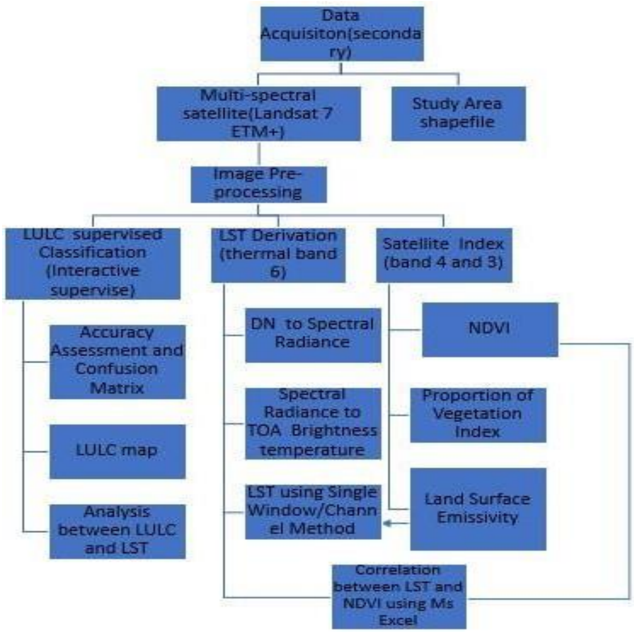

Figure 1.1 A Flow Chart Showing the Methods Used

The conversion from Spectral Radiance $L\lambda$ to At-Sensor Top-Of-Atmosphere Reflectance $\rho\lambda$ for Landsat ETM+ data is shown in equation (2).

$$\boldsymbol{\rho}\lambda = \frac{\boldsymbol{\pi} * \mathbf{L}\lambda * \mathbf{d}\,\hat{}\,\mathbf{2}}{\mathbf{ESUN}\lambda * \mathbf{cos}\theta\boldsymbol{s}} \qquad (2)$$

Where π = 3.14159

$ESUN\lambda$= ESUN values, $cos\theta s$= cos of Solar Zenith Angle (θ),

d= Earth–Sun distance (d)

$L\lambda$= the radiance bands calculated previously

The Normalized Difference Vegetation Index (NDVI) is standardized way to measure health of vegetation as

green plants reflect near infra-red and absorbs red light. NDVI was calculated for the various years, using equation (3) as shown below.

$$\textbf{NDVI} = \frac{(\textbf{NIR} - \textbf{Red})}{(\textbf{NIR} + \textbf{Red})} \qquad (3)$$

With the Landsat 7, the near-infrared (NIR) band corresponds to band 4, and the red band (Red) corresponds to band 3. NDVI ranges from -1 to +1.

Creating the LST Map

The LST map was generated from the thermal bands of the Landsat images acquired. The thermal band for Landsat 7 is band 6. The thermal band was converted from the Digital Number (DN) to Top of Atmosphere (TOA) radiance to make correction for the satellite atmospheric errors using equation (1) and then converted into the satellite temperature brightness using equation (4).

$$\boldsymbol{BT}\ (°\mathrm{C}) = \left(\frac{\boldsymbol{K2}}{\ln(\frac{\boldsymbol{K1}}{\mathrm{L}\lambda}+1)}\right) - \mathbf{273.15} \qquad (4)$$

Where;

BT ºC = satellite band temperature in degree Celsius,

$L\lambda$= the radiance bands calculated previously

K1 and K2 are Temperature constant values from the meta data related to the Landsat 7 satellite.

The satellite band temperature is then used in the single window method (equation (5)) to estimate the LST for the acquired Landsat images.

$$\boldsymbol{LST}\ (°\mathrm{C}) = \frac{\mathbf{BT}°\mathrm{C}}{\mathbf{1}+\boldsymbol{W}*(\frac{\mathbf{BT}°\mathrm{C}}{\boldsymbol{\rho}})*\mathbf{ln}(\boldsymbol{e})} \qquad (5)$$

Where;

LST =Land surface temperature in degree Celsius

BT ºC = satellite band temperature in degree Celsius

W= wavelength of emitted radiance (thermal band)

$\boldsymbol{\rho} = \boldsymbol{h} * \frac{\boldsymbol{c}}{\boldsymbol{s}}$ = 1.4388 ∗ 10−2 m K = 14388 μm K

h= Planck’s constant = 6.626*10-34 J s

s = Boltzmann constant =1.38*10-23J/K

c= velocity of light = 2.998*108m/s

e = land surface emissivity = 0.004PV + 0.986

where PV =Proportion of vegetation = (NDVI-NDVI min /NDVI max-NDVI min)2

Nexus between LST and NDVI

The LST and NDVI of the study area was used for correlation analysis to examine how relationship between LST and NDVI varies for dry and wet seasons in the years 2010 and 2020. Linear regression analysis of the scatter plots of the two seasons were analyzed for the corresponding years under study. Equation (6) was subsequently used to measure and analyze the variables using Pearson's correlation coefficient (r).

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})*(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2} * \sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \qquad (6)$$

where x stands for the independent variables measuring the value of x_i; y stands for the dependent variable measuring the value of y_i; x_i and y_i stand for the individual sample points indexed i and $\bar{x}$ and $\bar{y}$ stand for the mean of the samples. r stands for the Pearson's correlation coefficient.

Land Use Land Cover Influences on LST

When the terms "Land Use" and "Land Cover" are used combined, it often refers to the grouping or classification of human activities and natural elements on the landscape throughout a certain period of time using recognized scientific and statistical methods of analysis of pertinent source materials (Jansen and Di Gregorio, 2002). At the local, regional, and national levels, LULC maps are crucial to the design, management, and monitoring of programs. On the one hand, this information aids in a better understanding of land utilization issues, and on the other, it is also crucial in the establishment of the policies and programs needed for development planning. However, land use land cover has positive and negative influence on the LST of a particular geographical area (Hussain et al., 2022).

The land use land cover maps in this study were created by compositing the Landsat bands with the exception of the thermal band after all the corrections were done using equations 1 and 2 to produce the map with help of the ArcGIS software. Interactive supervised classification was done by creating signature file for the ground types consisting of water bodies, bare lands and settlement and vegetation by digitizing the area that represent their pseudo natural colours in the composite band to create the final land use land cover map.

Table 3.1 Spectral Bands Colour

Ground Cover Types	Pseudo Natural Colour (7,4,2) Representation
Vegetation/ Crops	**Shades of green**
Water	**Black to dark blue**
Settlement / Bare Soil	**Lavender /pale pink**

(Source: Mantey, 2020)

Representation

The error matrix computed from the accuracy assessment points, which displays properly and wrongly identified pixels of the ground types and was used to evaluate and validate the accuracy evaluations for each season using the Kappa coefficient

RESULTS AND DISCUSSION

Temporal Variation of NDVI from 2010 and 2020 for both Seasons

Figure 3.1 shows the results obtained from the NDVI patterns for 2010 and 2020 wet and dry seasons respectively.

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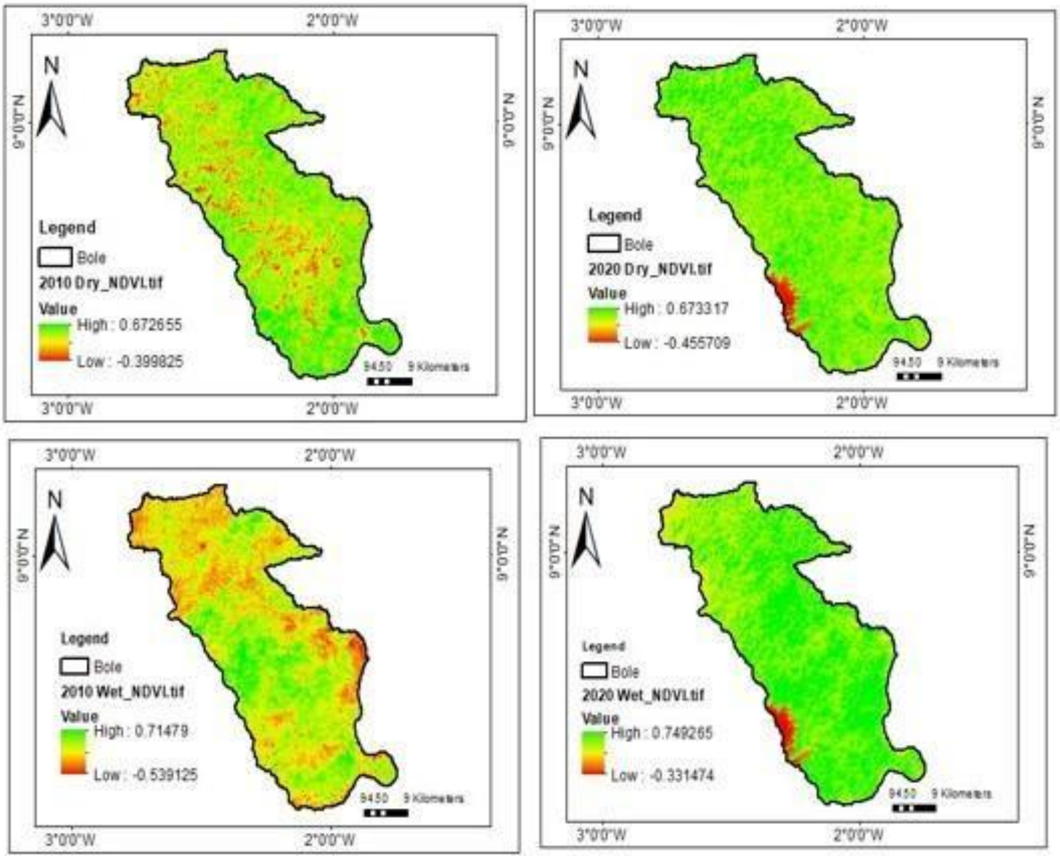

Figure 3.1 NDVI Patterns for 2010 and 2020 Wet and Dry Seasons

The NDVI values obtained ranges between -1 and +1 which detects the presence of green vegetation and quantifies the health status. From Figure 3.1, the green colour shows area with high NDVI index values which indicates presence of vegetation, the yellow to red colour (NDVI<0.33) represent no or dead plants or unhealthy plants in the area. During the dry season in 2010, the NDVI values for the study area ranges from - 0.40 to + 0.67 with a mean value of 0.27 which generally indicates unhealthy vegetation status. Similarly, the NDVI values determined for the dry season in 2020 has a mean of 0.22 which corresponds generally to unhealthy plant status in the study area. This gives an indication that there is generally stunted plant health during the dry season with scanty rains in the area.

The NDVI values determined during the wet season for 2010 ranges from -0.54 to +0.72, with a mean vaue of 0.39, whereas the NDVI values for 2020 in the wet season range between – 0.33 to + 0.75 with a mean value of 0.47. This exhibits a general moderate health condition of plants in the area. The yellow colour which represent crops and the green colour represent relatively denser vegetation which are evenly distributed. The red portion shows the minimum values which corresponds with water bodies as shown in the land use land cover map in Figure 3.5. The northern part of the study area falls within the low to medium values of the NDVI index. A quick look at the 2020 image taken during the dry and wet seasons respectively show that there was not much difference in the NDVI index values. The change in vegetation, crops and bare lands or settlement was minimal. Comparing the mean NDVI values obtained for the 2010 and 2020 images taken during the wet season, there is an improvement in the health status of vegetation for the 2020, this improvement could be attributed to the afforestation programs organized by Government to plant more trees in the country. The study has demonstrated that changes have occurred in the vegetation cover of the study area over the ten-year period of the study. Plant health status, which is portrayed in the amount of light reflected in the visible and near-infrared bands by vegetation, varies with changes in the seasons. During the dry season some of trees shed their leaves (deciduous) as an adaption to the climatic conditions in the study area.

The confusion matrix accuracy was found to be ranging from 97 % to 99% with a kappa accuracy range of 94% to 98%. The overall accuracy rates were above 90%, indicating a trustworthy land use land cover classification and strong agreement between classified maps and referenced maps of both seasons of the year 2010 and 2020.

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Table 4.1 NDVI Index Statistics

Season of the year	Minimum value	Maximum value	Mean value	Standard deviation
2010 dry	-0.3998	0.6727	0.2746	6.6911
2020 dry	-0.4557	0.6733	0.2192	9.1196
2010 wet	-0.5391	0.7148	0.3867	8.1206
2020 wet	-0.3315	0.7490	0.4732	0.1121

LST for 2010 and 2020

Figure 3.2 shows LST for the 2010 and 2020 for wet and dry seasons respectively.

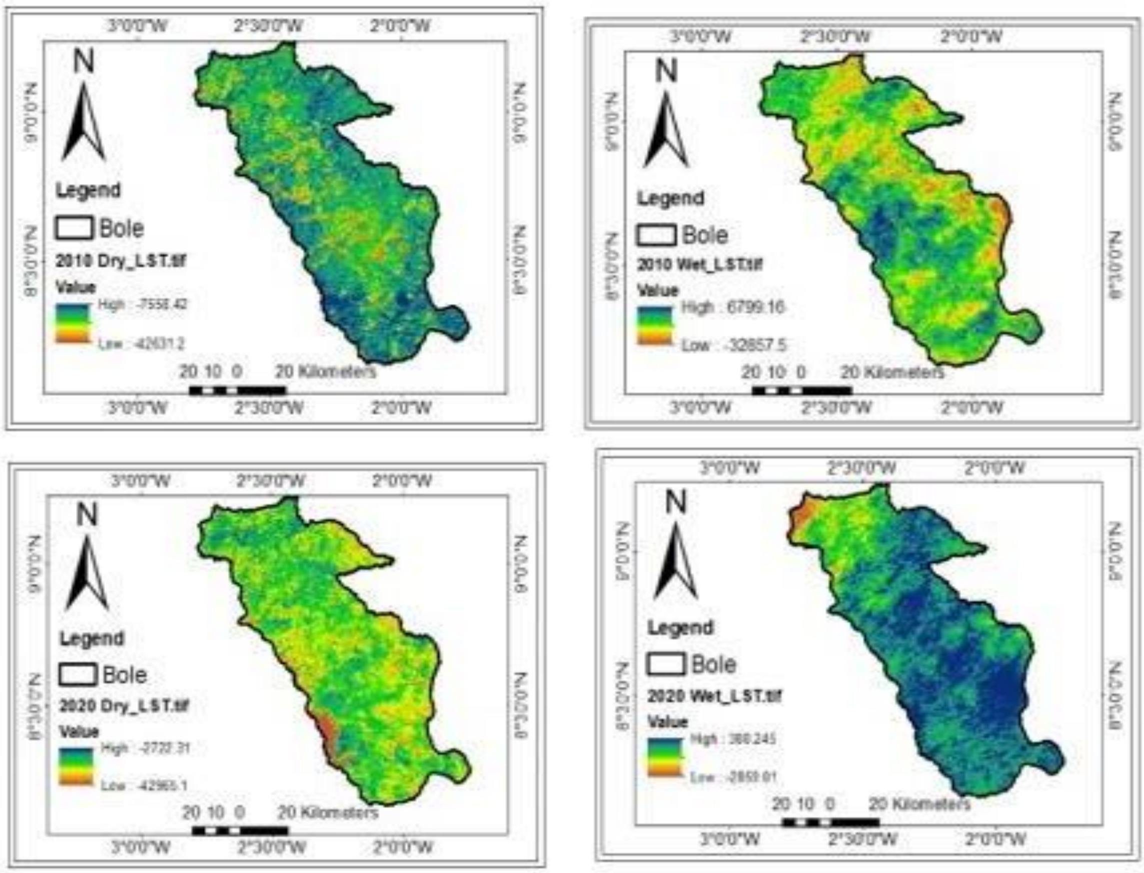

Figure 3.1 Maps Showing the Variation of LST Patterns for 2010 and 2020 Wet and Dry

From Figure 3.2, the green to dark blue colour indicates areas with high LST values, yellow to green colour is the area with medium LST values and brown to yellow colour represent areas with the least values of LST. The LST values determined for 2010 in the dry season ranged from-42631.2 to -7558.42 ℃ with a mean value of -24232.14 ℃ , whiles the value determined for 2020 also range from-42965.1 to -2722.31 with a mean value of -24163.06 ℃ . The negative values of LST connotes areas with non- vegetation. Thus, the effect of vegetation become recessive whereas other LULC types such as water bodies and bare lands or settlement become dominant during the dry seasons.

On the other hand, during the wet seasons (2010), the LST values stretches from -32857.5 to 6799.16 ℃ **(**degree Celsius) with the mean value being 3576 ℃ (degree Celsius) whereas in 2020, the LST stretches from -2859.01 to 380.245 ℃ with a mean value of 312 degree Celsius. More than half of the study area recorded high values of

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LST with small portion in the northern part of the study area falling recording low to medium LST values. A quick analysis with its corresponding NDVI maps in Figure 3.1 shows that where there is relatively dense vegetation or high value of NDVI index values has low to medium LST values and where there is bare land or settlement or places with low to medium NDVI index values corresponds to medium to high LST values. The differences between the LST maps for the years 2010 and 2020 for the two seasons show how the LST of the study area is been influenced by the NDVI and also indicates the difference in the LST of the study area.

Table 4.2 LST Index Statistics

Season of the year	**Minimum value**	**Maximum value**	**Mean value**	**Standard deviation**
2010 dry	- 42687.22	-7558.42	-24232.14	3109.06
2020 dry	- 42965.12	-2722.31	- 24163.06	3488.87
2010 wet	- 3287.52	6799.16	-8207.41	3576.19
2020 wet	-2859. 01	380.25	-459.15	312.30

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Relationship between NDVI and LST for Various Years and Seasons

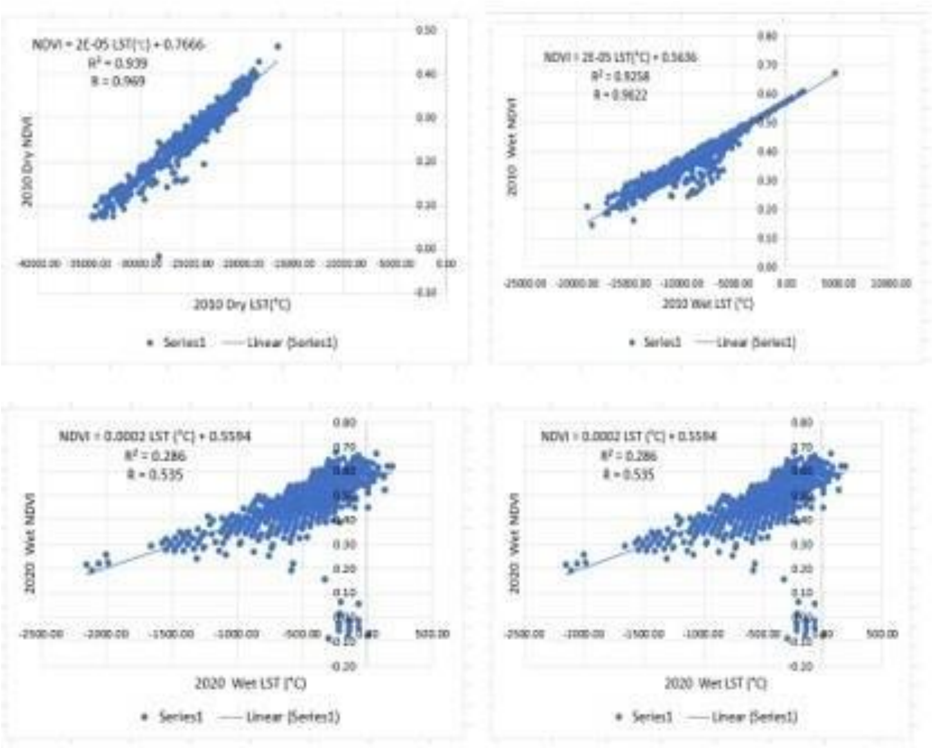

Figure 3.3 Map Showing the sample points of LST and NDVI values for the 2010 and 2020 Wet and Dry respectively.

Figure 3.3 is a Map Showing the sample points of LST and NDVI values for the 2010 and 2020 images taken during the Wet and Dry respectively. The values of NDVI and its corresponding LST values for the years 2010 and 2020 of the two seasons were derived using the sample point generated. Figure 3.4 also shows a scatter plot of NDVI values against the LST values and a linear model fitted for the 2010 and 2020 images taken during the Wet and Dry respectively

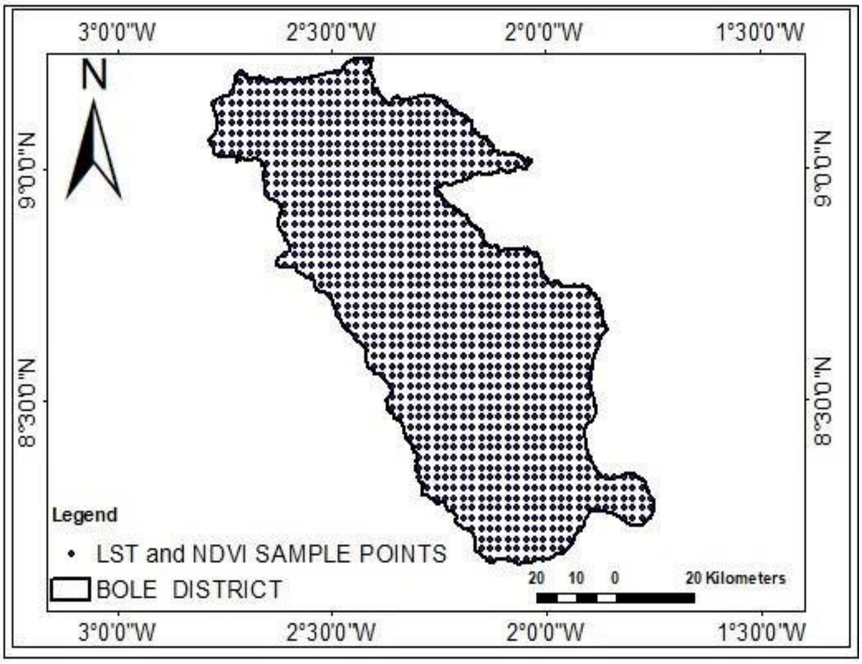

Figure 3.4 Graph Showing the Relationship Between Sample Points of LST and NDVI for 2010 and 2020 for both seasons

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From Figure 3.4, it is clear that as the values of NDVI increases, the LST also increases accordingly for the 2010 and 2020 images taken during the dry season. The linear equation shows a very strong correlation between LST and NDVI for the 2010 image taken during the dry and wet seasons for the study area. This implies over 93% of the variations in the NDVI is accounted for by the LST values during the dry and wet seasons in 2010. Similarly, as the NDVI values increases, the corresponding LST values also increases for the 2020 image; however, strong positive correlation exists between the NDVI and LST for the 2020 image taken during the dry season whereas a weak positive correlation exists between the NDVI values and the corresponding LST values for the 2020 image taken in the wet season. This indicates that only about 50% of the variation in the NDVI is explain by variations in the LST of the wet season. factors such as other LULC types example bare land, settlement also can contribute to the variations in the NDVI. It can therefore be deduced from the result obtained that NDVI may have direct or indirect relationship with the LST depending on the geographical location's conditions like weather seasons. However, anthropogenic activities in the study area may also contributes considerably to the LST produced in a district.

Land Use Land Cover Effects on LST

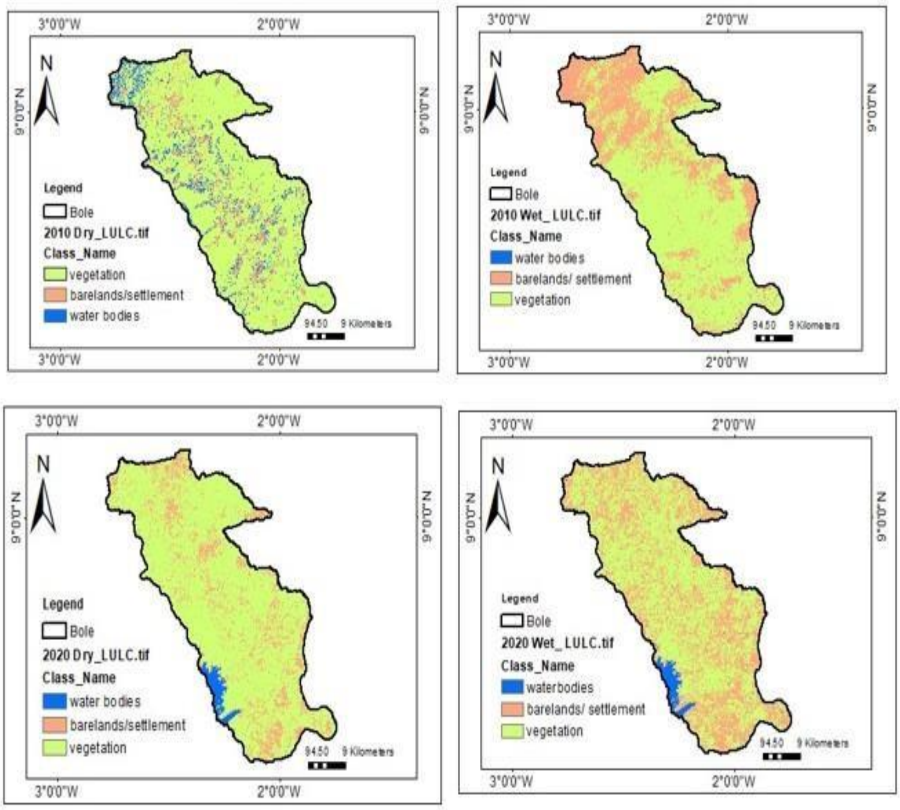

Figure 3.5 Maps of LULC for 2010 and 2020 Wet and Dry

Figure 3.5 shows the LULC maps for the years 2010 and 2020 taken during the wet and dry seasons respectively. The LULC maps were classified into three ground cover types namely; water bodies or wetlands, vegetation or crops and bare lands or settlement using interactive supervised classification. From Figure 3.5, the green colour shows vegetation which stands for relatively dense vegetation and crops, the blue colour represent water bodies and wetlands and the peach colour indicates bare lands or settlement. A close comparison of Figure 3.5 to Figure 3.1, Figure 3.2 and Figure 3.4, it can be deduced that areas with vegetation or crops have medium to high values of NDVI index values as shown in Figure 3.1. Similarly, in Figure 3.2, area with vegetation or crops have medium to low values of LST which correspond with Figure 3.4. This can be attributed to high evapotranspiration of the vegetation as vegetation absorbs and reflects sun rays to cause cooler or lower temperatures leading to cool island effect which may provide ecological comfort zone. Also, areas with bare lands or settlement were seen to be having low to medium NDVI index values in Figure 3.1 and medium to high LST values in Figure 3.2 as there are no vegetative cover at those portions of the study area to absorb and reflect sun rays, causing high temperatures in such zones and this can lead to urban heat island or zones which may affect the environmental quality and the health of the inhabitants if not controlled. This can prevent ecological zone comfort of the inhabitants.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The study has analyzed the relationship that exists between LST and NDVI in the Bole District of Ghana and further explored these variations during the dry and wet seasons for a ten-year period. The study has shown that variation in the patterns of LST and NDVI in the Bole district differs with the seasons - the dry seasons recording less values compared to the wet seasons for the study area. On the average, less vegetation was detected during the dry seasons in 2010 and 2020 compared to their corresponding values recorded in the wet seasons. The status of the plants was unhealthy while those recorded during the wet season were in moderate health condition. The mean value of NDVI recorded increased from 2010 to 2020, which gives an indication of conscious afforestation program of Government in the region or the effect of education for tree planting activities in the Savannah region. However, no significant variation was obtained in the mean values of NDVI measured for the dry season in 2010 and 2020.

The NDVI values determined for the district during the dry seasons were largely positive (medium to high) values which connotes areas with vegetation. On the other hand, the average NDVI values determined for the district during the wet seasons were positive (medium to high) values which shows presence of vegetation in the district in the year 2020 but in the year 2010, the NDVI values ranges from medium to low values denoting less vegetation in the district as at the year 2010.

Very strong positive correlation exists between NDVI values and LST for the study area, except for the 2020 image for the wet season where the relation was weak.

Areas which were mapped to have more vegetation were areas with lower LST values and higher NDVI values but the areas mapped to have bare lands or settlement were areas with medium to high LST values and lower NDVI index values respectively.

Recommendations

It is recommended that more research work be carried out in the study area using other methods such as artificial neural networks and machine learning to model the relationship between the LST and NDVI. In addition, state institutions should intensify afforestation programs and projects started by Government to protect the environment through effective planning in order to sustain life on the land for sustainable development and public ecological zone comfort. Also, strict laws should be enacted and enforced to regulate anthropogenic activities that tends to degrade the environment and prevent the negative impact of LST such as heat zones to promote sustainable life on land.

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AUTHORS

Abigail Asare is a Graduate of the University of Mines and Technology, Tarkwa. She is a teaching assitant at the Geomatic Engineering Department of UMaT. She is a student Member of Ghana Institution of Surveys. Her research interest is in Application of GIS and Remote Sensing for Environmental monitoring.

Cynthia Borkai Boye is an Associate Professor of Geomatic Engineering Department at the University of Mines and Technology, Tarkwa, Ghana. She holds BSc in Geodetic Engineering from KNUST, Professional Masters in GeoInformatics from ITC Netherlands and a PhD from the University of Ghana, Legon. Her research interest include Shoreline Change Modelling and Prediction, GIS Applications, Fluvial Sediment Analyses and Prediction, Application of Remote sensing in Environmental studies. She is a fellow of WWAIM, member of Ghana Institution of Surveyors, Ghana Institution of Engineering, and a member of the Association of Licensed Surveyors.

P. E. Baffoe is currently an Associate Professor at the Department of Geomatic Engineering, University of Mines and Technology. He holds PhD degree (Geomatic Engineering) from University of Mines and Technology. His research interests include Monitoring, Prediction and Modelling of Noise Levels, application of GIS in Environmental issues, 3D Modelling, Digital Photogrammetry and Mine Surveying.