



# Class dynamics and relationship between land-use systems and surface temperature in south-eastern Ghana

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## Abstract

A fifty-year study of land cover changes in Ghana's south-eastern region is conducted to identify major shifts and new avenues for justifiable growth and development. This study sought to assess the historical changes (1970–2020) associated with the region's land use systems, topography and land surface temperature. It further investigated the relationship between some given remotely sensed variables using autocorrelation and geoinformatics. Findings proved socio-political and economic factors have caused massive shift in land cover and prevailing climatic conditions through increasing settlements and migration, the extensiveness of agriculture, poverty, unregulated and unreported logging of trees, small-scale mining intensification, and weak governance systems. We discovered that the natural vegetation had dramatically reduced (– 52.01%), whilst built-up (+ 406.05%), farmlands/shrubs (+ 86.47%), and waterbodies (+ 47.35) were faced with a drastic increase. Class contribution rates show built environment massively influenced land modification, compared to other surveyed classes. In light of the major influences observed, it can be concluded that dynamics in land-use systems caused a substantial drift in local temperature. Temperature and built-up index correlated strongly ( $R^2=0.959$ ,  $p < .0001$ ), whilst depicting a negative association against vegetation ( $R^2=0.959$ ,  $p < .0001$ ) and water index ( $R^2=0.958$ ,  $p < .0001$ ). Variance assessment proved that the linear correlation model for the understudied elements is suitable. The study provides policy guidance amid sustainability concerns on streamlining land use activities in development planning and preservation of forests and river ecosystems that protect flora and fauna to enhance biodiversity and sustainable use of land and water resources.

**Keywords** Contribution rate · Volta River Basin · Driving forces · Land use · Slope analysis · Ghana

## Introduction

Like most developing countries, Ghana is making gains towards structural transformation; thus, moving from a raw to a well-industrialized economy. This extensive economic drive is catalyzed by increasing population, commercialization and extensiveness in agriculture, thereby amplifying the competition for essential resources like land. Competing interests among relevant stakeholders are tied to several needs, leading to the transformation of one form to the other. In simple terms, land use is classified as human activities, and the multifarious purposes which takes place on land. Land cover, on the other hand, entails pristine environments, man-made cover, among other features, observable over the

land. “Land Use Cover Change (LUCC)” is imbibed in two main components; thus, modification and conversion. As the name suggests, conversion involves changing one feature to another, whereas modification is maintenance of the broad cover while effecting changes to its attributes (Prakasam 2010). Land cover is more obvious to notice than land use, as the term denotes the surface cover over the land. Ellis and Pontius (2010) define land cover as “the physical and biological cover over the surface of land, including vegetation, water and bare soil.” Some scientists delineate some man-made designs as “land cover.” Conversely, different scientists have developed several meanings from “land use”, considering its complexity. As explained by Prakasam (2010), the term could describe how land surface is used to sustain agricultural activities, forestry, and construction works, while social scientists define it as how the land is used essentially for socio-economic gains (Ellis and Pontius 2010).

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On global, regional, and local scales, LUCC plays an important role in climate variation. By disrupting terrestrial soils and vegetation, LUCC can amplify atmospheric CO<sub>2</sub> concentrations (Ellis and Pontius 2010). Some researchers posit that most cities across the globe are faced with urban temperature rise, as a result of rapid urbanization (Zhu et al. 2012; Wang et al. 2016). Urbanization results in the amplitude of buildings in cities, people and road networks. Currently, the world's population is being sensitized about the long-term threat of LUCC on food, water, air and energy resources. For instance, Ogou et al. (2022) in their study entitled "Hydro-climatic and water availability changes and its relationship with NDVI in Northern Sub-Saharan Africa" discovered water resources in the region were subjected to increasing temperatures, which adversely affected the diversity and productive shifts of several ecosystems. Recognizing the consequences of historical, present and prospective trends of the diverse uses of environmental resources remain crucial in the application of theoretical knowledge, linked to the underlying concepts of this study. Global population has been projected to hit 9.7 billion between 2020 and 2050. The United Nations Department of Economic and Social Affairs/Population Division (2014) assumes 40% of Africa's population are urban dwellers. Several scholars (Kpare 2016; UN 2015; Amproche et al. 2020; Ampim et al. 2021) opine that population growth is critical to LUCC and sustainable development in least developed countries.

Comparatively, Ghana's Statistical Service (GSS) (2020) report revealed a 2.2% growth rate with a higher proportion of its population, residing in urban centers. South-eastern Ghana possesses peculiar natural characteristics that positively influence several livelihoods and micro-climatic conditions. It houses the highest peak in Ghana, Mountain Afadjato. Again, a quarter of Ghana's high forest zone, wildlife/natural reserves, along with the largest river basin in West Africa (i.e., the Volta River Basin), Keta Lagoon (recognized globally as a RAMSAR site), Densu, Birim, Afram and Ayensu rivers lie in this area. Due to the unique biological characteristics of the study setting, diverse conflicting interests in the utilization of natural capital have arisen. Additionally, the study domain presents several attractions to the citizenry and international folks. The domain's contribution to Ghana's Gross Domestic Product (GDP), coupled with the direct and indirect benefits trickled down to the indigenes cannot be overlooked. That said, information about the overall ambience of land use development and the interrelationship between some land use features and surface temperature, among other climatic variables in South-eastern Ghana is rare.

Modern techniques such as Geographic Information Systems (GIS), Principal Component Analysis (PCA), ratioing and image differencing, Artificial Neural Network (ANN), post classification, and Decision Trees (DTs) have been

applied in various studies on different scales. To quantify some remotely sensed indices, coupled with ascertaining some core and potential drivers and implications of LUCC over a range of geographical and temporal dimensions, a multidisciplinary collection of physiological and socio-scientific approaches remain paramount. Addo et al. (2019) analyzed forest resource use trends, mapped out preserved areas, and proposed measures to sustain large scale plantations amidst increasing activities in and around the Volta River Basin. Amproche et al. (2020) elucidated land use and land cover (LULC) within the Black Volta Basin between 2000 and 2018 using multi-spectral imagery. They revealed four land features had experienced massive decline, except barren areas and settlements which experienced immense change. Kpare (2016) explored the implications of deforestation on livelihoods around the Red Volta East Forest Reserve, whilst Kyere-Boateng and Marek (2021) argued that Deforestation & Forest Deforestation (D & FD) are caused by several demands tied to different needs. They acknowledged that despite the initiation of several ministerial policies and interventions to avert this trend, the ultimate purpose of ensuring sustainable use and management of forest resources had not been realized. Purwins (2020) revealed the government of Ghana considered the open and close vegetative regions as key resources, symbolized to propel job creation and industrialization, whilst the environmentalists viewed the forest as a way to supply conservation benefits. Standpoints in early studies revealed problems identified in South-eastern Ghana cannot be examined narrowly, but require an in-depth review of socio-cultural, economic, political and environmental factors that cumulatively led to the drastic shift and undesirable experiences, faced today. Calls for further studies that extensively utilize geospatial technology to detect and explore changes at the various levels have persistently gained grounds. Again, emphasis on the need to analyze issues from a sociological standpoint through a systematic assessment of major influences, conditions, ramifications, and reactions from different angles are targeted at addressing these bottlenecks inclusively.

This paper draws on these knowledge gaps and opportunities identified in existing land use studies in South-eastern Ghana, and beyond to establish its research objectives. Ultimately, this research sought to assess the historical changes (1970–2020) associated with land use systems, topography and land surface temperature in South-eastern Ghana. The task of developing reliable future LUCC models in the study domain and Ghana to a large extent, is further complicated by limited accurate baseline data on vegetative cover, water, barren and built-up areas. Hence, the necessity and timeliness of conducting this study. Our study attempts to (1) provide a comprehensive analysis on the major drivers influencing LUCC in South-eastern Ghana (2) investigate class contribution rates in vegetative, water and built-up indices

against land surface temperature (3) conduct slope analysis considering the physiological nature of the area, and (4) establish a spatial relationship between the given variables using autocorrelation analysis.

## Methods

### Geographical settings

The study was conducted in South-eastern Ghana. It occupies about 39,893 km<sup>2</sup> within latitudes 6.812052°N and longitude 0.060734°W. It hosts three administrative regions as illustrated in Fig. 1 (see appendix A). Agriculture, commercialisation and tourism remain the predominant activities in the domain. It is characterized by tropical climate with an annual average temperature range of 21–32 °C, with marshy and mangrove swamps along its low-lying coastal plains, semi-deciduous forest and savanna woodland at the center and Guinea savanna in its northern zone. It hosts Ghana’s main mountains constituting Mountain Afadjato (885 m), the tallest peak, the Kwahu Mampong scarp (788 m above sea level), the Atiwa-Atwaredu ranges (731 m), the Akuapem

highland (466 m) and the isolated Krobo and Yogaga mountains. Some mineral deposits in the domain consist of gold, diamond, bauxite, limestone, kaolin and clay. Soils and micro-climatic conditions in the domain are favorable for the cultivation of food and cash crops like cocoa, rice, palm oil, cola-nut and cassava. The region (Fig. 1) houses part of Ghana’s high forest zone in its mountainous areas, notably the Atiwa-Atwaredu, Akuapem, Krobo and Shai extensive ranges of forest highlands.

The population growth and distribution for the study area are presented in Table 1 and Figs. 2 and 3.

\*\*\* Oti region = separated from the Volta region of Ghana in 2018. For the purpose of analysis and clarity, we merged the population of Volta and Oti regions for 2010 and 2020. (Total population for Oti region ~2010 = 605,725; 2020 = 759,799). The annual percentage growth rate (APR) was expressed as:

$$APR = \left( \frac{V_{Present} - V_{Past}}{V_{Past}} \times 100 \right) \div N_{Years} \tag{1}$$

Where; APR = The annual percentage growth rate, V<sub>present</sub> = Present or future value, V<sub>past</sub> = Past value or base

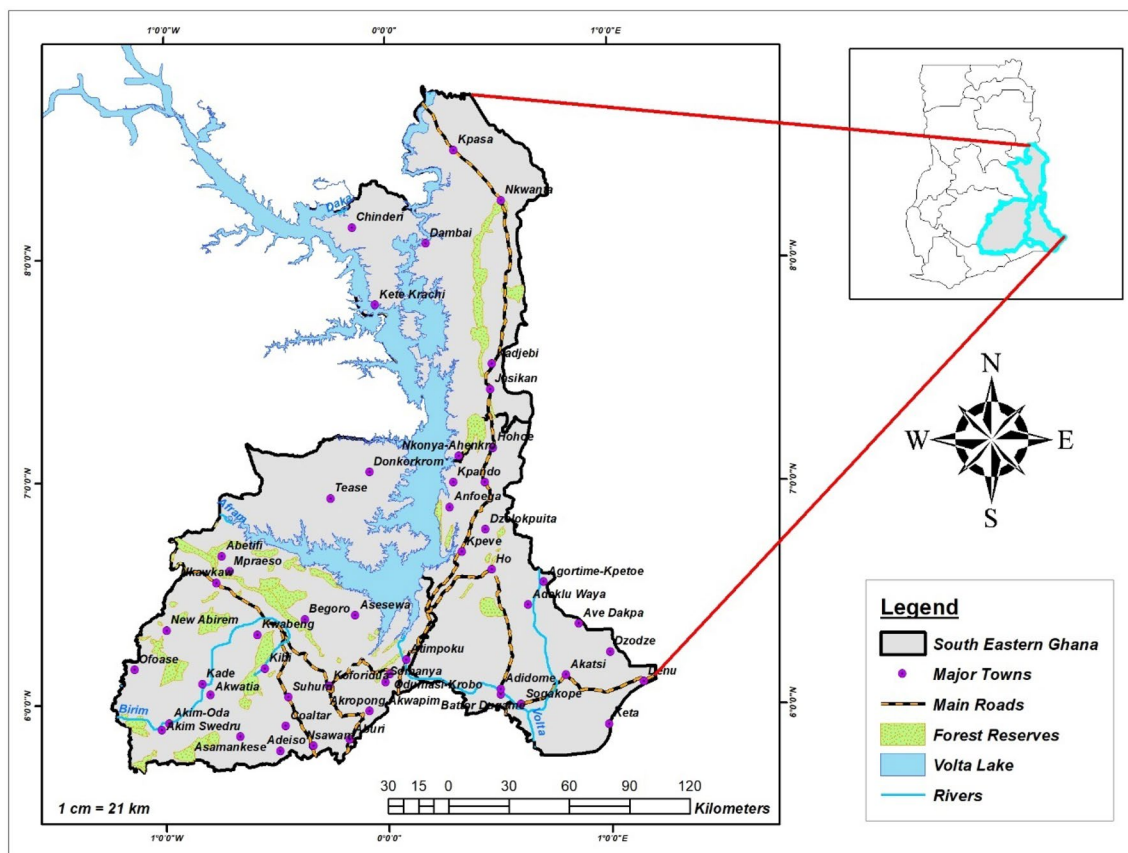
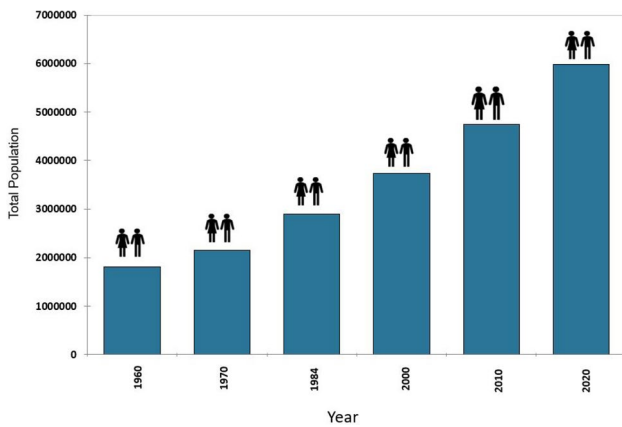


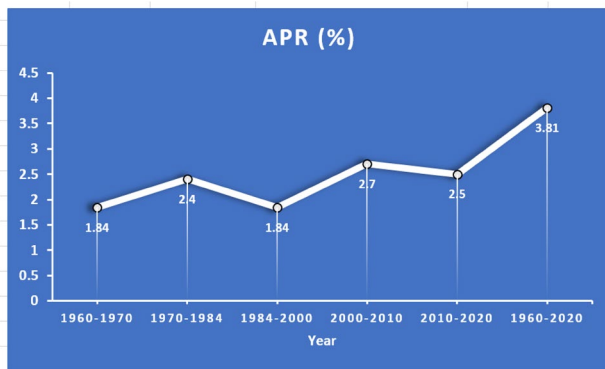
Fig. 1 Geographical location of South-eastern Ghana

**Table 1** Population growth statistics of South-eastern Ghana

Region/year	Eastern region	Volta region (incl. Oti region)
1960	1,044,080	777,285
1970	1,209,828	947,268
1984	1,211,907	1,680,890
2000	2,106,696	1,635,421
2010	2,633,154	2,118,252
2020	3,318,853	2,667,478



**Fig. 2** Population growth for South-eastern Ghana between 1960 and 2020



**Fig. 3** Percentage of growth rate (APR) (%) for South-eastern Ghana (1960–2020)

year value,  $N_{Year}$  = Number of years or year interval between base year and current year.

**Data acquisition and classification of images**

The United States Geological Survey (USGS) website (<http://earthexplorer.usgs.gov/>) provided six Landsat images

stored for Landsat 1 MSS, Landsat 4 TM, Landsat 5 TM, and Landsat 7 ETM + (Table 2). Image pre-processing and enhancement were carried out with the aid of ArcGIS 10.6, ENVI 5.0, and 5.3.

The description of each class or feature in the study area is briefly highlighted in Table 3.

Figure 4 presents the workflow for this study which constitute reference or source data, image pre-processing and enhancement, post classification/change detection analysis, accuracy assessment, slope and correlation analysis for the study area based on the study objectives. Colors presented in Fig. 4 capture key research questions that this study sought to explore.

**Change detection statistics**

In South-eastern Ghana, a multitemporal technique was used to determine land use patterns and their determinants. To investigate the observable development of LUCC, we combined image differencing, vegetation index, post classification, and geospatial approaches. These expressions were used for the quantification of various parameters:

$$\text{Change in LUCC}(x^2) = \frac{\text{LUCC}_{\text{Current year}} - \text{LUCC}_{\text{Past year}}}{\text{LUCC}_{\text{Past year}}} \tag{2}$$

$$\begin{aligned} \% \text{Change in LUCC}(x^2) &= \frac{\text{LUCC}_{\text{Current year}} - \text{LUCC}_{\text{Past year}}}{\text{LUCC}_{\text{Past year}}} \\ &\times 100 \end{aligned} \tag{3}$$

$$\begin{aligned} \text{Rate of Change in LUCC per year} &= \left[ \left( \frac{\text{LUCC}_{\text{Current year}} - \text{LUCC}_{\text{Past year}}}{\text{LUCC}_{\text{Past year}}} \right) \times 100 \right] \div 50 \text{ years} \end{aligned} \tag{4}$$

Quantification of other remotely sensed variables used in the current study have been summarized in Table 4.

**Data analysis**

**Elevation and slope analysis**

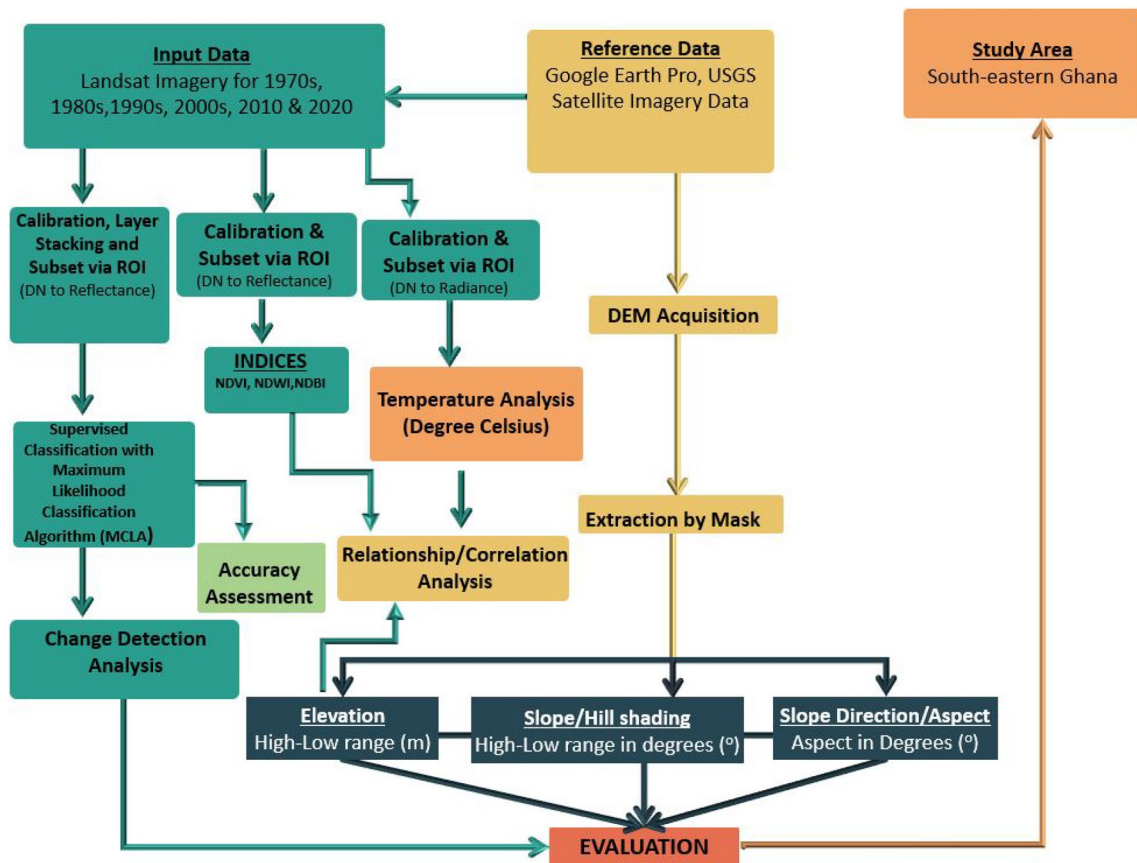
Digital Elevation Model (DEM) covering the entire South-eastern region was downloaded from the USGS’s website for the elevation, slope and aspect analysis. For elevation analysis, the DEM was imported into ArcMap. With the slope analysis, the spatial analyst tools (i.e., hill shade tool) in ArcMap was used to create a shaded relief from the surface raster. It factored into consideration, the illumination source angle. In other words, the hill shade aided in obtaining the

**Table 2** Details of imagery type utilized for South-eastern Ghana

Data	Acquisition Year	Row	Path	Resolution
LANDSAT 1 MSS	1970s	054/055/056	193/194/207/208	30 m
LANDSAT 4 TM	1980s			
LANDSAT 5 TM	1990s			
LANDSAT 7 ETM+	2000			
	2010			
	2020			

**Table 3** Classification of features identified in South-eastern Ghana

Feature/Class	Definition
Forests	Closely interwoven trees and lush vegetation dominate these areas. It also includes all vegetative regions with no exposed soil
Built-up	Urban, business, and industrial regions. This category also includes community green spaces, playing fields, and truck terminals
Barren areas or bare land	Bare sections of soil or rocks that haven't been covered by greenery. In and around built-up regions, barren areas are noticeable. It constitutes terrains that have been cleared in preparation for redevelopment or cultivation
Farmlands and shrubs	Widely distributed trees, hedges or bushes, secluded thickets, and non-tree crops
Waterbodies	Rivers, lagoons, lakes, and other bodies of water are all part of this ecosystem



**Fig. 4** Flow diagram of data acquisition sources, design and evaluation procedure

**Table 4** Quantification of various variables

Indices	Quantification	Source
Normalized Difference Vegetative Index (NDVI)	$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \dots (5)$ <p>Here, NIR means Near-infrared, RED connotes Red visible bands</p>	Lin et al. (2015); Abu Bakar et al. (2016)
Normalized Difference Built-up Index (NDBI)	$NDBI = \left( \frac{(SWIR-NIR)}{(SWIR+NIR)} \right) \dots (6)$	Xu (2007)
Normalized Difference Water Index (NDWI) or Modified Normalized Vegetative Index (MNDWI)	$NDWI = \left( \frac{(NIR-SWIR)}{(NIR+SWIR)} \right) \dots (7)$ $MNDWI = \left( \frac{(Green-SWIR)}{(Green+SWIR)} \right) \dots (8)$	
Temperature analysis Image Calibration (Radiance)	$L_{\lambda} = \frac{(LMAX_{\lambda}-LMIN_{\lambda})}{(QCALMAX-QCALMIN)} \times (DN - QCALMIN) + LMIN_{\lambda} \dots$ $L_{\lambda} = \frac{(LMAX_{\lambda}-LMIN_{\lambda})}{(QCALMAX-QCALMIN)} \times (DN - QCALMIN) + LMIN_{\lambda} \dots (9)$ <p><math>L_{\lambda}</math> = cell value, defined as radiance in <math>W/(M^2 * sr * \mu m)</math></p> <p><math>LMAX_{\lambda}</math> = sensor spectral radiance scaled to <math>(QCALMAX)</math> in <math>W/(M^2 * sr * \mu m)</math>; <math>LMIN_{\lambda}</math> = sensor spectral radiance scaled to <math>(QCALMIN)</math> in <math>W/(M^2 * sr * \mu m)</math>. <math>(QCALMAX)</math> = maximum quantized calibrated pixel value that corresponds to <math>LMAX_{\lambda}</math> [DN], <math>(QCALMIN)</math> = minimum quantized calibrated pixel value corresponding to <math>LMIN_{\lambda}</math> [DN]; and <math>QCAL</math> = quantized calibrated pixel value [DN]. The <math>LMIN</math> and <math>LMAX</math> are the spectral radiances for each band at DN 1 and 255 for Landsat 7 ETM+; 1 and 65,535 for Landsat 8 OLI/TIRS. <math>\lambda</math> represents the wavelength</p> <p>-Spectral Radiance (<math>L_{\lambda}</math>) to Kelvin conversion is done with emissivity value:</p> $T = \frac{K_2}{\ln\left(\frac{K_1 + E}{L_{\lambda}} + 1\right)} (10)$ <p>As a result, the coefficients <math>k_1</math> and <math>k_2</math> are defined by the functional wavelength of a satellite signal</p> $BT = \frac{K_2}{\ln\left[\frac{K_1}{L_{\lambda}} + 1\right]} (11)$ <p>Temperature is needed to be in Degree Celsius (<math>^{\circ}C</math>) (<math>T_c</math>), the given temperature values are required to be converted from Kelvin (K) satellite brightness temperature (<math>T_B</math>) to (<math>^{\circ}C</math>) (<math>T_c</math>)</p> $T_c = T_B - 273.15 \dots (12)$	Coll et al. (2010); Ghulam (2010); Avdan and Jovanovska (2016)

angles, in relation to their steepness. For aspect, analysis was done to determine the direction of slopes from the origin. The aspect tool (spatial analyst tool) was used to perform this task. The aspect basically identifies the compass direction that the downhill slope faces, and assigns values based on the direction.

**Spatial autocorrelation: pearson’s coefficient of determination ( $R^2$ )**

Values for the understudied variables namely LST, NDBI, NDWI and NDVI were classified into eleven classes each, using ArcMap 10.6 to extract the values for autocorrelation analysis. The values (Table 5) were exported to SPSS version 22 for further analysis.

**Table 5** Values used for autocorrelation analysis

LST ( $^{\circ}C$ )	NDBI	NDWI	NDVI	Elevation (m)
33.73	0.99	- 0.98	- 0.99	0
32.98	0.79	- 0.78	- 0.79	45.3
31.73	0.59	- 0.58	- 0.59	85.3
30.87	0.39	- 0.38	- 0.39	185.3
29.77	0.19	- 0.18	- 0.19	285.3
28.52	0	0	0	385.3
28.12	- 0.19	0.18	0.19	485.3
27.73	- 0.39	0.38	0.39	585.3
27.34	- 0.59	0.58	0.59	685.3
26.85	- 0.79	0.78	0.79	785.3
26.47	- 0.96	0.96	0.95	885.3

The degree of proof or substantiation described as insignificant, relatively weak, or weak; least reasonable, or reasonable; and significant, or substantial connection was determined through this research.  $R^2$  justified the level of variation in a model. Thus, a model's capacity to forecast or justify an event in a logistic regression scenario. Maximum  $R^2$  score means the deviation in an outcome may be clarified by estimation, using the specified parameters.  $R^2$  solely delves into magnitude of the association, and not ascertaining one variable as the cause of the other.

$1 \leq R^2 \geq 0.8$  means substantial or significant association between the given parameters.

$0.7 \leq R^2 \geq 0.5$  indicates reasonable or least reasonable association.

$0.49 \leq R^2 \geq 0.2$  indicates weak or relatively weak association

Less than 0.2 indicates insignificant or no association.

### Validation of generated satellite imagery

For each year, validation of satellite imagery created for this study was carried out using ENVI and ArcGIS to ground truth selected points from random geographical locations. The images were verified by overlaying them on Google Earth Pro. For precision assessment, 100 samples were obtained from each class (i.e., built-up, barren areas, waterbodies, forests, and farmlands/shrubs) in the characterized imagery. We employed Sarfo et al. (2022) confusion matrix (Eq. 13) to validate the spatial results obtained for this study.

Here:

T.S.P = Total Sample Points obtained (T.S. P = 500).

A.S.P = Average number of sample points that accurately fall on each required feature (A.S. P = 465)

$$\text{Accuracy Assessment} = \left[ \frac{\text{A.S.P}}{\text{T.S.P}} \times 100 \right] \quad (13)$$

Considering the samples gathered, the investigation exhibited a 93% accuracy rate across the study period (see appendix C for accuracy assessment details for each given study period).

### Class contribution rate (CRC) for each index

Over the course of the study, the understudied indices (vegetation, water, and built-up) were reclassified. Using ArcMap (spotting tool), five classes were created for each of the indices. The classes were created using the output of the indices' value range outcomes, which ranged from the lowest to highest.

We employed the zonal geometry tool in ArcMap to estimate the area coverage in square meters ( $\text{m}^2$ ) for each feature upon extracting the values for each class. The output was

exported to SPSS v.22 for further conversion of the area (i.e., in  $\text{km}^2$ ), and percentage allocation or rate of change for the given classes.

### Contribution Rate of Change (CRC)

$$= \frac{\text{LUC}(\text{sq.km})_{\text{Present/future year}}}{\text{LUC}(\text{sq.km})_{\text{Past/Previous year}}} - 1 \quad (14)$$

Indicatively;

CRC means contribution rate of change; LUC means land use class. The rate of change is shown by the value of change for each class given the output. Reasonably high numbers imply an increase in area coverage (i.e., contributing rate) for a specific feature throughout the research period. Negative numbers, on the other hand, indicate a reduction in area coverage for a given category. The rate of change ( $\pm$ ) provides further details of each feature's class contribution (Eq. 14), which differs from the conventional change detection analysis for land use classes.

## Results

### South-eastern Ghana's area coverage and change detection statistics

Based on classification and differencing results, land cover categorization from the five features (1970–2020) indicates a remarkable modification in land use systems (see also appendix b.8). Land use features that increased progressively were built environment and farmlands/shrubs (Fig. 5). Change detection statistics presented show built-up obtained an area of 2024.56  $\text{km}^2$ , following an increment of 1710.19  $\text{km}^2$  from other classes. Barren areas obtained an area of 12.62  $\text{km}^2$ , and lost 1070.98  $\text{km}^2$  to other classes. Waterbodies covered an area of 4483.47  $\text{km}^2$ , following an increase of 1476.06  $\text{km}^2$  from other classes. Natural vegetation occupied an area of 11,364.16  $\text{km}^2$ , and lost 16,204.64  $\text{km}^2$ . Croplands and shrubs obtained 21,953.55  $\text{km}^2$ , following an increment of 14,073.62  $\text{km}^2$  from other classes.

Geospatial results and change detection statistics (Table 6) show settlements expanded by 406.05% (at an annual rate of +8.1%), barren areas reduced by 0.99% (at an annual rate of -1.97%), farmlands and shrubs gained 86.47% (at an annual rate of +1.73% increment each year) and areas covered by waterbodies gained 47.35% (at an annual rate +0.95%). In the same vein, the natural vegetation reduced by 52.01% (at an annual rate of -1.04%). Considering the unparalleled and unregulated modifications which are evident across the length and breadth of South-eastern Ghana, built-up areas, as well as farmlands and shrubs increased exponentially and evenly, particularly

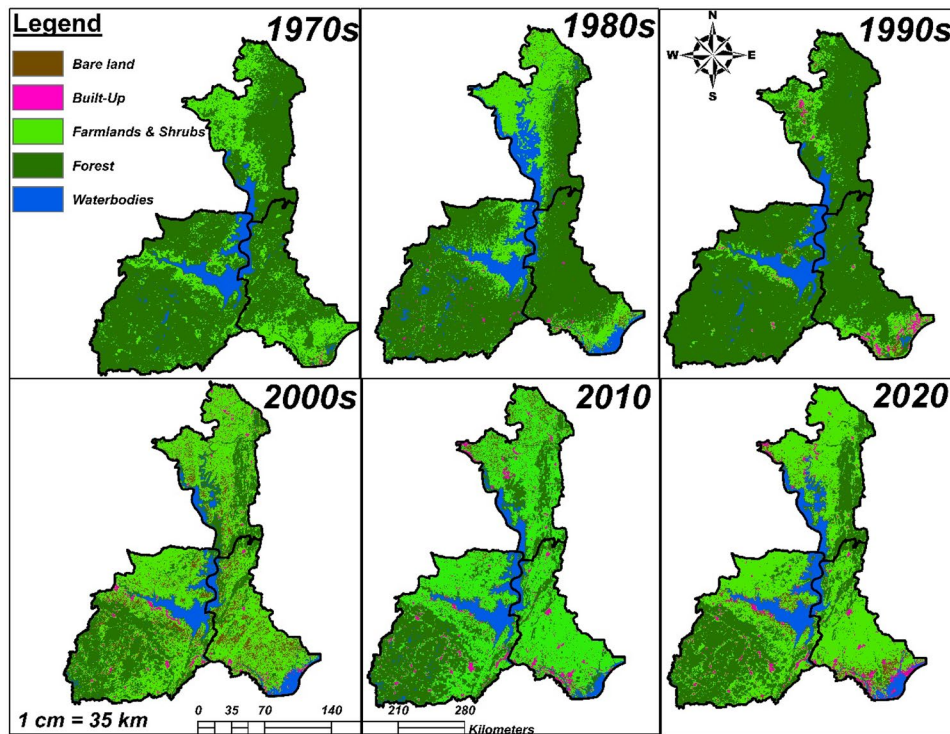


Fig. 5 Fundamental shift in land use systems in South-eastern Ghana (1970–2020)

Table 6 South-eastern Ghana’s change detection statistics during the last 50 years

Changes in area coverage (km <sup>2</sup> ) for each feature during the last 50 years							
Feature	1970’s	1980’s	1990’s	2000	2010	2020	
Forests	23,678.4	23,560.5	15,375.58	12,159.36	11,371.27	11,364.16	
Barren areas (bare land)	966.82	582.52	28.97	208.62	12.61	12.62	
Farmlands and shrubs	11,773.54	9592.32	19,008.1	20,620.13	21,948.17	21,953.55	
Built-up	400.07	435.86	795.84	1720.07	2041.77	2024.56	
Waterbodies	3042.84	5688.82	4645.7	5138.09	4484.09	4483.47	
Total	39,861.67	39,860.02	38,742.04	39,846.27	39,857.91	39,838.36	
South-eastern Ghana’s magnitude and rate of change (km <sup>2</sup> )							
Feature	2020 (km <sup>2</sup> )	1970 (km <sup>2</sup> )	Rate of Change (%) per year (±)	Magnitude of change (km <sup>2</sup> ) per year (±)	Magnitude of change (km <sup>2</sup> )		
Forests	11,364.16	23,678.4	− 1.04	− 246.29	− 12,314.24		
Barren areas (bare land)	12.62	966.82	− 1.97	− 19.08	− 954.2		
Farmlands and shrubs	21,953.55	11,773.54	+ 1.73	+ 203.6	10,180.01		
Built-up	2024.56	400.07	+ 8.1	+ 32.49	1624.49		
Waterbodies	4483.47	3042.84	+ 0.95	+ 28.81	1440.63		
Changes in land-use/land cover classes or features (%) over the past 50 years							
Feature	1970–1980	1980–1990	1990–2000	2000–2010	2010–2020	1970–2020	
Forests	− 0.49	− 34.74	− 20.92	− 6.48	− 0.06	− 52.01	
Barren areas (bare land)	− 39.75	− 95.03	+ 620.12	− 93.96	+ 0.08	− 0.99	
Farmlands and shrubs	− 18.53	+ 98.16	+ 8.48	+ 6.44	+ 0.03	+ 86.47	
Built-up	+ 8.95	+ 82.59	+ 116.13	+ 18.7	− 0.84	+ 406.05	
Waterbodies	+ 86.96	− 18.34	+ 10.59	− 12.73	− 0.01	+ 47.35	



**Table 7** Contribution rate of change (CRC) for each index

Feature/Period	1970–1980	1980–1990	1990–2000	2000–2010	2010–2020	1970–2020
<b>NDVI</b>						
Forests	– 0.07	– 0.09	– 0.12	– 0.07	– 0.18	– 0.43
Barren areas (bare land)	– 0.67	– 0.50	0.33	0.00	0.25	– 0.17
Farmlands and shrubs	0.36	0.07	0.19	0.08	0.05	<b>0.95</b>
Built-up	0.14	0.13	0.11	0.10	0.09	<b>0.71</b>
Waterbodies	– 0.30	0.21	– 0.18	– 0.14	0.58	– 0.05
<b>NDWI</b>						
Forests	– 0.11	0.02	– 0.07	– 0.10	– 0.21	– 0.40
Barren areas (bare land)	1.00	– 0.50	0.50	0.33	0.25	<b>1.50</b>
Farmlands and shrubs	0.29	– 0.03	0.13	0.06	0.25	<b>0.88</b>
Built-up	0.33	0.25	0.30	0.23	0.06	<b>1.83</b>
Waterbodies	– 0.20	0.00	– 0.25	0.17	0.00	– 0.30
<b>NDBI</b>						
Forests	– 0.17	0.04	– 0.13	– 0.11	– 0.25	– 0.50
Barren areas (bare land)	– 0.33	– 0.50	1.00	– 0.50	1.00	– 0.33
Farmlands and shrubs	0.50	0.07	0.09	0.06	0.22	<b>1.25</b>
Built-up	0.60	0.13	0.11	0.30	0.15	<b>2.00</b>
Waterbodies	– 0.17	– 0.40	0.33	0.13	– 0.11	– 0.33

Bold values indicate the said classes contributed the most to land cover changes and surface temperature in the given remotely-sensed indices

in the northernmost, southernmost and the belly of the study area.

Contribution rate of change (CRC) statistics for each remotely sensed index are presented in Table 7.

**Evaluation of LST**

A remarkable increase in LST was experienced between the 1970s and 1980s. Bushfires, prolonged and persistent droughts were experienced in the early 1980s across the country. The mean temperature over the study period ranges between 30.41 °C and 24.72 °C with a difference of about 5.62 °C (1970–2020). Fluctuations in temperature in South-eastern Ghana are mainly associated with anthropogenic influence, linked to the driving forces highlighted in Table A.1 (see Appendix) and Fig. 6. The temperature range for the given periods were validated with observed temperature range datasets, recorded by the local stations under Ghana Meteorological Agency to ensure consistency and reliability in results generated.

The study area is characterized by tropical climate with moderate temperatures, ranging from 21 °C at nightfall and 32 °C during the day. Given the results presented in Fig. 6, it can be observed that some areas along the Volta River Basin in the northernmost (i.e., Dambai, Kete Krachi, Chinden, among other towns) and southernmost zones (i.e., Ho, Keta, Denu, Adidome, Sogakope, Odumasi-Dugame and other communities) of the Oti and Volta regions, respectively, have been experiencing high temperatures. In the eastern region of Ghana (i.e., the belly of the study domain, extremely warm temperatures can be observed in and along the following locations and ecological zones: Begoro, Abetifi Mpraeso, Koforidua, Nkawkaw, Kade, Akwatia and other towns). The dominant land-use feature in these areas with high temperatures entail high density of human settlements. Areas spotted in blue and transient colors are primarily characterized by forest/game reserves and waterbodies; thus; Afram, Birim, and the transboundary river Basin, running through the Eastern, Volta and Oti regions of Ghana.

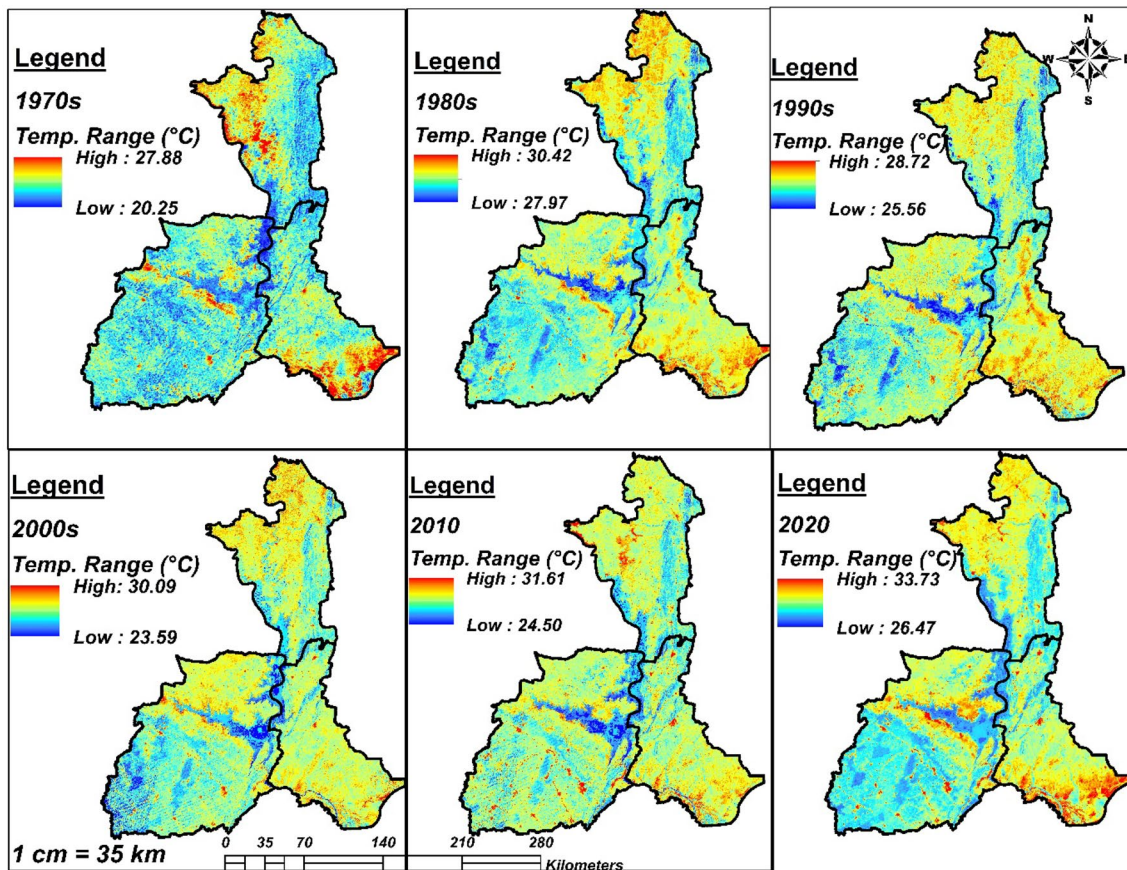


Fig. 6 LST variations (1970–2020) in South-eastern Ghana

### Elevation and slope analysis

Early studies that explored elevation, slope and aspect found these features to be key contributors to fluctuations in climatic conditions. South-eastern Ghana has several unique relief features. Considering the suitability of the study area for agriculture, mining and post-mining land use activities can be further explored for efficient utilization and growth of resources in the area. Figure 7 presents three geospatial images/maps which constitute elevation, slope and aspect (slope direction). From the map of elevation, areas covered by red color indicate regions with high altitudes/topographical features. Such areas are mountainous in nature. Examples are Mountain Afadjato (885 m); Kwahu Mampong scarp (788 m above sea level); the Atiwa-Atwaredu ranges (731 m); the Akuapem highland (466 m); and the isolated Krobo and Yogaga mountains. Yellowish regions mark hilly areas, whilst green/

white and blue regions represent low-lying areas and Lake Volta, Birim, Afram and Ayensu rivers, streams, estuaries and lagoons (i.e., Keta Lagoon), respectively.

Dark brown spots indicate high slopes, whereas regions marked as yellow and green/white suggest moderately high and medium slopes, respectively, for slope analysis. Waterbodies are symbolized by deep blue spots. Observations based on geospatial images (Figs. 5 and 7) presented in this study show areas with high topographical features had limited human disturbances or activities. The aspect map presented in this study will be beneficial to land use planners and policy makers in formulating and implementing sustainable land management policies, plans, programs and projects. The legend for the aspect map shows ten directional aspect categories expressed in degrees (°). It was measured clockwise from true north. The map indicates the dominant slope directions in South-eastern Ghana are Northwest to North trending.

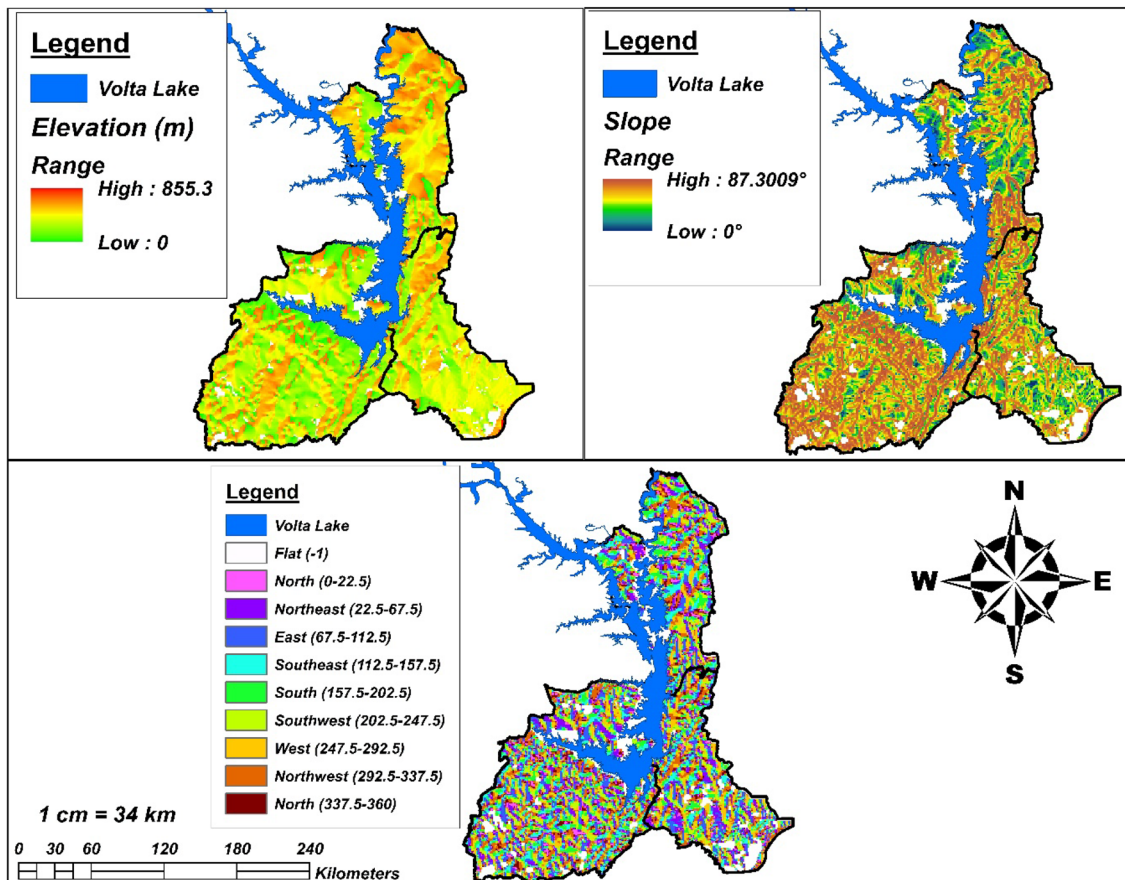


Fig. 7 Elevation and slope analysis for South-eastern Ghana

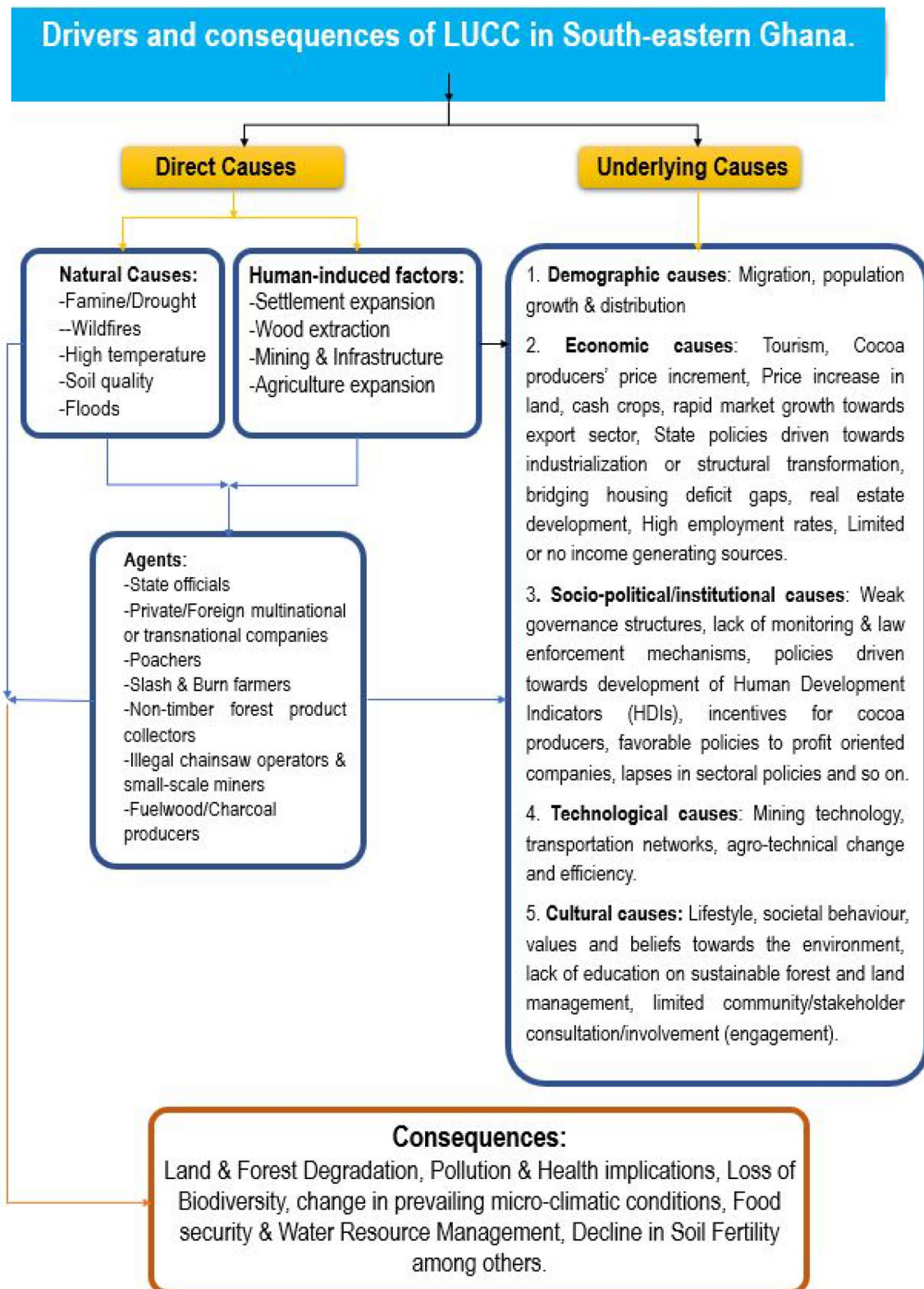
## Discussion

### Direct and indirect factors influencing LUCC in South-eastern Ghana

Roughly six primary drivers have been identified and documented as the driving forces of LUCC in South-eastern Ghana by early studies based on political, social, economic, scientific, and environmental influences (Fig. 5) (see appendix; Tables A.1 and A.2). The consequences of the alterations taken from the stand points include important pre-historic events and connections between the core factors and essential LUCC shifts. Existing positions and geospatial results compiled for this study suggest similar conclusions. Drastic increase in built-up areas and farmlands/shrubs based on study results agrees with the assertions of Amproche et al. (2020), Ampim et al. (2020) and Kpare (2016). They attributed the massive drift to constant rise in human population (Figs. 2 and 3) (Table 1) which drives migration and amplitude of settlements, agricultural expansion, deforestation, small-scale mining activities,

illegal harvesting of trees and timber, poverty, policy gaps, and underlying factors.

The Volta Basin and its tributaries, as well as the forest belts and game reserves in the Eastern region (i.e., Atewa Forest reserve and Akuapem ranges) per evidence presented in Fig. 5 have been heavily encroached. These alterations are associated with increasing settlements, mainly as a result of multifaceted factors such as influx of multinational and transnational companies in the tourism and real estate industries, as well as the energy/mineral resource sectors due to the area's abundant resources. Extension of agricultural activities (farming/fishing activities) to meet growing demands of the increasing population, coupled with being the last resort to employment for most indigenes play a critical role in the modification of land use systems, according to the spatial results and population statistics presented. The central business districts (CBDs) across the selected regions; thus, Ho and Keta in the Volta region, Dambai in the Oti region, and Koforidua in the Eastern belt have experienced rapid growth in human population (i.e., primarily as a result of migration and high fertility/mortality rates) (Table 1) and development of infrastructure, according to GSS (2020)



**Fig. 8** Driving forces, agents and implications of land cover conversions in South-eastern Ghana

in recent decades. The area’s untapped and underutilized resources have exacerbated unregulated mining activities, particularly in the Eastern region. According to Table 1, population grew annually by 3.81% between 1960 and 2020, substantiating diverse needs in the utilization of essential resources. In addition to tourist attraction as highlighted in the methodology section, there are several prospective mining segments spotted in the region (Amproche et al. 2020), which drive continuous socio-economic growth and development (Fig. 8).

The dramatic change observed over the study domain over the last 50 years is partly as a result of natural disasters or climate-induced factors that occurred in 1983 (i.e., prolonged droughts and famine, bushfires and increasing temperatures that occurred nationwide). Technological advancement and modernization in the transportation sector through rail networks development that links urban to non-urban areas, connecting cocoa/cash crop growing communities to cities, coupled with oil and mining exploration has contributed to the remarkable change in built environment. Several livelihoods are equipped on adopting modernized equipment, aimed to enhance agricultural yield in the region. Demand to meet growing needs of the

ever-increasing population, as well as boosting exports has constantly resulted in the dramatic change of land use systems, thereby affecting soil quality in the area. These have eventually underplayed the perpetuation of flora and fauna, among other ecosystem functions, provided by the forests and wildlife reserves in the area (Fig. 8) (see appendix; Table A.1).

### CRC assessment based on change detection statistics

Given the results in Figs. 9, 10 and 11, along with CRC statistics presented in Table 7, increasing settlements feature contributed largely to built-up index (2.00); NDVI (0.71) and NDWI (1.83), followed by farmlands/shrubs (1.25, 0.95 and 0.88 according to the given variables). However, there was a steady decline in other land-use features. Settlement patterns (built environment) show progressive growth. Illustrations in Table 7 and Fig. 6 (LST) depict a statistically strong positive association between LST and settlements.

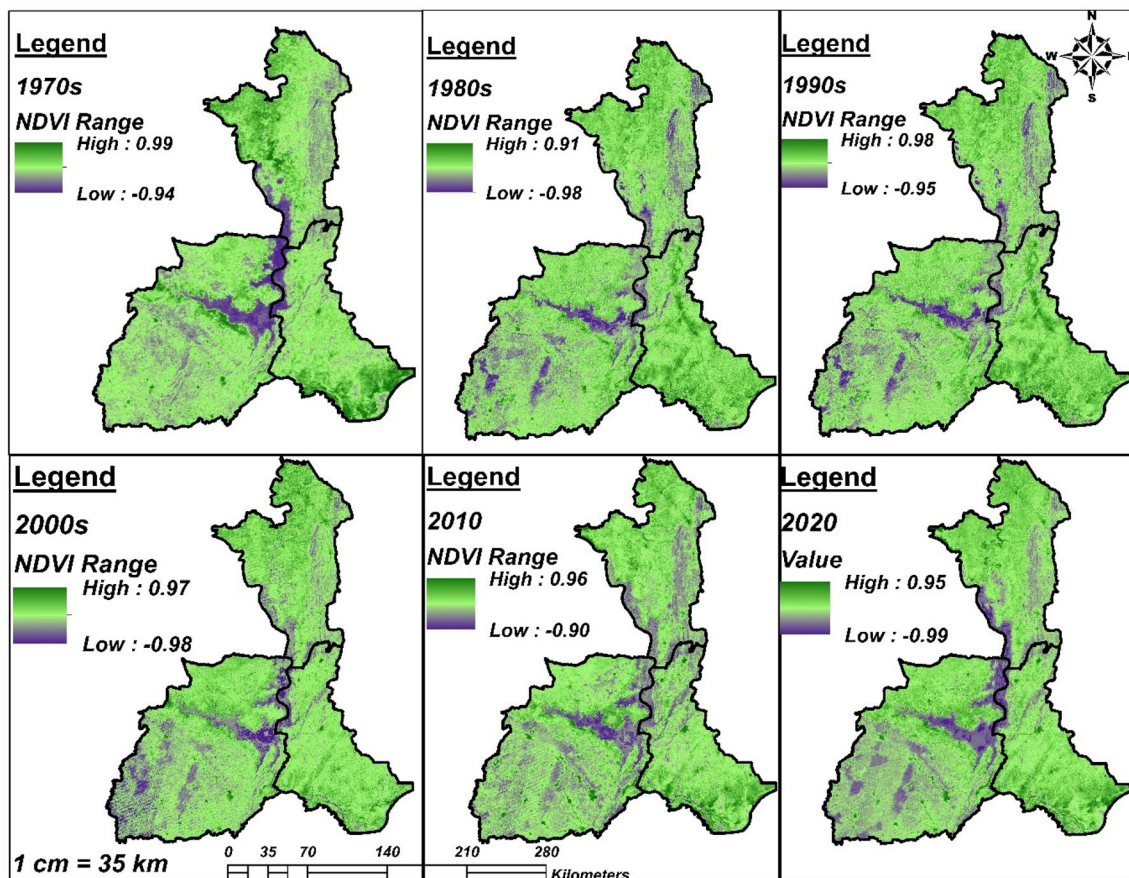


Fig. 9 Changes in NDVI over the study period (1970–2020) in South-eastern Ghana

### Vegetative index evaluation for South-eastern Ghana

NDVI declined steadily over the study period as shown in Fig. 9. In forest areas, NDVI values are higher because trees and other lush zones produce greener biomass. Forest and wildlife reserves/parks make up a huge proportion of these areas, together with open and closed canopy areas. Declension in NDVI could be attributed to the main drivers highlighted in Table A.1 and Fig. 8, mainly population growth and distribution (increase in human settlements), extensiveness of agriculture, illegal mining and extraction of wood, weak governance systems and policy gaps, along with technological advancement and environmental factors like: wildfires and irregular precipitation and temperature patterns.

The Atewa Range Forest Reserve which is situated in the belly of the study area, in recent decades, has been heavily encroached by chainsaw operators, small-scale mining and human settlements. The far east zones entail Volta and the Oti regions, characterized by marshy and mangrove swamps along its low-lying coastal plains, semi-deciduous forest and savanna woodland at the center and Guinea savanna in its northern zone. Major land use systems or activities, mainly

farmlands and shrubs, fishing, mining, lumbering of trees per spatial results and existing literature are housed in the forest belts, mountainous ranges and watersheds (Abungba, 2020).

### Built-up index evaluation for South-eastern Ghana

Observed reddish and yellowish areas mark positive changes (presence) in the built-up areas. There are two types of green zones: light green represents farmland and shrubs (less dense vegetation zones) and dark green represents forests. As illustrated in Fig. 10, areas colored blue represents water bodies. Built-environment has increased drastically over the past five decades in South-eastern Ghana. Evidence presented in Fig. 10 shows massive shift in built-up areas, observed in the northernmost and southernmost parts of the Oti and Volta regions. Again, forest reserves (Atewa Range Forest Reserve in the Eastern region among other forest fringe communities in the Volta and Oti regions) and watersheds (i.e., Volta Basin and the Keta/Songhor Lagoons) have undergone several changes, mainly as a result of human-induced factors. These factors are socio-political and economically driven. Presently, discovery of oil fields in Keta in the Volta region

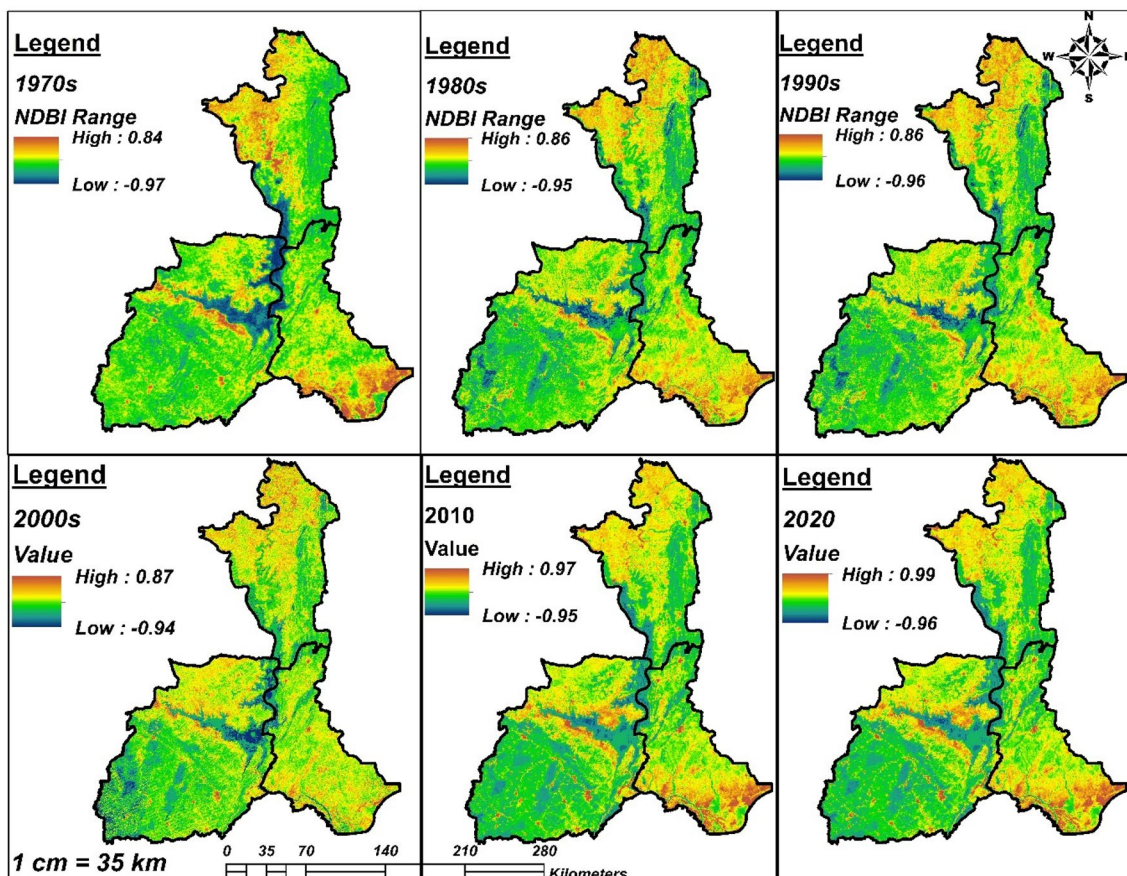


Fig. 10 NDBI variations (1970–2020) in South-eastern Ghana

and small-scale mining activities in the Eastern region (i.e., gold and diamond, are the only minerals, currently exploited for commercial gains) have facilitated the influx of profited-oriented transnational and multinational companies to harness the resources in the region. Other minerals discovered in the region constitute bauxite, limestone, kaolin and clay. Again, a number of mineral deposits discovered recently in the Volta/Oti regions, thus; serpentinite and jasper in Jasikan; iron ore in Hohoe municipality; slime deposits in Ho and Klefe; granite in Abutia, Agortime and Adaklu; gold, diamond, lithium spodume and lepidolite in Keta, among other scenic attractions will drive socio-economic growth and development in the region, at the expense of the natural environment.

State policies like the 200-community day school policy, one-district-one-hospital, construction of railway systems and cocoa roads/transportation networks that links non-urban to urban areas, community and market centers, bridging job-housing ratios, among other infrastructural development have assiduously increased built-up areas. Governance systems (i.e., practicing neo-liberalism and capitalism system of governance in recent years) and economic policies targeted at enhancing market forces, people’s welfare and

standard of living, as well as policies like Planting for Food and Jobs (PFJ), one-district-one-factory (industrialisation) and bridging housing deficit gaps that dwell on consolidating Ghana’s fiscal policy, putting the country on a sustainable economic pathway and enhancing productivity or food security have facilitated the dramatic change in NDBI. Unemployment and poverty rates in the study domain underlie the increasing rate of built-up, farmlands and shrubs as indicated in Fig. 10.

### Water index evaluation for South-eastern Ghana

Observations in the last 50 years considering evidence presented in Fig. 11 have green areas being covered by natural vegetation, forested areas, or parks and settlements. Lake Volta is illustrated in deep blue, while rivers like Birim, Afram, Densu and Ayensu rivers, the Keta Lagoon, estuaries and streams are shown in light blue. Lime and yellow areas are those covered by farms, shrubs, and built-up areas (settlements), respectively. There were no major recurrent changes for the NDWI, except for prolonged drought and bushfires that occurred in the 1980’s that caused water index to plummet dramatically in the 1990’s. Furthermore,

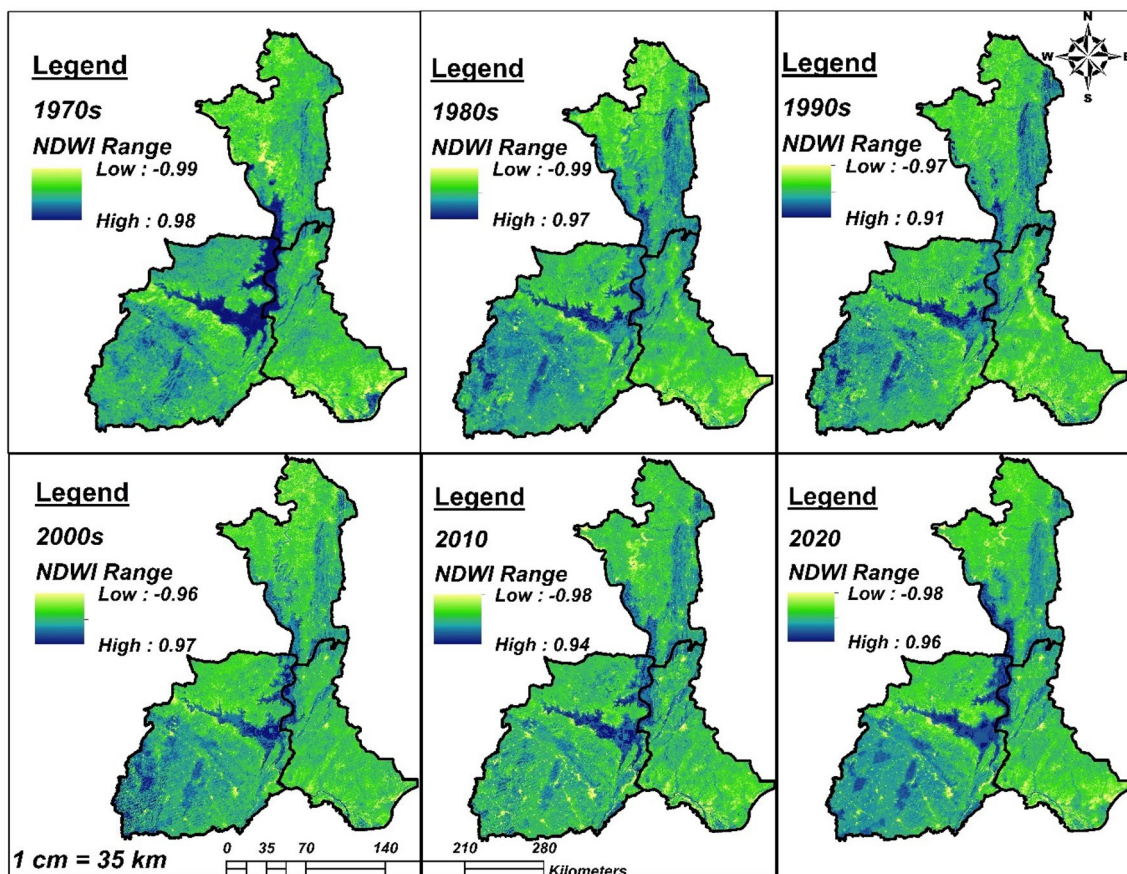


Fig. 11 NDWI variations (1970–2020) in South-eastern Ghana

the dramatic increase in built-up areas, as well as farmlands and shrubs during the study period, as represented in Fig. 10, may also elucidate the slight decline in areas covered by waterbodies. A climate change-induced increase in surface temperatures (Fig. 6) among other factors in South-eastern Ghana, in conjunction with fluctuations in rainfall patterns, could contribute to the loss of water coverage in the area.

The Volta River Basin as observed in Fig. 11, encapsulates the Black Volta, the White Volta, and the Red Volta. This transboundary basin remains one of the largest river systems in Africa covering approximately 400,000 km<sup>2</sup>. This asymmetrical inland basin, which hosts several economic activities in its agro-ecological areas, occupies more than a quarter (about 40%) of Ghana's continental landmass. This basin presents unique opportunities that sustain livelihoods through irrigation/dam schemes, scientific/research analysis through river basin modeling and assessments, and supports economic dynamics through energy or power generation and water management (Abungba et al. 2020). The basin among other waterbodies like the Keta lagoon in the Volta/Oti regions, as well as Densu, Ayensu and Birim rivers in the Eastern region are currently under severe threats. The Densu river for instance, is included among the most efficient and productive agricultural zones in Ghana according to Ayivor and Gordon (2012). The quality of these waterbodies, ecological endpoints and functions have experienced severe stress, alluding to the major driving factors highlighted in this study. The significance of waterbodies in the study area to livelihoods in the region and Ghana through hydropower generation, tourism among other services, make NDWI assessment valuable and a source of reference for future studies. Water is an essential component needed for different purposes. It is regarded as the next "gold" considering the benefits it protrudes. Waterbodies influence micro-climatic conditions, ecological processes and sustain the lives of different ecosystems. Its presence influences geopolitical decisions which drives migration and resource management related conflicts across the globe, particularly in developing countries. Hence, the Volta River basin's impact, coupled with recognition of the Keta/Songhor lagoons as international RAMSAR sites cannot be overlooked. NDWI as a remotely sensed index in the study area was inculcated to see how they influence other indices or study variables. The increasing rate of deforestation, human settlements and mining activities could catalyze the rapid conversion of forests, farmlands/shrubs and areas covered by waterbodies into other land-use forms.

The Volta River Basin, among other notable rivers mentioned above are of significant importance to various industries, households and individuals, among other ecosystems in South-eastern Ghana. Dynamics in land-use systems have dire repercussions on the quality, composition and overall health of the river systems. Ayivor and Gordon (2012)

observed some actions at the local level that drive significant changes over the major river basins in South-eastern Ghana over the past three to four decades, as a result of LUCC. Dominant land use classes, identified in their study which corroborate with our standpoints encapsulate urban development/increasing settlements, agriculture and transportation development. They further revealed other land use activities like mining (i.e., diamond mining in and around Akwatia and Kwabeng areas), indiscriminate disposal of waste in satellite towns like Oda, water extraction and deforestation adversely influenced the health of river systems in the area through habitat fragmentation, sedimentation/turbidity, erosion, water shortage and so on. Spatial results and historic data indicate some underlying factors like prolonged dryness, famine and droughts at the national level in the 1980's and global level (i.e., large scale climatic events) affected river systems in the study domain. These proximate and underlying factors that influence the health of river systems, as a result of land use change create the need for decision-makers to circumvent in averting or regulating activities that alter ecological processes and harmony. Considering urban and non-urban dwellers' (i.e., industries, rural and urban folks, flora and fauna, and the state) reliance on the Lake Volta, Densu, Ayensu, Birim and Afram basins, there is no doubt that these vital ecosystems are subjected to constant pressure. Hence, the need for urgent interventions backed by scientific proof using studies of this nature to inform decisions.

### Link between the various study variables

The essence of establishing a relationship (Table 8) between LST against other remote sensing indices and elevation is critical in gaining a broad understanding of the encompassing nature of environmental studies. Identifying and monitoring such undesired fluctuations in land use patterns validate strategic efforts, aimed to address the causes of undesirable change. An aggregate of these changes at the local and regional levels, across the globe results in global environmental change (climate and earth's observational systems).

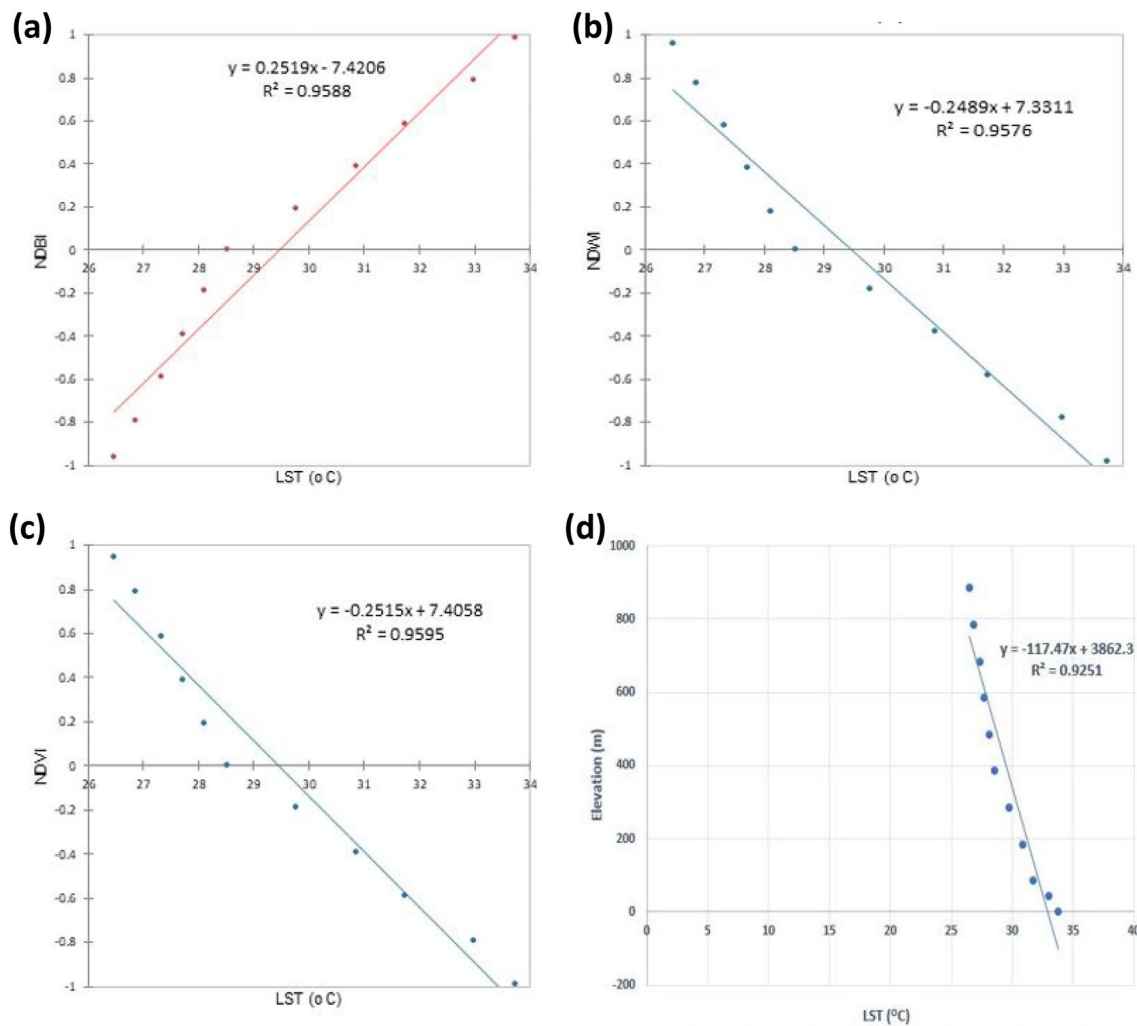
Plotting LST values against the NDBI depicted a strong positive association ( $R^2 = 0.959$ ,  $p < 0.0001$ ). Here,

**Table 8** Pearson's coefficient of determination

Variables	LST (°C)	NDBI	NDWI	NDVI
LST (°C)	<b>1</b>	0.959	0.958	0.960
NDBI	0.959	<b>1</b>	1.000	1.000
NDWI	0.958	1.000	<b>1</b>	1.000
NDVI	0.960	1.000	1.000	<b>1</b>

Bold values indicate constants considering the variables being measured

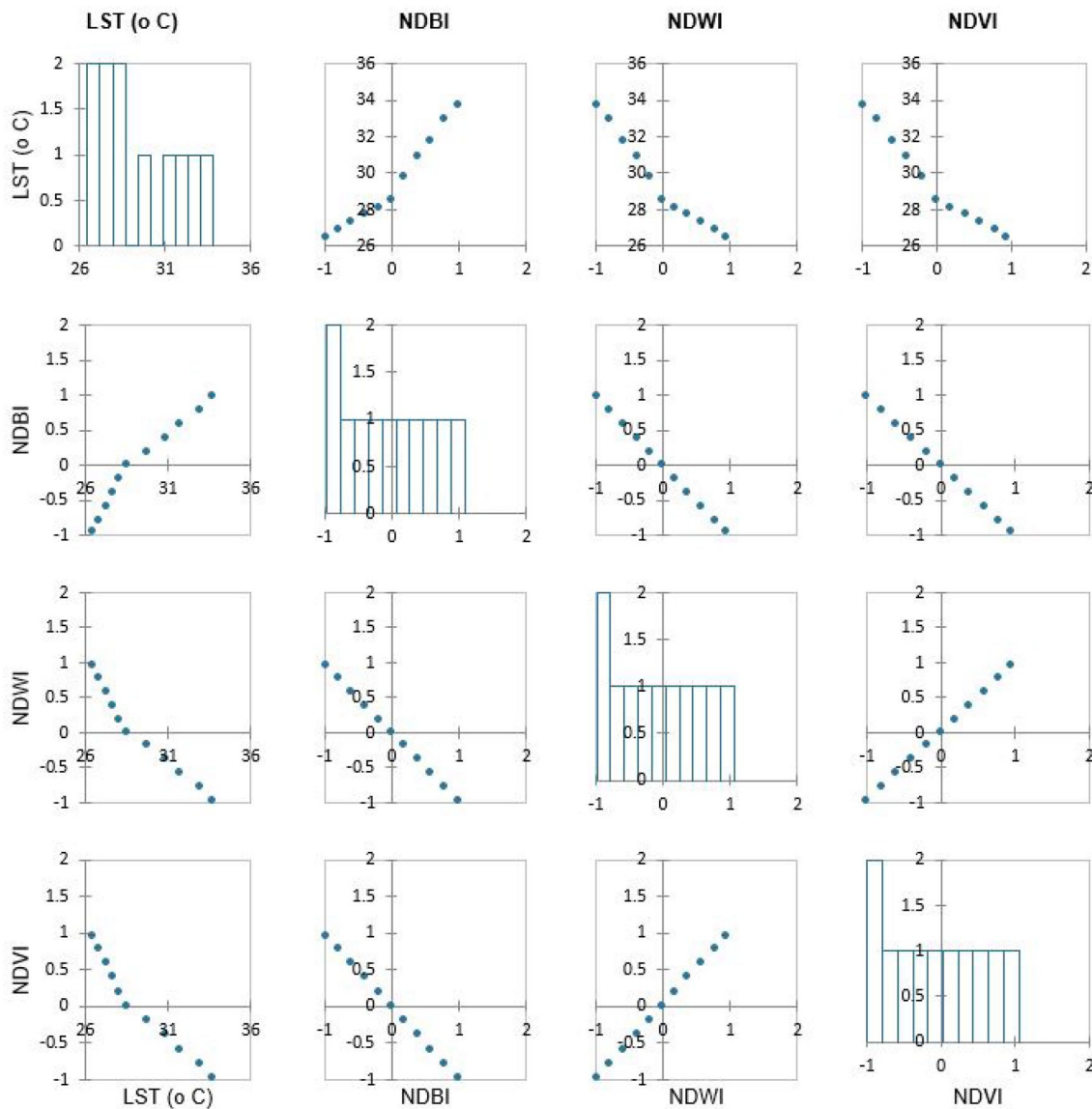




**Fig. 12 a–d** Correlation between LST, elevation and indices

$R^2 = 0.959^2 \times 100\% = 91.97\%$ . This shows 91.97% of the variation in LST is explained by NDBI. Here, the strong positive correlation generated indicates the study identified robust or strong evidence, in relation to the link between the two variables. Based on the illustration above (Fig. 12a), it is evident that built-up increases with temperature in the South-eastern belt of Ghana. This could be attributed to the drastic decline in forests, converted to other land use systems. Contextually, spatial analysis proved a remarkable and steady increase in built-up (Fig. 10) and LST (Fig. 6), respectively. Considering the growth in human settlements among other socio-economic activities in the study area. Previous studies (Aduah and Baffoe 2013; Abbam et al. 2018; Oduro et al. 2021) have reported a direct or positive relationship between NDBI and LST. Findings reported in this study is in tandem with the results mentioned by the studies above.

Generally, LST and NDWI plots in Fig. 12b presents an inverse or negative relationship ( $R^2 = 0.958$ ,  $p < 0.0001$ ). Here,  $R^2 = 0.958^2 \times 100\% = 91.8\%$ . This means 91.8% of the variation in LST is explained by NDWI. Figure 12b gives clear evidence that amplification of LST induces evaporation (i.e., rate of evaporation becomes high). This is in line with the positions of early researchers (Abbam et al. 2018; Aduah and Baffoe 2013). Despite the increase in LST expanding most water bodies (Table 6), results proved increasing temperatures led to a reduction in the level of waterbodies; hence, water index declines as temperature rises (Fig. 6). Besides, reasons for the decline could be attributed to the increasing rate of deforestation in the domain, as trees serve as shades or cover for waterbodies. NDVI and NDWI, according to Fig. 13, depicts a negative correlation between both variables. This corroborates with the results of Abungba et al. (2020) and Ogou et al. (2022) who reported warming trends over water resources due to a host of local



**Fig. 13** Correlation analysis for the given variables used in this study

and external factors driving undesired changes in vegetation, agriculture (Kasri et al. 2021), hydrology and climatic parameters in the Sub-Saharan region. Abungba et al. (2020) cited hydropower generation issues using drop in water storage or levels in the Bui hydropower dam's case scenario or water-energy assessment. Likewise, the said analysis is congruent with the case of the Akosombo Hydroelectric Dam, situated in the Volta region of Ghana which serves as the backbone (i.e., largest source of power provision since the country's independence) of Ghana, in terms of the total amount of energy or power generated (about 915 Megawatts). Climatic factors have significantly influenced the volume of water or water-levels needed to generate power. This adversely resulted in load shedding and intermittent

power-outages that influenced several businesses/jobs and Ghana's economy entirely. Additionally, the increasing rate of deforestation in the area is mainly as a result of growing human settlements, mining activities, illegal logging of trees, extensiveness of farming activities, as reported in early studies (Kpare 2016; Amproche et al. 2020; Ampim et al. 2021; Kyere-Boateng and Marek 2021). These findings agree with the assertions of early studies on LST and NDWI that revealed a negative link between NDWI and LST.

Ideally, plotting LST against NDVI should generate an inverse relationship between LST and the health of vegetation (NDVI). Individual plots considering the two parameters given over the given study period indicate a statistically significant strong negative correlation ( $R^2 = 0.959$ ,  $p < 0.0001$ ).

Here,  $R^2 = 0.959^2 \times 100\% = 91.97\%$ . This shows 91.97% of the variation in LST is explained by NDVI. The generated results align with the findings of Guo (2002) and Wang et al. (2010). This highlights strong evidence was identified by this study in establishing a link between the two given variables. This means 91.9% of the variation in LST is explained by NDVI. Figure 12c shows prolonged increase in temperature results in most plants losing their chlorophyll content due to high rates of metabolism and dryness; this eventually led to the recording of low NDVI values. Overall, the negative correlation recorded between LST and NDVI (Fig. 13) could be attributed to the significant decline in forests areas. Geo-spatial analysis based on LUCC and LST proves a drastic decline in forests (Table 6), and steady increment in LST (Fig. 6). The existence of significant waterbodies in sampling zones, as seen in this study, may have influenced NDVI and LST to be positively associated, as demonstrated by the results (Wang et al. 2010; Guo 2002). More so, aside dense vegetation that significantly impact prevailing micro-climatic conditions, farmlands and shrubs despite the greenness they project does not have substantial influence on LST.

Increasing temperatures in the region could significantly affect the tourism industry considering South-eastern Ghana serving as a major hub for both domestic and foreign visitors. Similarly, the region projects the cultural (i.e., through eco-tourism) and physiological characteristics of Ghana. Hence, unfavorable temperatures could have devastating effects on the direct and indirect gains, accrued from the sector. Again, the agriculture/fisheries, energy and water resource sectors could be heavily impacted, as temperature plays a major role in the diversity and productivity of these locations/climate-sensitive sectors which employ thousands of indigenes. Our results align with the findings of Oduro et al. (2021), Kasri et al. (2021) and Krisnayanti et al. (2021), whose arguments substantiate the need for proactive, tailored and results-oriented systems that mitigate the risks of droughts, floods and warming trends over water resources to sustain sectors sensitive to climate hazards in Ghana and semi-arid regions like the Southwestern part of Morocco and the East Nusa Tenggara in the Eastern part Indonesia. Kasri et al. (2021) quantified the seasonal and annual variability of some climatic variables over the past three decades, whilst Krisnayanti et al. (2021) applied a novel technique to ascertain real-flood flows through a digital map of soil type, topography and land-use, among other parameters.

Plotting LST against elevation revealed an inverse or negative relationship between LST and elevation as illustrated in Fig. 12d. Here,  $R^2 = 0.925^2 \times 100\% = 85.56\%$ . This shows 85.56% variation in LST is explained by elevation. Land surface temperature is influenced by terrain. Elevation impacts on surface temperature mainly as a result air temperature. Temperature value gradually decreases with increasing elevation (Fig. 12d). Peng et al. (2020) asserted

that the higher the atmospheric troposphere is away from the ground, the less long-wave radiation energy is absorbed. Less storage of heat energy by the atmosphere results in lower temperatures. Again, areas with higher elevations, slope and aspect (Fig. 7) have less human disturbance or activities. This eventually reduces anthropogenic heat emissions in relation to land surface temperature in South-eastern Ghana. The cooling impact of dense vegetation causes LST to drop with increasing elevation and slope in south-eastern Ghana, which is characterized by many physical characteristics. Findings agree with the assertions of Peng et al. (2020). Figures 12a–d and 13 show the analysis of variance (appendix b.1) and correlation analysis which indicate the overall correlation model is good fit for the given data.

## Conclusion

In this study, we showed how land use, biodiversity and land surface temperature are interlinked. Local or regional studies of this nature are needed to explicitly understand various practices and actions which drive change cumulatively on different scales. Land remains the most fundamental asset for most individuals living in developing countries. This research has depicted the widespread and rapid changes in land use systems and developments in South-eastern Ghana. Between 1970 and 2020, forests and barren areas reduced substantially at a rate of  $246 \text{ km}^2\text{yr}^{-1}$  and  $19.08 \text{ km}^2\text{yr}^{-1}$ , respectively. A sharp gain was observed for farmlands/shrubs ( $203.6 \text{ km}^2\text{yr}^{-1}$ ) and built-environment ( $32.49 \text{ km}^2\text{yr}^{-1}$ ), at the expense of other classes. Coefficient of determinant analysis proved increasing settlements (i.e., NDBI) through population growth and distribution caused massive shift in LST. Similarly, the inverse relationship between NDWI and NDVI against LST indicated changes in surface temperature could be explained by the variations in vegetative and water indices. Surface temperatures rose considerably during the course of the investigation, according to study findings.

CRC analysis introduced in this study substantiated the fact that the positive and consistent gains in farmlands and shrubs, and built-up areas over the study period contributed massively to land alterations and temperature rise among other classifications. Based on spatial results and existing literature, it can be contended that socio-political and economic factors which primarily constitute extensive agricultural activities, increasing settlements, poverty, intensiveness of small-scale mining activities, illegal logging of trees and chain sawing of timber plantations, weak governance systems, and defects in policy frameworks are all major contributors to the substantial change in land use and land cover in the study domain. To address concerns

associated with efficient use of land resources, further research is required to tackle specific land and resource management practices, considering the core and potential drivers highlighted in this study. Our study provides decision support for development strategists and the international research community to circumvent or re-evaluate critical areas and performance criteria for measuring development and sustainability, respectively. The rapid and significant changes in the area's LUCC could have devastating impacts on Ghana's tourism, livelihoods, agriculture and energy sectors; hence, the urgent need for proactive and ecologically sound interventions that address these concerns.

**Supplementary Information** The online version contains supplementary material available at <https://doi.org/10.1007/s12665-023-10755-z>.

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**Data availability** The data that backs up the study's conclusions are accessible and will be provided upon request.

## Declarations

**Conflicts of interests** There are no conflicts of interest declared by the authors.

## References

- Abbam T, Johnson FA, Dash J, Padmadas SS (2018) Spatiotemporal variations in rainfall and temperature in Ghana over the twentieth century, 1900–2014. *Earth Space Sci* 5:120–132. <https://doi.org/10.1002/2017EA000327>
- Abu Bakar SB, Pradhan B, Lay US, Abdullahi S (2016) Spatial assessment of land surface temperature and land use/land cover in Langkawi Island. *IOP Conf Ser Earth Environ Sci* 37:012064. <https://doi.org/10.1088/1755-1315/37/1/012064>
- Abungba JA, Khare D, Pingale SM et al (2020) Assessment of Hydroclimatic Trends and Variability over the Black Volta Basin in Ghana. *Earth Syst Environ* 4:739–755. <https://doi.org/10.1007/s41748-020-00171-9>
- Aduah MS, Baffoe PE (2013) Remote sensing for mapping land-use/cover changes and urban sprawl in Sekondi-Takoradi, western region of Ghana. *Int J of Eng and Sci* 10:66–73. <https://doi.org/10.6084/M9.FIGSHARE.848547.V1>
- Ampim PAY, Ogbé M, Obeng E, Akley EK, MacCarthy DS (2021) Land cover changes in Ghana over the past 24 years. *Sustainability* 13(9):4951. <https://doi.org/10.3390/su13094951>
- Amproche AA, Antwi M, Kabo-Bah AT (2020) Geospatial assessment of land use and land cover patterns in the black volta basin. *Ghana J Remote Sens GIS* 9:269. <https://doi.org/10.35248/2469-4134.20.9.269>
- Avdan U, Jovanovska G (2016) Algorithm for automated mapping of land surface temperature using LANDSAT 8 satellite data. *J Sensors* 2016:8. <https://doi.org/10.1155/2016/1480307>
- Ayivor JS, Gordon C (2012) Impact of land use on river systems in Ghana. *West African J Appl Ecol* 20(3):83–95. <https://doi.org/10.4314/WAJAE.V20I3>
- Coll C, Galve JM, Sanchez JM, Caselles V (2010) Validation of Landsat-7/ETM+ thermal-band calibration and atmospheric correction with ground-based measurements. *IEEE T Geosci Remote* 48(1):547–555. <https://doi.org/10.1109/TGRS.2009.2024934>
- Ellis E, Pontius R (2010) Land-use and land-cover change. In: *Encyclopedia of Earth*. Eds. National Council for Science and the Environment. [http://www.eoearth.org/article/Land-use\\_and\\_land-cover\\_change](http://www.eoearth.org/article/Land-use_and_land-cover_change). Accessed on December 16, 2020
- Ghana Statistical Service (GSS) (2020) Annual District/Regional Report Summary: Population and Housing Census- Accra, Ghana.
- Ghulam A (2010) Calculating surface temperature using Landsat thermal imagery. Department of earth & atmospheric sciences, and center for environmental sciences. St. Louis University, MO, p 63103
- Guo X (2002) Discrimination of saskatchewan prairie ecoregions using multitemporal 10-day composite NDVI Data. *Prairie Perspectives* 5:174–186
- Gyasi EA, Agyepong GT, Ardayio-Schandorf E, Enu-Kwesi L, Nabila JS, Owusu BE (1994) Environmental Endangerment in the Forest-Savanna Zone of Southern Ghana. UNU, Tokyo. <https://archive.unu.edu/env/plec/country/ghana/Ghana.doc>. Accessed on October 11 2020.
- Hall JB, Swaine MD (1976) Classification and ecology of closed-canopy forest in Ghana. *J Ecol* 64:913–951. <https://doi.org/10.2307/2258816>
- Huq M, Tribe M (2018) *The economy of Ghana: 50 years of economic development*. Springer Palgrave Macmillan, London. <https://doi.org/10.1057/978-1-137-60243-5>
- Kasri JE, Lahmili A, Soussi H, Jaouda I, Bentaher M (2021) Trend analysis of meteorological variables: rainfall and temperature. *Civ Eng J* 7(11):1868–1879. <https://doi.org/10.28991/cej-2021-03091765>
- Koranteng A, Adu-Poku I, Zawila-Niedzwiecki T (2019) Land use and land cover dynamics in the Volta River Basin surrounding APSD forest plantation, Ghana. *Folia Forestalia Polonica Series A Forestry* 61(1):78–89. <https://doi.org/10.2478/ffp-2019-0008>
- Kpare B (2016) Effects of Deforestation and Forest Degradation in the Red Volta East Forest Reserve of the Upper East region on the Livelihoods of adjoining communities. University of Development Studies, Ghana. <http://hdl.handle.net/123456789/884>. Accessed on June 8 2021.
- Krisnayanti DS, Bunganaen W, Frans JH, Seran YA, Legono D (2021) Curve number estimation for ungauged watershed in semi-arid region. *Civ Eng J* 7(6):1070–1083. <https://doi.org/10.28991/cej-2021-03091711>
- Kyere-Boateng R, Marek MV (2021) Analysis of the social-ecological causes of deforestation and forest degradation in Ghana: application of the DPSIR framework. *Forests*. <https://doi.org/10.3390/f12040409>
- Lin WX, Chen HF, Zhang ZX, Xu JH, Tu NM, Fang CX et al (2015) Research and prospects on physio-ecological properties of ratoon rice yield formation and its key cultivation technology. *Chin J Eco-Agri* 23:392–401 (**(in Chinese with English abstract)**)
- Ministry of Lands and Natural Resources (MLNR) (2012) implementation of Ghana shared growth and development agenda, annual progress report. national development planning commission (NDPC). <https://new-ndpcstatic1.s3.amazonaws.com/pubication/Min+of+Lands%26amp;NaturalRes+2012+APR.pdf>.

- Oduro C, Shuoben B, Ayugi B, Beibei L, Babauosmail H, Sarfo I, Ullah S, Ngoma H (2021) Observed and Coupled Model Inter-comparison Project 6 multimodel simulated changes in near-surface temperature properties over Ghana during the 20<sup>th</sup> century. *Int J Climatol*. <https://doi.org/10.1002/joc.7439>
- Ogou FK, Ojeh VN, Naabil E et al (2022) Hydro-climatic and water availability changes and its relationship with NDVI in Northern Sub-Saharan Africa. *Earth Syst Environ* 6:681–696. <https://doi.org/10.1007/s41748-021-00260-3>
- Peng X, Wu W, Zheng Y, Sun J, Hu T (2020) Wang P (2020) Correlation analysis of land surface temperature and topographic elements in Hangzhou. *China Sci Rep* 10:10451. <https://doi.org/10.1038/s41598-020-67423-6>
- Prakasam C (2010) Land use and land cover change detection through remote sensing approach: a case study of Kodaikanal Taluk. *Tamil Nadu Int J Geomat Geosci* 1:46–55
- Purwins S (2020) Bauxite mining at Atewa Forest Reserve, Ghana: a political ecology of a conservation-exploitation conflict. *GeoJournal*. <https://doi.org/10.1007/s10708-020-10303-3>
- Sarfo I, Bi S, Otchwemah HB, Darko G, Kedjanyi EAG, Oduro C, Folorunso EA, Alriah AAM, Amankwah SOY, Ndafira GC (2022) Validating local drivers influencing land use cover change in Southwestern Ghana: a mixed-method approach. *Environ Earth Sci* 81:367. <https://doi.org/10.1007/s12665-022-10481-y>
- Tan CM, Rockmore M (2018) Famine in Ghana and Its Impact. In: Preedy V, Patel V (eds) *Handbook of Famine, Starvation, and Nutrient Deprivation*. Springer, Cham, pp 1–15. [https://doi.org/10.1007/978-3-319-40007-5\\_95-1](https://doi.org/10.1007/978-3-319-40007-5_95-1)
- Tuffuor K (2012) Ghana's Forestry Report draft: Towards ECO-WAS Forest Convergence Plan. Ministry of Lands and Natural Resources, Ghana. <http://www.fao.org/3/i3825e/i3825e29.pdf>. Accessed on November 1 2020
- United Nations (2015) *Transforming Our World: The 2030 Agenda for Sustainable Development*. UN Publishing, New York
- United Nations Department of Economic and Social Affairs/Population Division (2014) *World Urbanization Prospects*. United Nations, New York, pp 1–32. <https://doi.org/10.18356/527e5125-en>
- Wang T (2016) Vegetation NDVI Change and Its Relationship with Climate Change and Human Activities in Yulin, Shaanxi Province of China. *J Geosci Environ Prot* 4:28–40. <https://doi.org/10.4236/gep.2016.410002>
- Wang J, Price KP, Rich P (2010) Spatial patterns of NDVI in response to precipitation and temperature in the central Great Plains. *Int J Remote Sens* 22:3827–3844. <https://doi.org/10.1080/01431160010007033>
- Xu H (2007) Extraction of urban built-up land features from Landsat imagery using a thematic-oriented index combination technique. *Photogramm Eng Rem S* 73:1381–1391. <https://doi.org/10.14358/PERS.73.12.1381>

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