Abstract

Changes in land cover have persisted throughout the history of mankind, and are the direct and indirect consequence of human actions to secure essential resources. Understanding direct and indirect factors that influence land use cover change (LUCC) is essential for modelling future LUCC in developing countries. The study analyses local drivers of LUCC in Southwestern Ghana using the mixed-method approach. The approach aided in identifying key drivers of LUCC, using different research strategies for comparisons through confidence level analysis and Analytic Hierarchy Process (AHP). We used expert interviews, literature review and geostatistical tools to ascertain causative factors triggering such unprecedented changes. Geospatial analysis depicted a decline in forests (-1.65 km^2yr^{-1}.) and areas covered by waterbodies (-0.55 km^2yr^{-1}.). A remarkable increase in built-up (+25.77 km^2yr^{-1}.) and farmlands/shrubs (+7.4km^2yr^{-1}.) areas were also observed. Population growth, expansion of settlements and infrastructure, coupled with agricultural expansion are at the centre of the LUCC-environment nexus, based on the confidence level table. A steady increase in surface temperature can be attributed to the unprecedented LUCC over the past 50 years. Socio-economic development in Southwestern Ghana is fuelling interest in the relation between LUCC and environmental change. Biophysical, cultural and technological factors are also considered key drivers despite the "medium-to-very low confidence" in results generated. They could potentially impact climate-sensitive sectors that significantly modify land-use systems from the pessimists and optimist's perspective. We, therefore, propose further analyses of LUCC drivers with medium to very low confidence levels.

Keywords: Land Use Cover Change, Drivers, Confidence level, AHP, Southwestern Ghana

1. Introduction

Land use and forest management remain pivotal in achieving the United Nations' Sustainable Development Goals (SDGs). Studies have comprehensively reflected on the linkage between 'Sustainability' and Forest Transition Theory 'FTT' (Rudel et al. 2010; Turner et al. 2007; Mather et al. 1998). When viewed through the lens of the SDGs, making gains in FTT application may complement global efforts at achieving SDGs 1 (No Poverty), 2 (End Hunger), 13 (Climate Action), and 15 (Life on Land) in various ways. Meyfroidt and Lambin (2011), in their research on FTT, reinforced the connection between land use change dynamics and the FTT concept, as seen in earlier studies such as Foley et al. (2005). Arguably, both studies implicitly and explicitly provide opportunities for forest transition to 'reinstate' poorer, forest dependent populations into more favourable socio-economic positions as access to natural capital becomes possible. This must however, be supported by enabling factors, mainly a corruption free system. There is also a possibility for a non-realisation of the 'full potential' of natural resource access alone in reducing poverty, considering arguments brought forward by studies which explore the five capitals model (Fig.1) (Gazzola and Querci, 2017; Sim et al. 2004; Angelsen and Wunder 2003; Smith and Scherr 2002; Hyden 1998). They argued that effective poverty reduction is achieved when access to all five capitals (Fig.1) (Gazzola and Querci 2017) exist, hence, possibly undermining positive forest transition outcomes in poverty alleviation; highly possible in the tropics and less developed countries.

Systems responsible for sustainable use of forest resource are essential (Damnyag et al. 2017; FAO 2013) in themselves, and for contributing to forest transition (Waggoner and Ausubel 2001). In the same vein, forest transition can contribute to sustainable forest resource management (Lambin and Meyfroidt 2011). Land cover requires robust use of the elements of Sustainable Forest Management (SFM); "extent of forest resources; forest biodiversity; forest health and vitality; productive functions of forest resources; protective functions of forest resources; socio-economic functions of forests; legal, policy and institutional framework" (FAO 2013). Various studies support the central idea that efforts geared at the SFM elements remain critical for a fair forest resource use regime across all facets of socio-economic status, underscored by transparency in the context of forest transition (Rudel et al. 2020; Southworth et al. 2012; Lambin and Meyfroidt 2011; Meyfroidt and Lambin 2011). Concepts of "ecoconsumerism" (Meyfroidt and Lambin 2011), and "new corporate environmentalism" (Nasi and Frost 2009), re-emphasise rigorous SFM approaches through forest transition. These ensure land cover related benefits mainly ecosystem/ecological service advantages, and forest product use benefits among others become, and remain (if existent), reality.

The human-environment relationship varies in time and space. LUCC is often caused by an interplay of multiple factors (Tolessa et al. 2019; Lambin and Meyfroidt 2011; Sim 2004). The dynamic interactions result in diverse chains and trajectories of change, depending upon the specific environmental, social, technological, political and historical contexts from which they arise. In response to the growing demands of human survival and developmental needs, the earth 's surface is continuously altered. Changes in land cover have persisted throughout the history of mankind, and are the direct and indirect consequence of human actions to secure essential resources (Mensah et al. 2019; Acheampong et al. 2018). Firstly, this may have occurred through clearing of land for farming activities and hunting. These events accelerated substantially with the birth of agriculture, resulting in the extensive clearing (deforestation) and management of terrestrial systems. More recently, economic growth through industrialization has encouraged the concentration of human populations within urban areas (urbanization) and the depopulation of rural areas, accompanied by the intensification of agriculture in the most productive lands and the abandonment of marginal lands (Damnyag et al. 2017; Saad et. al. 2013; Ellis and Pontius 2010; Kusimi 2008). Biodiversity among other ecosystem end-points and functions are often reduced dramatically by LUCC. When land is transformed from a primary forest to a farm, the loss of forest species within deforested areas occurs. Similarly, undisturbed environments are relatively transformed to more intensive uses, including livestock grazing, selective tree harvest and so on (Ellis and Pontius 2010).

Generally, using GIS and remote sensing techniques to identify, monitor and analyse changes on land are essential in supporting state policies aimed at enhancing efficient utilization of land and other natural resources. The Southwestern region of Ghana hosts two-thirds of Ghana's high forest zone and is the most endowed in natural resources among the sixteen (16) administrative regions in Ghana. We undertook this study to analyse the main drivers of LUCC in Southwestern Ghana using the mixed-method approach (MMA) (1970-2020). The MMA employs both qualitative and quantitative strategies to identify and analyse both direct and indirect factors that influence LUCC. It does not only detect changes but also validates information on dynamics in environmental issues that provide strategic directions for policy-makers and inform the choices of local communities. The present study identifies experts as relevant stakeholders, whose knowledge could be tapped to enhance the understanding of land use systems in Southwestern Ghana. Contextually, only few studies have attempted to quantify non-spatial/indirect drivers of LUCC (Kleemann et al. 2017; Jacobs et al. 2015; MA 2005). Long term residents and expert opinions are key in understanding why land use in the study area is constantly changing, since the triggering effects constitute direct and indirect drivers of LUCC (Kleemann et al. 2017). Surprisingly, indirect drivers of LUCC cannot be quantified using spatial or economic tools. Hence, the present study sought to employ the MMA to quantify both spatial and non-spatial drivers, aimed to enhance comparisons, consistency and confidence in study findings.

2. Methodology

2.1 Study area

The study was conducted in Southwestern Ghana as part of a broad study that analysed spatiotemporal development of land use systems and climate variability in Ghana between 1970 and 2020. The study domain (Fig.2) is located on latitude 5.3902°N and longitude 2.1450°W. It currently covers an approximate surface area of 23,921 km^2 (9,236 sq. mi) representing about 10 percent of Ghana's total land surface area. About 75 per cent of Ghana's high forest vegetation among other natural resources can be found in the region. The study area is embedded with two administrative regions; Western North and Western region.

2.2 Image classification of land use systems

In this study, six Landsat images archived for the given period (1970-2020) (Table 1) from Landsat 5 MSS, Landsat 4 TM, Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI/TIRS were acquired from the United States Geological Survey's (USGS) website (http://earthexplorer.usgs.gov/). ArcGIS 10.6, ENVI 5.0 and 5.3 were used for the image pre-processing. Other image pre-processing procedures which were performed include image calibration, layer stacking and supervised classification (Table 2).

2.3 Change Detection Analysis

Change detection analysis was run to ascertain the regularity of land use systems and its drivers in southwestern Ghana (1970-2020). The present study applied image differencing, NDVI, post-classification and GIS techniques in determining the spatiotemporal development of land use systems in the area. LUCC was computed based on the following expressions:

$$Change \in LUCC\left(x^2\right) = \frac{LUCC_{Current\ year} - LUCC_{Past\ year}}{LUCC_{Past\ year}} \cdots Eqn\,1$$

$$\%\,Change \in LUCC\left(x^2\right) = \frac{LUCC_{Current\ year} - LUCC_{Past\ year}}{LUCC_{Past\ year}}\, x\, 100\,\% \cdots Eqn\,2$$

$$Rate\ of\ Change \in LUCC\ per\ year = \left[\left(\frac{LUCC_{Current\ year} - LUCC_{Past\ year}}{LUCC_{Past\ year}}\right) x\, 100\,\%\right] \div 50\ years \cdots Eqn3$$

The change detection statistics for the study period (1970-2020) was obtained using pixel count, area in km^2 and percentages for the purpose of analysis. This facilitated the generation of statistical data of change occurrence over the years in relation to each class.

2.4 Temperature analysis

2.4.1 Image Calibration (Radiance)

Radiometric correction (radiance) was done to rectify atmospheric effects and enhance clarity. There may be stripes in some of the images acquired; hence, subjected to gap-filling. Gap-filling was done for images that may have had stripes in them. Distortions in images were removed in the calibration process.

2.4.2 Digital Number (DN) to Radiance

The ETM+ DN values range between 0 and 255. A conversion of DN to spectral Radiance was done according to Coll et al. (2010) as retrieved from USGS Landsat User handbook. The mathematical expression below was used to determine the radiance for the study area.

$$L_\lambda = \frac{\left(LMAX_\lambda - LMIN_\lambda\right)}{\left(QCALMAX - QCALMIN\right)}\, x\left(DN - QCALMIN\right) + LMIN_\lambda \cdots Eqn.4$$

Where L_λ is cell value as radiance in $W/\left(M^2 * sr * \mu m\right)$;

$LMAX_\lambda$ is the sensor spectral radiance that is scaled to $\left(QCALMAX\right)$ in $W/\left(M^2 * sr * \mu m\right)$; $LMIN_\lambda$ is the sensor spectral radiance that is scaled to $\left(QCALMIN\right)$ in [$W/\left(M^2 * sr * \mu m\right)$]. $\left(QCALMAX\right)$ is the maximum quantized calibrated pixel value to $LMAX_\lambda$ [DN], $\left(QCALMIN\right)$ is the minimum quantized calibrated pixel value corresponding to $LMIN_\lambda$ [DN]; and QCAL is the quantized calibrated pixel value [DN]. Equation 4 can be observed from header files ETM+ and TM datasets from USGS website. The LMIN and LMAX are the spectral radiances for each band at digital numbers (DN) 1 and 255 for Landsat 7 ETM+, 1 and 65535 for Landsat 8 OLI/TIRS. λ is the wavelength. This was done using ArcGIS 10.6.

Conversion of Spectral Radiance (L_λ) to Kelvin with emissivity value:

$$T = \frac{K_2}{\ln\left(\frac{K_1 * E}{L_\lambda} + 1\right)} \cdots Eqn.5$$

Therefore, k_1 and k_2 become a coefficient determined by effective wavelength of a satellite sensor. ETM+ and TM Thermal Band Calibration Constants (Avdan & Jovanovska 2016; Ghulam, 2010) are depicted in Table 2.1 and Table 2.2.

$$BT = \frac{K_2}{\ln\left[\left(K_1 / L_\lambda\right) + 1\right]} \cdots Eqn.6$$

2.4.3 Conversion of Spectral radiance (L_λ) to Kelvin with emissivity value from Landsat 8

ENVI 5.0 software was used for the correction of thermal band 10 in order to remove atmospheric distortions from the thermal infrared data. Since temperature is required in Degree Celsius (**°C) (**T_c**),** results for various temperatures must be converted from Kelvin (K) (T_B) to degree Celsius (**°C) (**T_c**).** Conversion of Kelvin to Degree Celsius:

$$T_C = T_B - 273.15 \cdots Eqn.7$$

Where T_B is value at satellite brightness temperature (K) and T_C is temperature in Degree Celsius.

2.5 Data Collection

A semi-structured questionnaire was designed and administered to some experts in the study area. It was categorized into six (6) sections (Annex III). "Experts" in this study is defined as individuals with extensive knowledge and experience in relation to the scope of this study and have lived or worked in the area for more than 20 years. In-depth interviews were conducted among 30 experts to ascertain the major drivers of LUCC. Experts were chosen based on willingness and availability to contribute to the study.

2.6 Data Analysis

Mixed-method approach (MMA): Remote sensing analysis, expert interviews and literature review

The approach was primarily used in IPCC's fifth assessment report to validate the inconsistencies, associated with the various working groups' reports on indirect drivers of LUCC (Kleemann et al. 2017; Jacobs et al. 2015). The present study therefore sought to employ this appropriate technique to achieve its main objective. Excel and Statistical Package for Social Sciences (SPSS Inc. Chicago, USA, version 16) software were employed to capture, clean and analyse the data collected. Descriptive statistics were employed in the analysis of data. Categorical variables were measured in percentages. Results from respondents' knowledge were used to validate the outcome from satellite imagery over the study period. This clearly delineate major influences for the given period along with associated changes (consequences). The MMA designed for this study is presented in Fig.3.

2.6.1 Confidence Level Analysis

To express the validity and reliability of findings, we adopted the confidence level approach provided by Kleemann et al. (2017), Jacobs et al. (2015), based on Mastrandrea et al. (2011) for the IPCC AR5 and the Millennium Ecosystem Assessment (MA, 2005). They employed a combination of agreement and evidence levels to evaluate confidence in the validation of findings. This parameter is important in ironing the degree of inconsistencies or inaccuracies in various approaches used. The present study modified the matrix model from the aforementioned studies by specifying the level of agreement and level of evidence for the respective methods (Table 3 and Table 4).

2.7 Accuracy Assessment

Ground truthing

Ground truthing sampled points were taken using a Mobile Data Collection Application (MDC). The samples were imported unto the Southwestern Ghana shapefile in ArcMap for verification. Samples taken for each class (Table 2) were divided/distributed based on area coverage. Thus, bare land (70), built-up areas (177), waterbodies (20), forests (104) and farmlands/shrubs (153) sampled points were taken from the field, making a total of five hundred and twenty-four (524) samples. The map for the sampled points for the various land cover types are shown in Annex IV. Therefore, accuracy assessment for this study was calculated as:

$$Accuracy\ Assessment\left(A.A\right) = \left[\left(ASP / TSP\right) \times 100 \cdots Eqn.8\right]$$

where:

ASP = Number of sample points that accurately falls on each required feature (ASP=493).

TSP = Number of total sample points generated (TSP=524).
A.A = Accuracy Assessment [(493/524) X 100 =94.08%].
Therefore, the present study had 94% accuracy over the study period considering the samples collected.

2.8 Analytical Hierarchy Process (AHP) model for Land Use Cover Change

The AHP is an analytical tool that uses hierarchical structures to present a problem, analyze and advance priorities for alternatives based on the judgment of the user with the aim of solving complex problems (Saaty, 1980). This is based on pair-wise comparisons. Evaluation criteria and their weights are obtained per their importance. AHP analysis proceeds through the six steps (Saaty, 1980) as cited by Danumah et al. (2016): Breaking a complex unstructured problem down into its component factors; development of the AHP hierarchy; paired comparison matrix determined by imposing judgments; assigning values to subjective judgments and measuring the relative weights of each criteria; synthesize judgments to determine the priority variables and checking for consistency in assessments and judgments. The unique basic quality of AHP is the calculation of consistency ratio which reduces bias to a larger extent and determine how logical results are. If consistency ratio is less than or equal to 0.1, then the factor is considered as acceptable consistency. However, AHP approach is built on three levels as evident in Fig 3.1. Level 0 is linked to the main objective of the study; Level 1 shows criteria analysis which constitute biophysical and proximate/underlying factors whereas Level 2 lists the elements that constitute the biophysical and proximate factors (Danumah et al, 2016; Nejad et al. 2015; Chakraborty & Joshi, 2014; Pourghasemi et al. 2014; Saaty, 1980).

2.8.1 Principles for selecting each weight factor (AHP)

The reason is to build a matrix to express the relative values of biophysical and proximate factors responsible for land use land cover change in a hierarchy. Experts of these judgments are assigned a number according to Saaty's scale. A basic, but very reasonable assumption is that if for example element A is very strongly important than element B then A is assigned 7, whereas B becomes less important than A and B is valued at 1/7. A pair-wise comparison was carried out for all listed factors and their relative weights were calculated (eigenvector). Finally, the consistency ratio (CR) was calculated to determine whether consistency in results have been relative to large samples of purely random results. Therefore, a CR > 0.1 indicates the judgements maybe unreliable and the whole exercise must be re-conducted.

2.8.2 Pairwise Comparison

The binary combination is based on Saaty's (1980) proposition to compare risk and impact elements whilst the pairwise comparison is the basic element of AHP process. For pairing in each criterion, the preferable element is weighted on the scale ranging from 1 (equally good) to 9 (absolutely better), whereas the less preferred element is assigned a weight, reciprocal to this value. Each score shows how better element "X" meets criterion "Y". The ratings are normalized, and their consistency are being calculated (Table 4.1).

2.8.3 Development and Prioritization Matrix

Developing and prioritizing matrix are done to determine the eigenvectors (Vp) of each criterion for each item as expressed in eqn.9 where;

$$V_p = n\sqrt{W1x\ldots} Wn\ldots eqn(9)$$

n represents the number of parameters. Wn ratings are the main parameters. The criteria weight (Cp) is measured as:

$$C_w = \frac{V_p}{V_p1 + \ldots + V_{pn}} \ldots eqn(10)$$

The sum of criteria weights (Cw) of all parameters of a matrix equals 1 and expressed as a percentage. Normalize the matrix by dividing each element by the sum of the column as well as finding the average value of each line to determine the priority vector [C]. Multiply each column of the matrix by the priority vector that corresponds to decide the overall priority [D].

Moreover, each global priority is divided by the priority vector that corresponds to it to find the rational priority [E]. Equation 11 shows how the maximum Eigen Value (λ max) is calculated**;**

$$\lambda max = \frac{[E]}{n} \ldots eqn(11)$$

and Consistency Index (CI) is measured as:

$$CI = (\lambda max - n)/(n-1) \ldots eqn(12)$$

The CR is calculated using eqn. (13). The ratio of consistency is the probability that the croak is accomplished in a random manner. When CR ≤ 10 %, the results are considered to be pragmatic. However, a CR > 10 % indicates the need to revise the entire process again.

$$CR = \frac{CI}{RI} \ldots eqn(13)$$

(RI) represents the random index. The values for the random index (RI) are depicted in Table 4.2.

3. Results

3.1 Sociodemographic characteristics of respondents

Majority of the respondents interviewed were males (87%) whilst the remaining quota (13%) represented females in SW Ghana (Table 5). The distribution below (Table 5) shows 53% of respondents had an age range of 26-40 years while 47% ranged between 41-65 years. In terms of educational background, 27% of respondents had attained secondary education while 73% had obtained tertiary education with various degrees. Also, most (73%) of the respondents had been living or working in the study area for (±28) years. The remaining quota (27%) on the other hand asserted they have been living or working in the area for (±10) years.

3.2 Drivers of Land Use Cover Change

An array of factors that influence land cover types at the local, regional, national, continental and global scales are often anthropocentric and biophysical in nature. We identified over eight (8) major factors (proximate/ underlying) that drive LUCC in Southwestern Ghana. Key historical events along with some direct and underlying (indirect) drivers of LUCC as well as transitions are the implications of altercations drawn from the findings of existing literature (Table 7), expert interviews (Table 9) and spatial analysis generated for the present study (Fig.4). Results presented in Table 6 shows an area coverage for each class (sq.km) and evidence of considerable LUCC patterns in Southwestern Ghana between 1970 and 2020 (Fig.4). The main land use feature that increased progressively over the study period was built-up and farmlands/shrubs (Fig.6, Fig.9 and Fig.10). Additionally, bare land, waterbodies and forest areas experienced dynamic ebb over the given study period.

3.3 Temperature Analysis

Fig. 5 indicates temperature range on average was between 27.78° C and 20.23 ° C in the 1970s. However, the average temperature range for 1980s was between 30.44° C and 27.78 ° C, which could be attributed to biophysical factors (i.e., famine that occurred in the 1980s), which caused significant rise in surface temperatures in the study area. The range for the 1990s was between 28.88° C and 25.45 ° C. Average temperature range for 2000, 2010 and 2020 were between 30.12° C and 23.67° C, 31.66° C and 24.44° C, as well as 33.76° C and 24.54° C, respectively.

Generally, the overall conversions of LUCC systems (land cover changes between periods) as depicted in Fig. 6 and Fig. 7 indicate bare land decreased at a rate of 18.06% (with 0.36% decline per year), built-up increased at a rate of 1288.36% (with 25.77% increase per year), waterbodies declined by 27.39% (with 0.55% decline per year), farmlands and shrubs increased by 369.81% (at a rate of 7.4% increase each year) whilst forests over the study period declined by 82.41% (at a rate of 1.65% each year) as illustrated in Fig.7. Summary of existing literature on major events and land use studies in Southwestern Ghana (1970-2020) are presented in Table 7. Table 8 presents description of experts' rank on most influential drivers of LUCC in the study area whilst Table 9 shows confidence level analysis based on the MMA to ascertain local drivers of LUCC.

3.4 AHP Drivers of Land Use Cover Change

The risk factors stated by the study comprised biophysical and proximate/underlying drivers that influence LUCC in Southwestern Ghana (Tables 10 and 10.1).

3.4.1 Interpretation of results

The value of Consistency ratio (CR) of the drivers on the pair-wise matrix is 0.01. Therefore, it can be concluded that the outlined drivers in the pair-wise matrix is reasonably consistent. Hence, these criteria weights can be used (Table 10.1): High Temperature (**HT**) is given 30.88% weight representing the highest ranked biophysical driver and in descending order of severity, Bushfires/Wildfires (**BFW**) having 22.62% weight, Unpredicted/Fluctuations in rainfall patterns (**UFRP**) given 17.80% weighting, Floods (**FI**) and Famine (**F**) assigned 11.16% weighting respectively,whereas soil quality (**SQ**) obtained 6.37% weighting.

3.4.2 Proximate or Underlying Drivers of Land Use Cover Change

Pairwise comparison matrix of proximate/underlying factors are presented in Table 10.2. Table 10.3 shows the calculated consistency of proximate/underlying drivers of LUCC. Deforestation (**D**), Settlements (**S)** Mining/infrastructure (**MI**); Migration (**M**) and Population Growth and Distribution (**PGD**) are given 12.94% respectively; Agriculture Expansion (**AE**) and Poverty (**P**) again received 7.34% weightings; Wood Extraction (**WE**) and Setting up Profit Oriented Industries (**SPOI**) obtained 4.12% weightings while Technology (**T**); Weak Governance, Monitoring & Enforcement Mechanisms (**WGMEM**) and Cultural Values, Behaviours and Beliefs (**CVBB**) received 4.12% weightings. Fig. 8 was designed based on the weightings assigned to elements against pairwise comparisons. The pair-wise matrices were normalized, and their consistency were calculated as shown in Tables 10, 10.1, 10.2 and 10.3.

4. Discussion

4.1 Land use cover change in Southwestern Ghana

Per the conversions in various land cover types observed in Fig.4, Fig.6, Fig. 9, Fig. 10 and Fig.11, there is evidence of expansion in farmlands/shrubs and built-up areas over the given study period. Additionally, previous studies and experts' assertion highlighted in Table 7 and 8 respectively, illustrate recurrent changes in the study area. Findings based on geo-statistical analysis illustrated drastic increase in farmlands/shrubs (+369.81%) and built-up areas (+1288.36%) at the expense of a reduction in forested areas (-82%), waterbodies (-27%) and bare land (-18.06). Conversely, 73% of experts asserted that there has a decline in forest areas in Southwestern Ghana over the past 50 years. Results agree with the standpoints of Kusimi (2008), Damnyag et al. (2017), Kleemann et al. (2017), Acheampong et al. (2018) and Mensah et al. (2019), who attributed loss of forests areas over the past few decades to several socio-economic factors like rapid urbanization, population growth and distribution, agriculture and infrastructure expansion.

4.2 Identified drivers of LUCC based on Confidence level results

In this study, results from expert interviews revealed the substantial increase in built-up areas. Specifically, settlements and infrastructure are linked to the rapid growth in human population. All the respondents affirmed there had been a remarkable increase in human population over the past 50 years. The rapid growth in population based on experts interviewed were attributed to migration of people from other regions and towns of neighbouring countries. 53% of the experts asserted migration was the main cause of increasing population in the region, while 13% revealed high birth rate as the cause; with 33% attributing the reason to both migration and high birth rate. During the course of the interview, it was revealed people primarily migrated to Southwestern Ghana due to the region's endowment in natural resources. Most common activities constitute illegal small-scale mining, farming and construction works. Majority (77%) opined population growth exacerbated pressure on land, mineral and forest resources in the region. Hence, the conversion of forest, bare land and areas covered by waterbodies into built-up (Fig.6).

Considering the outcome presented in Table 9, it is evident that there is robust evidence and high agreement between the three methods. Therefore, experts' assertion of some proximate and underlying economic factors like deforestation of trees for foreign exchange and other domestic purposes, mining and oil exploration, population growth, poverty, migration among others, corroborate with the results of the spatial analysis (Fig.4) (Fig.6) and some previous studies conducted in Southwestern Ghana (Kusimi (2008); Damnyag et al. (2017); Kleemann et al. (2017); Acheampong et al. (2018) and Mensah et al. 2019). It can clearly be stated that there is "very high confidence" in the aforementioned drivers identified in this study. Results proved these economic driving forces causing the unprecedented LUCC in the region are influenced by some macro and micro-economic factors, primarily state policies, aimed towards poverty alleviation or improving living standards, as presented in Table 7. Intensification and extensification of agricultural activities (Table 9) (Fig.4 and Fig.6) in the area over the study period have been linked to the citizenry resorting to use of traditional and reserved lands and forest reserves (encroaching protected areas) as well as other natural resources as the last resort to employment. Experts revealed deforestation in the area was on the ascendency due to extensiveness of farming activities. They further revealed an increase in producer price of some commodities like cocoa on the international and domestic markets in recent times motivated most locals to venture into farming. This has resulted in cash cropping regimes, having a bearing on land cover change in the area. Among the major crops cultivated in the area as revealed by the experts and existing literature (Damnyag et. Al 2017; Noponen et al. 2014) constitute cocoa rubber, plantain, cassava and cocoyam. However, unfavourable climatic conditions coupled with rapid increase in illegal small-scale mining commonly known in local terms as "Galamsey (connotes gather and sell)", have propelled most of the youth to venture into mining instead of agriculture today.

Moreover, geospatial analysis presented in Fig.4 and Fig.6 between 1980 and 2000 presents significant changes through a reduction in areas covered by natural forests, and a substantial increase in farmlands/shrubs and built-up areas. Ghana in the early 1980s, specifically 1983 experienced famine along with recorded incidents of wildfires which claimed several forests and farmlands, thereby influencing prevailing micro-climatic conditions, specifically temperature. Post-famine period saw the formulation and effective implementation of an "Economic Recovery and Stabilization Program (ERP) in 1983" that boosted agriculture with the intention of enhancing food production and improving living standards. Provision of basic amenities and construction of quality transportation networks was intensified. These policies within the said period caused several conversions and modification of several land cover types. Despite the amplitude of several structural transformation programs to change Ghana's economy (2000-2020) from a raw to a manufacturing/industrialized economy, the country's commitment and zeal to achieve the SDGs 1, 2, 13 and 15 in recent years have significantly altered land use systems and prevailing micro-climatic conditions in the region (Table 7) (Fig.5) (Abbam et al. 2018; Aduah and Baffoe, 2013; Aduah et al. 2012; Logah et al. 2011). It was during the 1980-2000 era that natural factors significantly influenced modification of land cover systems. From the lens of the pessimists, despite increasing temperature (Fig.5) and recorded incidents of flood events in recent periods (Abbam et al. 2018; Damnyag et al. 2017), major events like prolonged dryness/famine, wildfires, flooding among others, have minimum influence on causing significant changes in land use systems. This however, reflected in responses given by the experts interviewed. As observed in Table 8, biophysical factors (5th) were ranked as the least influential factor that could drive LUCC in Southwestern Ghana. Among the factors ranked by experts as most influential local drivers were economic (1st), socio-cultural (2nd), political (3rd) and technological (4th) factors. Results from the table of confidence (Table 9) exhibited "very high-to-very low confidence" in some biophysical factors like temperature, bushfires, floods and soil quality, respectively. The distribution shows there was limited evidence provided by at least one method. Hence, providing "very high-to-very low confidence" for most direct and indirect drivers identified using the three (3) methods. There was however no spatial information on other natural factors other than temperature, which may partly influence confidence in results despite expert interviews and previous studies presenting evidence and agreement levels. With "very high confidence" changes in temperature based on spatial analysis, expert interviews and literature review (Table 7) (Table 9) (Fig.5) (Abbam et al. 2018; Aduah and Baffoe 2013; Aduah et al. 2012) show temperature as a climatic variable with spatiotemporal attributes capable of driving LUCC. In the same vein, there was agreement in results from the expert interviews and existing literature, in relation to other contributory factors like institutional/political (governance structures, monitoring and enforcement mechanisms), technology (science and research, agroforestry, climate-smart agriculture, mining operations, transportation networks and technical efficiency) as well as cultural and behavioural (lifestyle, beliefs, traditions and perception) factors. Evidence from these two methods coupled with the level of agreement between them proved there is "medium confidence" in the drivers identified. This eventually shows evidence provided to ascertain major influences of LUCC are valid and reliable based on the use of both qualitative and quantitative strategies to determine direct and indirect drivers of LUCC.

Some experts were of the view that political and technological factors could sooner or later become dominant drivers from the pessimist and optimist perspective. They attributed reasons to current trends and advocacy for intensive scientific research and innovation to enhance productivity to meet global demands. We considered technological, cultural and behavioural factors which are often overlooked or deemed irrelevant in other LUCC studies as drivers that could be further analysed and addressed against uncertainties or the unknown in future. Based on the aforementioned reasons, it is becoming increasingly evident that biophysical (emanating from climate disturbances/stressors), cultural and technological factors that had "medium-to-very low confidence" (Table 9) could potentially influence food security, water resources and livelihoods in the near future. For instance, steady increase in surface temperature (Fig.5) as observed in the study area shows modification in land cover types or land use systems have influenced prevailing microclimatic conditions in the region. Therefore, these parameters cannot be overlooked since in the distant future, they could be dominant in causing significant changes to land cover systems and forest resources. The overall aim of this study was to assess local drivers influencing LUCC in Southwestern Ghana using the mixed-method approach. The MMA approach affords researchers, the general public, policy-makers and development strategists the avenue to make comparisons, and combine data using different methods to gain a comprehensive view in the overall status of a country, region or locality. We therefore admonish the adoption of this framework, adapted and modified from Kleemann et al. (2017), Jacobs et al. (2015), Mastrandrea et al. (2011) and MA (2005) in ensuring accuracy, consistency and reliability of results using standardized means.

Table 11 presents the strengths and limitations of individual methods that could affect the validity and reliability of findings used in our study. Consequently, the adoption of MMA for analysing the main drivers of LUCC provides the needed platform for comparative studies. In the present study, we demonstrated that a combination of expert interviews, literature review and spatial analysis can be used to assess and improve confidence in results. Expert interviews through the use of questionnaires bridged paucity of information or gaps in existing literature and spatial analysis. Geospatial analysis provided vivid details of changes on the ground (Rindfuss and Stern 1998). This complements the limitation of subjectivity in the other two qualitative research strategies. Again, results from most qualitative research strategies are often regarded as less reliable based on several discretionary factors (Haradhan 2018; Queirós et al. 2017). Weight of importance are given to outcomes generated by quantitative tools. Qualitative methods used in this study aim at deepening our understanding on factors that cannot be quantified with a high rate of flexibility and exploratory analysis (Haradhan 2018; Queirós et al. 2017). Contextually, satellite imagery is limited in identifying indirect/underlying factors that drive LUCC. Here, we resorted to merge both strategies (Table 9), adhering to the strengths of these methods and restricting the limitations in the use of these methods to ensure "high confidence" in findings.

5. Conclusion

The paper primarily analyses local drivers that influence LUCC in Southwestern Ghana using the mixed method approach. Through this comprehensive study, we demonstrated using existing literature, geospatial analysis and expert interviews can enhance confidence and reliability of results generated using three (3) methods. Understanding direct and indirect drivers of LUCC along with its dynamics and prospect are essential in attaining United Nation's Sustainable Development Goals. Advocacy and concerns in the wake of our changing climate and observable changes in earth system propel the need for further research that improves existing knowledge, innovation and inform decision of development practitioners among other relevant stakeholders. Based on results obtained using the MMA, it can be concluded that:

- Southwestern Ghana has experienced significant changes in land cover systems, with evidence in the decline of its forests, bare land and areas covered by waterbodies.
- A substantial increase in built-up and farmlands/shrubs areas was observed in the region through the spatial analysis.
- Population growth, expansion of settlements and infrastructure, coupled with agricultural expansion are at the centre of LUCC-environment nexus, based on the confidence level table.
- Change in prevailing microclimatic conditions, specifically surface temperature can be attributed to the unprecedented LUCC over the past 50 years.
- Biophysical, cultural and technological factors can be considered as key drivers despite the "medium-to-very low confidence" in results obtained, as they could potentially impact climate sensitive sectors that could significantly modify land use systems.

We presented an objective and a detailed framework to enhance reliability and validity of study findings using confidence level analysis. The underlying theories for the present study are anchored in sustainable livelihood frameworks, FTT, land-use management and sustainable development. Therefore, the key drivers of LUCC that poses threats to livelihoods, ecosystem functions and endpoints can be examined holistically using an interdisciplinary approach to solve basic problems that stem regions without incurring unintended consequences. The present study hereby proposes further analyses of LUCC drivers with "medium to very low" confidence levels for further action.

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Conflict of Interest

The authors declare that they have no competing interests.