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Intensity Analysis to Link Changes in Land-Use Pattern in the Abuakwa North and South Municipalities, Ghana, from 1986 to 2017

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Abstract**—**The continuous increase in population implies increase in food demand. There is, therefore, the need to increase agricultural production and other forest products to ensure food security and economic development. This paper employs the three-level intensity analysis to assess the total change of land-use in two-time intervals (1986-2002 and 2002-2017), the net change and swap as well as gross gains and losses in the two intervals. The results revealed that the overall change in the 31-year period was greater in the second period (2002-2017). Agriculture and forest categories lost in the first period while the other land class gained. However, in the second period agriculture and built-up increased greatly while forest, water bodies and thick bushes/shrubland experienced loss. An assessment revealed a reduction of forest in both periods but was greater in the second period and expansion of agricultural land was recorded as population increases. The pixels gaining built-up targeted agricultural land in both intervals, it also targeted thick bushes/shrubland and waterbody in the second period only. Built-up avoided forest in both intervals as well as waterbody and thick bushes/shrubland. To help in developing the best land-use strategies/policies, a further validation of the social factors is necessary.

Keywords**—**Agricultural land-use, forest, intensity analysis, land-cover change, sustainable land-use.

I. Introduction

LAND use, which usually involves the modification of land cover, natural environment into settlements, arable fields, pastures, etc., has aided humanity to achieve its needs. Globally, changes to cropland, virgin forests, waterbodies and air have been and continues to be driven by the need to provide shelter, food, water, etc., for the increasing population. It has been projected that the world's population of 7.6 billion could balloon to 10 billion by 2050 and global food demand has also been estimated to shoot up by 50% within the same period generating fears that there will be much pressure on the available land resources which could be changed into residential areas, industrial areas, agricultural lands, etc. [1].

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Obviously, there will be the need to increase agricultural production and other forest products to ensure food security and development; this cannot be achieved without reducing the forest areas thereby denying the future of the next generation. Land degradation, soil pollution and erosion, loss of biodiversity, unhygienic water sources and the emission and release of carbon dioxide into the atmosphere have been attributed to land-use changes [2]-[4].

The land has changed to meet the needs of the time; forest lands, agricultural lands have been converted into other developmental use depending on the local, national and international economy. Land-use/cover change impact on climate has become a challenge in both policy and the academic circles on the global level since the mid-1970s and early 1980s. Some studies indicate how land-use/cover change influences climatic conditions mediated through the emission of carbon dioxide, and surface-atmosphere energy exchanges [5]-[7]. Ecosystem goods and services were also been impacted by the land-use/cover change, the impacts are felt on both biotic and abiotic diversity on the global level, soil degradation and the ability of biological systems to support human [9]-[11].

Population growth, coupled with the increasing demand for housing and commercial activities, has been pointed as one of the major causes of land-use change [12]-[14]. Urban sprawl as a result of rural-urban migration in search of greener pastures has also increased the dynamics of land-use [15], [16].

Though other researchers have refuted the simplistic attribution of land-use changes to population, they indicated that people's responses to economic opportunities at all levels mediated by institutions still cause land-use changes [17], [18].

It is important to note that the changing pattern of land-use is influenced by some underlying factors; this relationship helps to make future predictions about the rates and location of changes and hence, recommends policies to ensure sustainable land-use management [19]. Though poverty in Ghana is nationwide, it is more of a rural phenomenon especially among the rural communities of northern Ghana. Due to this, the north and southern Ghana response differently to macroeconomic policies. Therefore, land-use change in the north part of a country cannot be representative enough of the whole country. The current study in southern Ghana could be compared to a similar study conducted in northern Ghana to understand land-use dynamics over 31-year period better.

This paper applied intensity analysis at the three levels namely time interval, category and transition, and these levels helped to quantify the annual intensity of the changes. The case study intends to use three maps as was used in a similar study in northern Ghana [20]. Three maps of 1984, 1999 and 2018 will be generated at the study area to analyze the land-use changes over the identified periods.

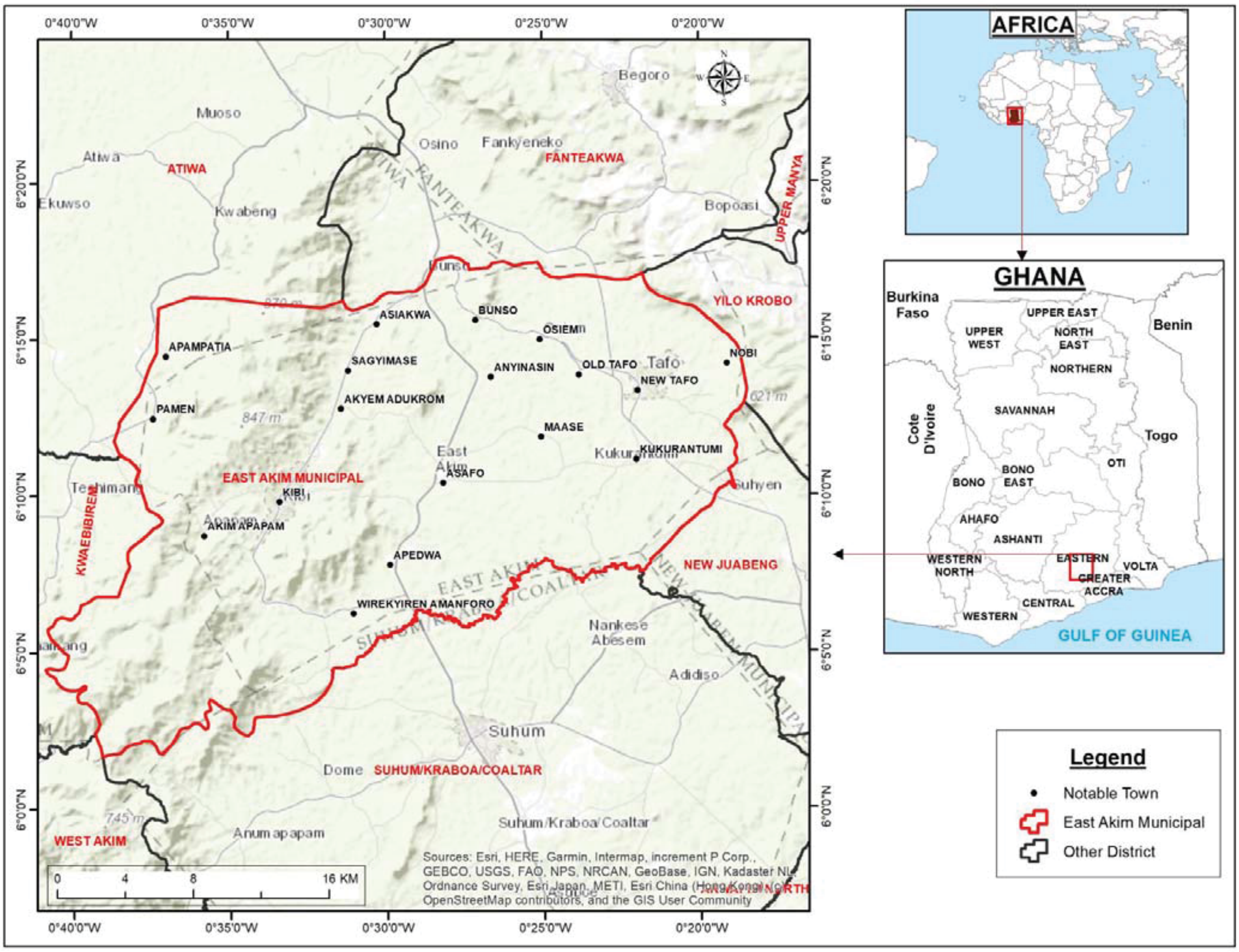

Fig. 1 Regions of Ghana and the location of the study area within the Eastern Region

The study seeks to determine whether land cover changes as a result of policies were different or consistent between the two periods. Furthermore, a discussion of how the land cover changes are associated with human-driven activities in each period was also done while analyzing its implications to ensure a sustainable land-use.

II. Materials and Methods

A. Study Area

Abuakwa North and South Municipalities (formerly known as East Akyem Municipal Assembly) are an approximately 752 km^2 area between latitude 6° 9' 53" N and longitude 0° 33' 13" W the Eastern Region of Ghana (Fig. 1)[1]. It has a mean temperature above 24.7 °C and receives an annual rainfall of about 1665 mm. Both municipalities are found within moist semi-deciduous forest ecoregion of Ghana with forest reserves covering about 108.8sq. km [21]-[23].

The terrain has a mean elevation of 318 m (1,043 ft). East Akim municipal assembly was first established as a District Assembly with legislative instrument (LI) 1420 in 1988 with Kyebi serving as the district capital. It was elevated to a Municipal status in 2008 with LI 1878 [21]-[23].

The soil type of the former East Akim Municipality is of two series; the Atiwa series made up of red and silty loam and the Peki series made up of brown to reddish yellow, moderately well-drained, very shallow and rocky. These series are suitable for the cultivation of cash crops such as oil palm, cocoa, citrus, cola and coffee as well as food crops like maize

[1]The writer was not able to prepare area map for each municipality because as at the time of writing this paper satellite images were only available for the former East Akyem Municipal Assembly (now Abuakwa North and South Municipalities).

(corn), plantain, cassava yam, cocoyam [21]-[23].

Both municipal assemblies are characterized by steep sloping ridges and they are about 240 to 300 meters above sea level. The Atiwa range, which is the highest point found in the Abuakwa South Municipality, rises over 350 meters above sea level, about 50 km long and 10-15 km wide [21]. The forest reserve has a large mineral deposit which includes gold, diamond, bauxite. Gold prospecting and small-scale mining (both legal and illegal) are on the increase in the municipality.

The Atiwa forest has become a source of heated debate in recent years as the government has resorted to using proceeds from mining in the Atiwa forest in exchange for a $2 billion Chinese loan. The river systems in the municipality that serve as a water source to the Ghana Water Company Limited have been negatively affected due to various forms of land-use activities such as mining, indiscriminate waste disposal, water extraction and deforestation for fuel wood and other domestic uses, excessive use of chemical fertilizers [22]. Communities surrounding the forest reserve depend on the reserve for their livelihood though these activities pose a serious threat to the sustainability of the forest's biodiversity.

The renamed Abuakwa South Municipality now shares a boundary with six districts and they are Fanteakwa South District to the north, Kwaebibrem Municipal to the west, Atiwa West to the North-West, Abuakwa North Municipality to the east, Denkyembour District to the south-west and Suhum Municipality to the south. According to the 2010 population and housing census, the municipality's projected population for 2019 is 104,189 with 51.3% female and 48.7% at a growth rate of 2.1% [24].

Farming is the main occupation in the municipality and about 65% of the population is actively working in the agrarian sector [24]. The municipality is home to Okyeman's Old Palace currently serving as a museum, Sagyimase Rain Forest, Agyemprem Watershed among the host of other ecotourist attraction centers. The first university (University College of Agriculture and Environmental Studies) to be established by a traditional council in the country is situated in the municipality.

The newly created Abuakwa North Municipal Assembly carved out of the erstwhile East Akim Municipality in 2017 with L.I 2305 has Kukurantumi as its capital. The municipality shares boundaries with Abuakwa South Municipality to the west, south-east with New Juaben North Municipality, north with Fanteakwa North District and to the east with Yilo Krobo Municipality. The municipality is situated very close to Koforidua, the Eastern Regional capital and it presents a great potential with a spill-over effect from activities in the regional capital.

The municipality's projected population for 2019 is 101,831 growing at a rate of 1.9% comprising 51% females and 49% males. According to the Ghana Statistical Services, about 60% of the municipality's population lives in the urban centers with 52.45% females while the remaining 47.6% are males [24]. But in the rural areas the males dominate with 50.3%. This is due to the fact that farming is the primary source of livelihood. Abuakwa North Municipality has a working population of 57.4% with a youthful population of 35.9%.

The agrarian sector employs 65% of the municipality's labor force and most farmers are into the cultivation of cash crops such as cocoa and oil palm and other staple crops like maize, vegetables, etc. Agro-processing has gained ground with the presence of the Cocoa Research Institute of Ghana (CRIG), established in 1938 to research into the embodiments of the production of cocoa. Some of the finished products include alcoholic beverages, chocolates, cosmetics, poultry feed, etc. The road network is hampering the growth of the agricultural sector, with only 25 of the 106.6 km road paved and is motorable.

The Abuakwa North and South Municipalities were selected, taking into consideration a number of factors including, familiarity and knowledge of the area, agrarian municipalities, availability of satellite data, demographic heterogeneity and agricultural, residential, water and forest land-use characteristics.

III. GIS-Based Land Use and Land Cover Changes Assessment

The employment of Remote Sensing and Geographic Information System (GIS) tools provided the platform for the acquisition of the initial spatially referenced attributed data to begin the research. The maps of the study area (refer to Figs. 1 & 2) were created with the help of ArcGIS 10.6 software while the classification of the images was conducted in the ENVI 5.3 software. The data obtained included medium-resolution satellite imagery of the East Akim Municipality showing the road network, residential footprints, forest and agricultural cover.

In preparing land-use/land-cover (LULC) maps it is necessary to go through the following processes: acquisition of the satellite image of the study area, data processing, identification of image features/class, classification, post-classification processes and finally the accuracy assessment is made [25]-[27].

Land-cover maps of the Abuakwa North and South Municipalities were generated for 1986, 2002 and 2017 from the Landsat Thematic Mapper satellite imagery obtained in August 2019 [28]. Each of the Landsat TM scenes was employed at a resolution of 30 m x 30 m. The classification involves three different procedures: data pre-processing activities, image classification (processing) and change detection (post-processing).

In the pre-processing stage, image band selection, calibration of the satellite images into surface reflectance, band stacking, image sub-setting, and image enhancement such as contrast-stretching, etc., characterized this stage.

The image classification or the processing stage involves the grouping of like pixels by conducting both unsupervised and supervised classifications. The unsupervised classification was used as a guide while the supervised classification employed training samples of the various classes gathered from during the field survey. The supervised classification scheme was carried out using the Gaussian Maximum Likelihood algorithm to classify the various land-cover classes because this algorithm was best at discriminating against the classes [29]. As a result, five land-cover categories were classified as built-up, waterbody, agriculture (cropland with crops and harvested agricultural land), thick bushes/shrubland (grasses and shrubs with or without less than ten trees per hectare) and forest reserve (Fig. 2).

The statistical methods of analyses and the map-making processes constitute the post-processing stage. A map showcasing the three different years of Landsat images classified was developed (Fig. 2)

In producing and evaluating both user's and producer's accuracies, field sampled points (coordinates) of the different classes of the study area were matched with the classified images.

Accuracy assessment is done to determine quantitatively how effectively pixels were grouped into the correct feature class in the study area. In other words, it measures the agreement between a standard assumed to be correct and a classified image of the unknown quality.

IV. Map Classification Error and Its Effects

Confusion or error matrix is a specific cross-tabulation that allows the performance of an algorithm, either supervised or unsupervised learning to be visualized [30]. It shows the predicted class against the reference data of a specific location; this provides the basis on which classification accuracy and errors of omission and commission can be defined [31], [32]. The predicted class is presented in each row of the matrix with the actual class in the column.

There are many measures classification accuracies that can be derived from the error/confusion matrix [33]. The overall accuracy of the confusion matrix is the total number of all class classified correctly; it is represented as a summation of diagonal members divided by the total sum of pixels of the matrix, refer to (1) [34], [35].

The error of commission is the proportion of pixels belonging to a targeted class but was wrongfully classified to another class according to the reference data while the error of omission describes the percentage of pixels belonging to a particular class according to the referenced data but failed to be classified into that type of class [36], [37].

$$\text{Overall accuracy} = \frac{\sum_{i-1}^{k} n_{ij}}{n}\ 100\% \quad (1)$$

The overall accuracy of the confusion matrix has been criticized that some classes may have been collected by chance into the correct class [38], [39]. In view of this, Cohen, introduced Kappa statistics (2) to capture the difference of the correctly classified pixels and the chance agreement through the summation of the rows and the columns [40]. Therefore, the Kappa coefficient statistics is employed as a measure of the degree of agreement between the predicted values and the validation data [41], [42].

$$\text{Kappa Coefficient} = \frac{n\sum_{i=1}^{k} n_{ij} - \sum_{i=1}^{k} n_i + n_i}{n^2 - \sum_{i=1}^{k} n_i + n_i} \quad (2)$$

In Table II is the interpretation of the Kappa coefficient proposed by [43]. The values proposed are a reflection of the overall of the classifications and the consistency between the classified image and the referenced data of the identified classes.

TABLE I
KAPPA COEFFICIENT INTERPRETATION [43]

Kappa coefficient value	Interpretation
$0.81 \leq \check{k} \leq 1$	Perfect agreement
$0.61 \leq \check{k} \leq 0.8$	Substantial agreement
$0.41 \leq \check{k} \leq 0.6$	Moderate agreement
$0.21 \leq \check{k} \leq 0.4$	Fair agreement
$0.0 \leq \check{k} \leq 0.2$	Poor agreement

Tables V-VII (refer to appendix) show error/confusion matrix for 1986, 2002 and 2017 respectively. The overall accuracy for 1986, 2002 and 2017 was 84.82%, 86.27% and 87.21%, respectively, with kappa coefficients of 0.81, 0.83 and 0.84 showing a perfect agreement between the validation data and the predicted data (refer Table I).

The 1986 accuracy assessment shows that 84.82% of the effective pixels were grouped into the correct feature class. The proportion of pixels belonging to a targeted class but was accidentally classified into another class represented by the error of commission ranges between 8% and 25.93% for 1986, between 10.87% and 18.18% for 2002 and between 10.53% and 18.52% for 2017. On the other hand, the percentage of pixels belonging to the ground truth class but failed to be classified into that type represented by the error of omission were between 6.25% and 25.45% for 1986, between 7.69 and 20.69% for 2002 and between 8.62% and 19.35% for 2017.

In 1986, the producer accuracy for the built-up class was 93.75% while the user's accuracy was 84.91%. This means that 93.75% of the referenced built-up areas are identified while, 84.91% of the areas classified as "built-up" were actually built-up. While in 2002, the producer accuracy for waterbody class was 86.96%, the user's accuracy was 74.07%. This means that out of the 86.96% of the referenced waterbody area, 74.07% of the class identified as "waterbody" were actually waterbody. Finally, in 2017, the producer accuracy for agriculture class was 87.93% while the user's accuracy was 74.07%. This means that even though 86.96% of the referenced agriculture has been correctly classified as agriculture, only 74.07% of the areas identified as "agriculture" were actually agriculture. A similar interpretation could be made for the rest of the classes in three different years.

V. Land Change Analysis

A. Land-Cover Transition Matrix

Land-use transition matrix aims at quantifying a system state and state transition through comparing maps of different periods, as it provides information on "from-to" class changes [44]-[46].

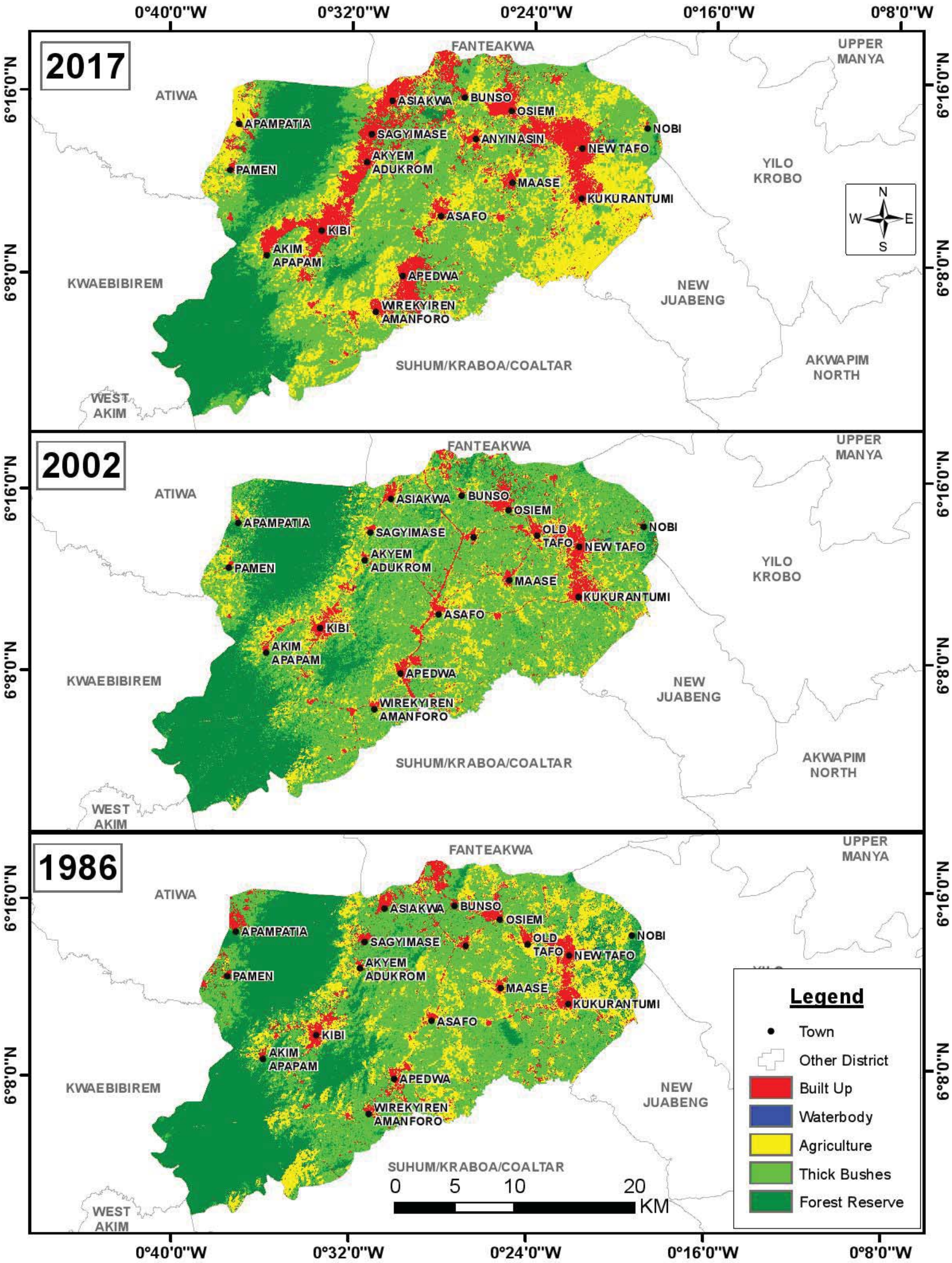

Fig. 2 Land-cover maps of the former East Akyem Municipality of the Eastern Region of Ghana derived from Landsat TM imagery in 1984, 2002 and 2017

The computed transition matrix consists of rows that display row and a class total of the various land classes and columns that show class total, class changes and image difference. The transition matrix is presented as area in percentages for the 1986-2002 and 2002-2017 periods (Tables I and II).

The class total is the total number of pixels in each initial state class while the row total shows a class-by-class summary of all final states pixel that fell into the initial state classes. The class changes in each matrix show the total number of pixels that changed class between two periods – viz, initial and final state. The image difference shows how a class has either grown or shrunken.

B. Intensity Analysis

The intensity analysis uses a cross-tabulation matrix of each time interval to examine the size and intensity change at three levels, namely: range, category and transition [47]. The interval subsection of the intensity analysis deals with the overall annual change of the time intervals; specifically, it examines the amount and change intensity of each period (size and speed of change). The category level analysis examines of the gross gains and gross loss intensity across categories for each time interval. An examination of the transition intensity to gaining categories from any particular losing categories and from losing categories to a specific gaining category is done using the transition level analysis.

The annualized percentage for each time interval of the various land classes that changed during each period denoted, S_t, was calculated by (3):

$$S_t = \frac{(Area\ change\ during\ [Y_t,Y_{t+1}])}{(Duration\ of\ [Y_t,Y_{t+1}])(Extent\ size)}\ 100\% = \frac{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tjj}\right]}{(Y_{t+1} - Y_t)\left(\sum_{j=1}^{J}\sum_{i=1}^{J} C_{tij}\right)} 100\% \quad (3)$$

Descriptions of symbols used in (3)-(8) in this paper are explained in Table II.

The uniform annual change rate of the interval's domain that would exist if the changing pattern was distributed uniformly in each period was compared with the yearly observed change percent of the interval's domain. The method test, if change pattern was stationary across time intervals denoted U, was calculated by:

$$U = \frac{(Change\ during\ all\ intervals)}{(Duration\ of\ all\ intervals)(Extent\ size)}\ 100\% = \frac{\sum_{t=1}^{T-1}\left\{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} - C_{tij}\right) - C_{tjj}\right]\right\}}{(Y_T - Y_1)\sum_{j=1}^{J}\sum_{i=1}^{J} C_{tij}}\ 100\% \quad (4)$$

The category level analysis is done to examine which of the categories is relatively dormant or active. The intensities of the total gain denoted G_{tj}, were calculated by:

$$G_{tj} = \frac{(Anual\ gain\ of\ category\ j\ during\ [Y_t, Y_{t+1}])}{(Size\ of\ category\ j\ at\ time\ Y_{i+1})}\ 100\% = \frac{\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C_{tjj}\right]/(Y_{t+1} - Y_t)}{\sum_{i=1}^{J} C_{tij}}\ 100\% \quad (5)$$

and the intensities of the gross losses denoted as L_{ti} were calculated by:

$$L_{ti} = \frac{(Annual\ loss\ of\ category\ i\ during\ [Y_t, Y_{t+1}])}{(Size\ of\ category\ i\ at\ time\ Y_i)}\ 100\% = \frac{\left[\left(\sum_{j=1}^{J} C_{tij}\right) - C_{tii}\right]/\ (Y_{t+1} - Y_t)}{\sum_{j=1}^{J} C_{tij}}\ 100\% \quad (6)$$

The uniform intensity calculated for each time interval from (3), S_t, was compared with the gross gain and gross losses intensities. In a case where G_{tj} is greater than S_t, then category *j* is an active gainer; and in a case where L_{ti} is less than S_t, then *i* is an active loser.

The transition level analysis was conducted to examine which of the transitions were intensive, i.e., the intensity of changes across the various categories. Equation (7) expresses the total gain of categories, R_{tin} in the form of the observed intensity of change to the category n from each category i, where $i \neq n$. The calculation leading to this was:

$$R_{tin} = \frac{(Annual\ transition\ from\ i\ to\ n\ during\ [Y_t, Y_{t+1}])}{(Size\ of\ category\ i\ at\ time\ Y_t)}\ 100\% = \frac{C_{tin}/(Y_{t+1} - Y_t)}{\sum_{j=1}^{J} C_{tij}}\ 100\% \quad (7)$$

Equation (8) calculates the uniform intensity for category *n*, W_{tn}, a category that spreads the intensity of annual transition gains to category *n* uniformly across the area as:

$$W_{tn} = \frac{(Annual\ gain\ of\ category\ n\ during\ [Y_t, Y_{t+1}])}{(Size\ of\ non-category\ n\ at\ time\ Y_t)}\ 100\% = \frac{\left[\left(\sum_{i=1}^{J} C_{tin}\right) - C_{tnm}\right]/(Y_{t+1} - Y_t)}{\sum_{j=1}^{J}\left[\left(\sum_{i=1}^{J} C_{tij}\right) - C\_tnj\right]}\ 100\% \quad (8)$$

In a case where R_{tin} is greater than Wt_n, the gain of category *n* was considered to target category *i* at time *t.* And in a case where R_{tin} is less than Wt_n, the gain of category *n* was considered to avoid category *i* at time t.

C. Hypothetical Error

Intensity analysis, developed by Aldwaik and Pontius Jr., is a mathematical framework that examines changes in land-use by comparing a hypothetical uniform intensity to observed change intensities among land categories [45]. As an extension to the intensity analysis, Aldwaik and Pontius Jr. proposed a new method to compute the minimum hypothetical maps error that could account for an observed deviation from an observed uniform change intensity [48]. Errors from maps of two different points could be from real change and map errors.

The observed change intensities are uniformly distributed among intervals, category and transition. It is in this sense that any deviation between the observed intensity and the uniform intensity could be attributed to data error. Intensity analysis and the hypothetical errors were calculated based on [47], [48].

TABLE II
MATHEMATICAL NOTATION FOLLOWING [47]

Symbol	Description
T	Number of time points
Y_t	Year at time point t
U	Uniform rate for the entire temporal extent of the study area
t	Index for the initial time point of the interval $[Y_t, Y_{t+1}]$, where t ranges from 1 to T−1
J	Number of categories
i	Index for a category at an interval's initial time point
j	Index for a category at an interval's latter time point
n	Index for the gaining category for the selected transition
C_{tij}	Size of transition from category i to category j during the interval $[Y_t, Y_{t+1}]$
S_t	Annual change during the interval $[Y_t, Y_{t+1}]$
G_{tj}	The intensity of annual gain of category j during the interval $[Y_t, Y_{t+1}]$ relative to size of category j at time t+1
L_{ti}	The intensity of annual transition from category i to category n during the interval $[Y_t, Y_{t+1}]$ relative to the size of category i at time t
R_{tin}	The intensity of annual transition from category i to category n during interval $[Y_t, Y_{t+1}]$ relative to size of category i at time t
W_{tn}	The uniform intensity of annual transition from all non-n categories to category n during the interval $[Y_t, Y_{t+1}]$ relative to the size of all non-n categories at time t

VI. Results and Discussion

A. Land-Cover Transitions/Changes

The nature of LULC changes revealed that built-up, waterbody and thick bushes/shrubland gain or grown by 5.76%, 67.35% and 18.22% respectively while agricultural land and forest cover lost/shrunk by 8.44% and 14.90% at the end of the first period of 1986-2002 (Tables III & IV). Waterbody was the biggest class gainer in the first-period, while forest land was the biggest loser among the classes. During this period, the effect of the Import Substitution Industrialization (ISI) and Structural Adjustment Program (SAP) was felt in almost all aspects of life. Among the SAP reforms in the first phase beginning in 1983 saw the agrarian sector removing subsidies on farm inputs such as fertilizers, liberalization of state control on marketing boards, over-valued exchange rates.

The program, though, geared towards the revitalization of agriculture, ended up being a macroeconomic and sectoral intervention-focused program instead of addressing microeconomic policies to improve agricultural technologies. This account for the reason why agricultural land lost 8.44% whiles waterbody gained 67.35% due to the absence of agricultural activities as agriculture depends on these water bodies. In this same way, thick bushes/shrubland grew due to the dormant agricultural sector.

During the second period of 2002-2017, built-up continues to grow, but this time at a higher percentage of 100.71%, this reflects the growing number of people during this period. The built-up class was the biggest gainer with waterbody is the most significant loser class in the second period. Agriculture recovered and began to expand to feed the growing population; this class of land grew by 52.07% in this period. Waterbody, thick bushes/shrubland and forest lands lost 45.12%, 19.78% and 28.93%, respectively. The loss of forest cover was almost double in the second period compared to the first.

TABLE III
1986-2002 Transition Matrix (Area in Percentages)

Land classes	Built-Up	Waterbody	Agriculture	Thick Bushes/ Shrubland	Forest	Row Total	Class Total
Built Up	49.92	0.00	10.58	3.59	0.94	100.00	100.00
Waterbody	0.01	85.71	0.00	0.00	0.01	100.00	100.00
Agriculture	30.82	0.00	46.73	14.70	5.23	100.00	100.00
Thick Bushes/Shrubland	16.29	2.04	36.94	71.30	23.36	100.00	100.00
Forest	2.97	12.25	5.74	10.41	70.46	100.00	100.00
Class Total	100.00	100.00	100.00	100.00	100.00		
Class Changes	50.08	14.29	53.27	28.70	29.54		
Image Difference	5.76	67.35	-8.44	18.22	-14.90		

TABLE IV
2002-2017 Transition Matrix (Area in Percentages)

Land classes	Built-Up	Waterbody	Agriculture	Thick Bushes/ Shrubland	Forest	Row Total	Class Total
Built Up	70.02	21.95	22.25	10.65	2.25	100.00	100.00
Waterbody	0.00	50.00	0.00	0.00	0.00	100.00	100.00
Agriculture	19.36	0.00	57.26	34.04	6.63	100.00	100.00
Thick Bushes/ Shrubland	10.42	2.44	20.24	53.20	23.27	100.00	100.00
Forest	0.19	25.61	0.25	2.10	67.86	100.00	100.00
Class Total	100.00	100.00	100.00	100.00	100.00		
Class Changes	29.98	50.00	42.74	46.80	32.14		
Image Difference	100.71	-45.12	52.07	-19.78	-28.93		

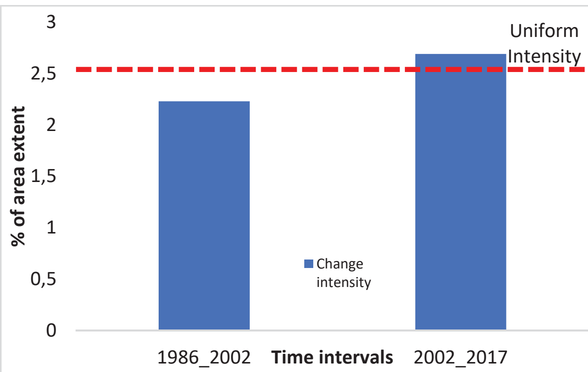

Fig. 3 Hypothetical uniform annual change between 1986-2002 and 2002-2017

B. Intensity Analysis

Interval Level

Figs. 3 and 4 show the interval intensity analysis of hypothetical uniform annual change and commission and omission errors of 1986-2002 and 2002-2017 time periods. The results show that yearly change intensity was greater in the second period (2002-2017) than the uniform intensity but lower for the first period (1986-2002). This is an indication of a faster land change in the second time interval.

Category Level

Below is the intensity analysis for the category level during the 1986-2002 and 2002-2017 periods for the Abuakwa North and South municipalities of Ghana. Figs. 5-8 (a) show the observed gain and loss intensities for each land category whiles Figs. 5-8 (b) show the percentage of area that changed category over the two given intervals. They also present error of omission and commission in change classification in a scenario where the hypothesis of uniform change over both intervals was found to be true.

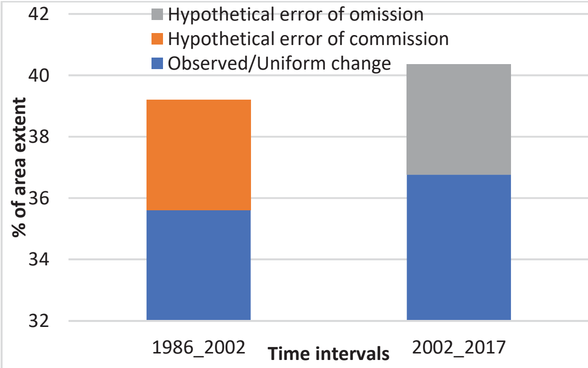

Fig. 4 Hypothetical commission and omission errors during 1986-2002 and 2002-2017 intervals

The results of the category intensity analysis are graphically represented in Figs. 5-8. Figs. 5-8 (a), (b) are sets of bars that show the annual gain or loss intensity of each land-cover category. is the Transition intensity and is the Observed/Uniform annual gain/loss. is the Hypothetical error of commission and is the Hypothetical error of omission. In explanation, in a case where the annual gain or loss intensity is greater or larger than the annual uniform intensity level, then, it means that the gain or loss of the particular category is relatively active compared to the uniform; therefore, the summation of the uniform change and possible commission error is equal or the same as the size of annual gain or loss. On the other hand, where the annual gain or loss intensity is less or smaller than the yearly uniform intensity, then, it means that the gain or loss of the category is relatively dormant compared to the uniform; therefore, we can say that the size of the annual gain and loss is a summation of the observed gain or loss and the hypothetical omission error.

Four categories, built-up, waterbody, agriculture and thick bushes/shrubland area, were active gainers and the forest was the only dormant gainer in the first interval. Built-up and agriculture were active gainers in the second interval while waterbody, thick bushes/shrubland and forest area were dormant gainers. Therefore, built-up and agriculture were active gainers in both intervals. Agriculture was the only category that became the active loser in both intervals; in the same way, the forest was also the only dormant loser in both intervals. Waterbody and thick bushes/shrubland were dormant losers in the first interval but were active losers in the second interval. Overall, waterbody and thick bushes/ shrubland.

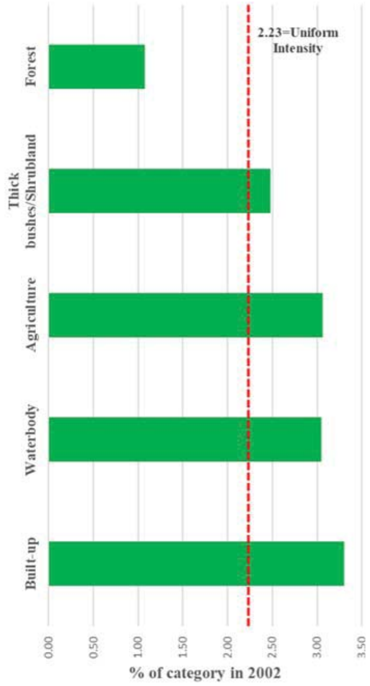

Fig. 5 (a) Gain intensity in 1986-2002

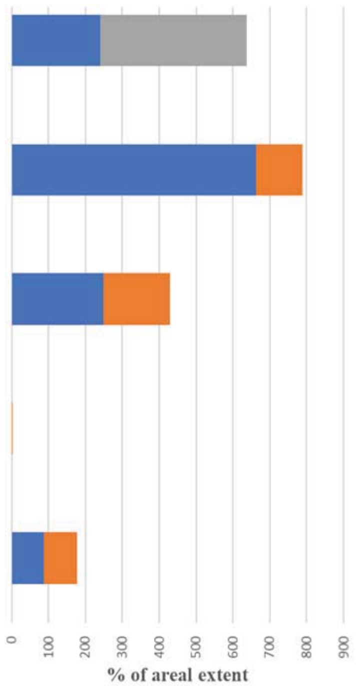

Fig. 5 (b) Hypothetical error of commission/omission

Forest and agriculture were stationary[2] as the intensity of the forest's loss and intensity of agriculture's gains for all intervals were less than and greater than the uniform intensity, respectively. Forest and agriculture experienced the largest

[2] A category is defined as stationary to mean that the intensity of a category's gain is either greater than the uniform line or less than the uniform line for all intervals. Similarly, if the intensity of a category's loss is either greater than the uniform line or less than the uniform line for all intervals, then we call that category stationary in terms of losses [47].

gain and loss in both intervals. From the results above, forest gain and loss were below the uniform intensities, which turns to suggest that forest area was not either an active gainer or loser. On the other hand, the loss and gain intensities of agriculture were above the uniform intensities in both time intervals, which suggest that agriculture was both active gainer and loser in both intervals.

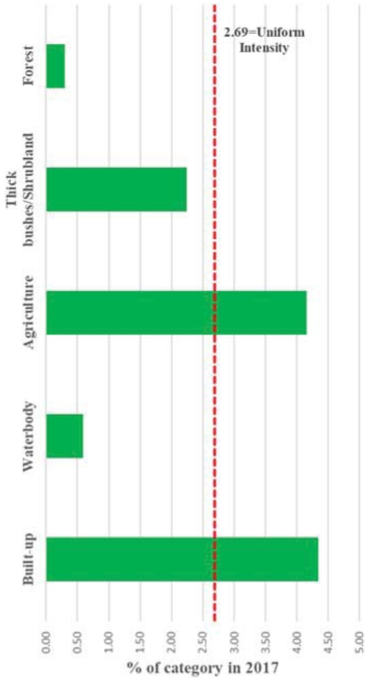

Fig. 6 (a) Gain intensity in 2002-2017

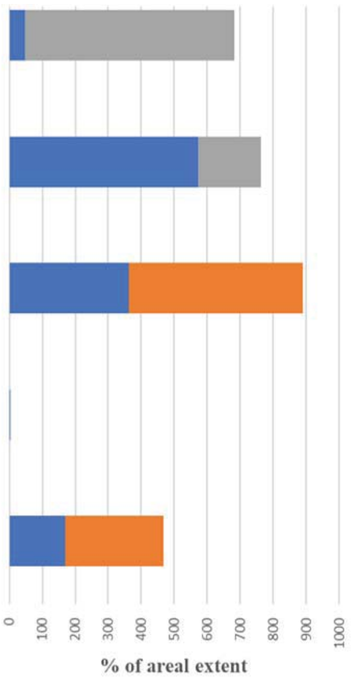

Fig. 6 (b) Hypothetical error of commission/omission

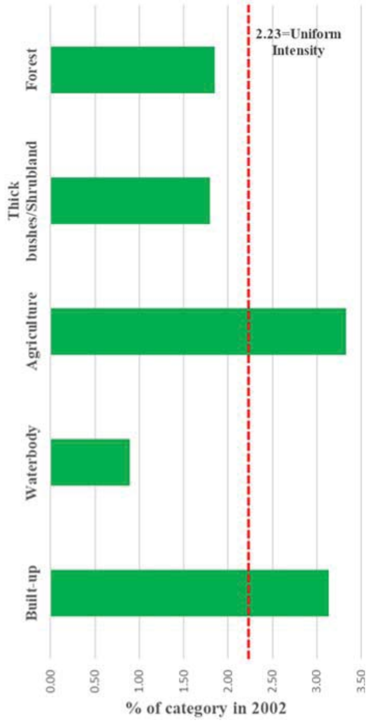

Fig. 7 (a) Loss intensity in 1986-2002

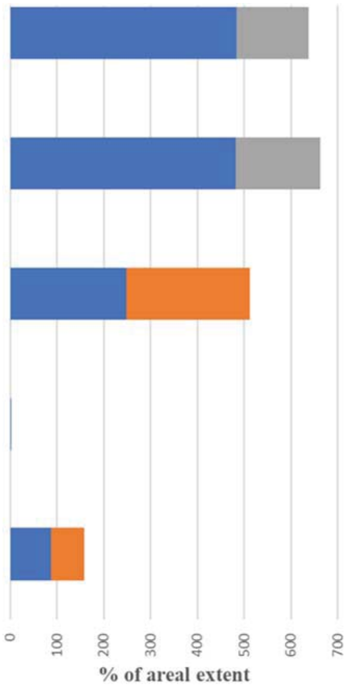

Fig. 7 (b) Hypothetical error of commission/omission

Waterbody and thick bushes/shrubland also experienced annual gain and loss such that both category's gain intensities were above the uniform intensity in the first interval but were both dormant in the second interval. This means that waterbody and thick bushes/shrubland experienced gain more intensively than the study area in general in the first interval and, at the same time, experienced loss intensively in the second interval than the general study area. However, both were dormant losers in the first interval but was an active loser in the second interval.

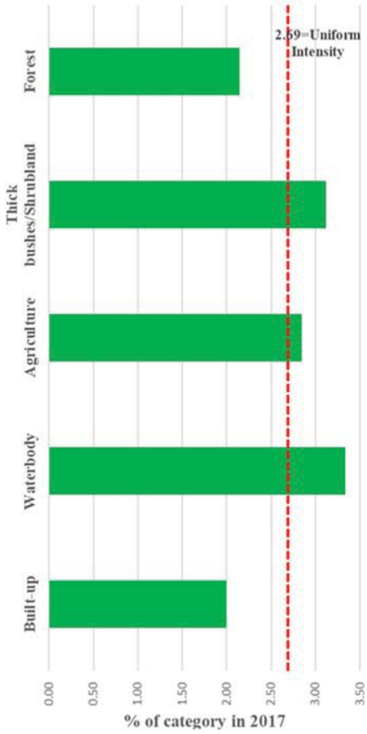

Fig. 8 (a) Loss intensity in 2017

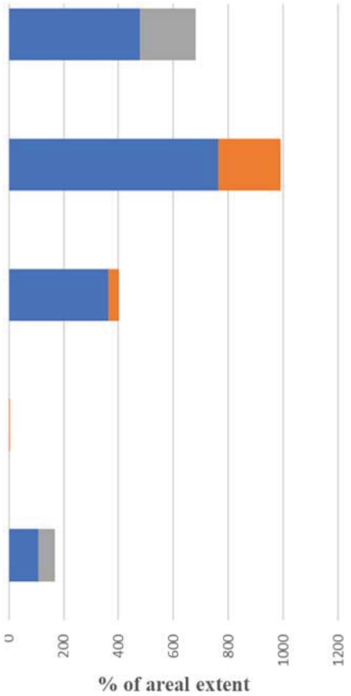

Fig. 8 (b) Hypothetical error of commission/omission

Built-up experienced annual gain and loss, with the exception of this category being a dormant loser in the second period; it was an active gainer in both periods and active loser in the first period. This suggests that built-up's gain intensities were greater than the uniform intensity in both periods while its loss intensities were greater in the first period but lesser in the second period.

From Figs. 5-8, the changes with respect to the intensities are not evenly distributed across all the categories since all the gain or loss intensities did not end at the uniform intensity line for all time intervals. Therefore, each category is stationary between the two-time intervals with respect to its status of being either active or dormant.

Transition Level

Figs. 9-18 present the graphs of the intensity analysis for transition-level during the 1986-2002 and 2002-2017 periods for the Abuakwa North and South municipalities of Ghana. Figs. 9-18 (a), (b) show the observed gain and loss intensities for each land category and the percentage of area that changed category over the two given intervals. They also present error of omission and commission in change classification in a scenario where the hypothesis of uniform change over both intervals was found to be true.

The results shown in Figs. 9-18 are the transition level analysis for each of the gaining land-use categories in the 1986-2002- and 2002-2017-time intervals. is Transition intensity and is Observed/Uniform annual gain/loss. is Hypothetical error of commission and is Hypothetical error of omission. The annual transition intensity of each category is shown on Figs. 9-18 (a), while the size of the annual transition of each category for the two intervals is displayed on Figs. 9-18 (b). Gaining category targets a losing category when the annual transition intensity of the gaining category is larger than the uniform intensity; therefore, the summation of the uniform changes the hypothetical error of commission is the annual transition. In the same way, the gaining category avoids a losing category when the annual transition intensity is smaller than the uniform intensity. Therefore, the annual transition change is the sum of the hypothetical error of omission and the observed change.

The pixels gaining built-up targeted agricultural land in both intervals though it also targeted thick bushes/shrubland and waterbody in the second period only, built-up avoided forest in both intervals and two categories in the first interval, namely: waterbody and thick bushes/shrubland (Figs. 9 (a), (b) and 11 (a), (b)). The intensity level of transition targeting agriculture was above the annual uniform intensity in both intervals, which suggests that built-up targeting agriculture was greater. This suggests why the built-up grown from 5.76% to 100.71% at the end of the second interval.

Figs. 10 (a), (b) and 12 (a), (b) show transitions to waterbody in both intervals. Waterbody targeted forest and avoided agriculture, thick bushes/shrubland in both intervals. The pixels gaining agriculture targeted thick bushes and shrubland, but it avoided forest, waterbody in both intervals (Figs. 13 (a), (b) and 15 (a), (b)). The gaining pixel targeted built-up in the first intervals but avoided it in the second interval.

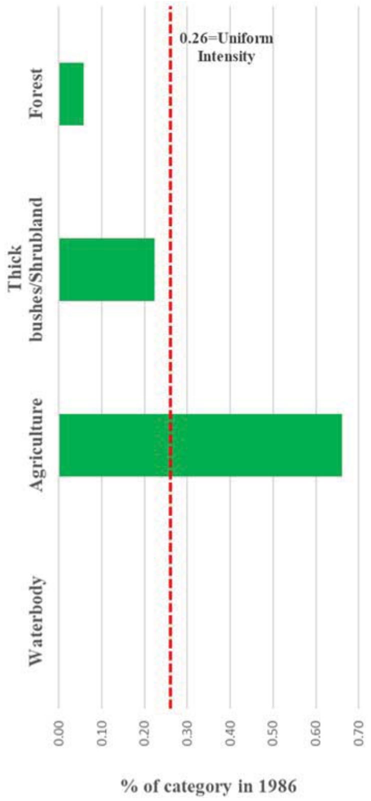

Fig. 9 (a) Transition to Built-up in 1986-2002

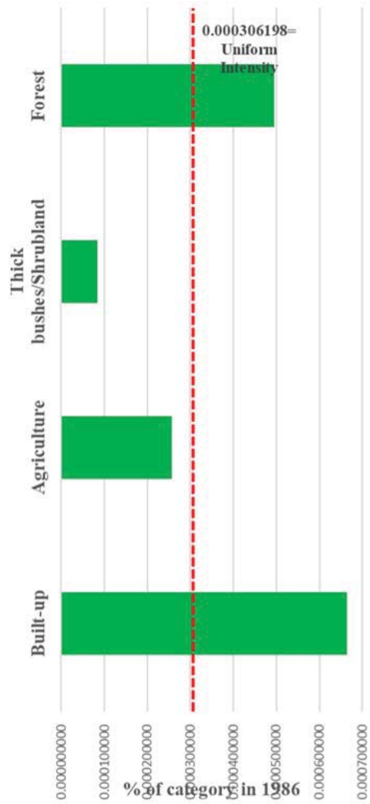

Fig. 10 (a) Transition to Waterbody in 1986-2002

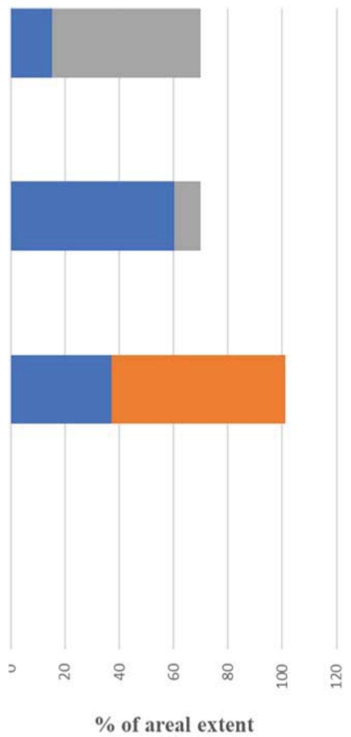

Fig. 9 (b) Hypothetical error of commission/omission

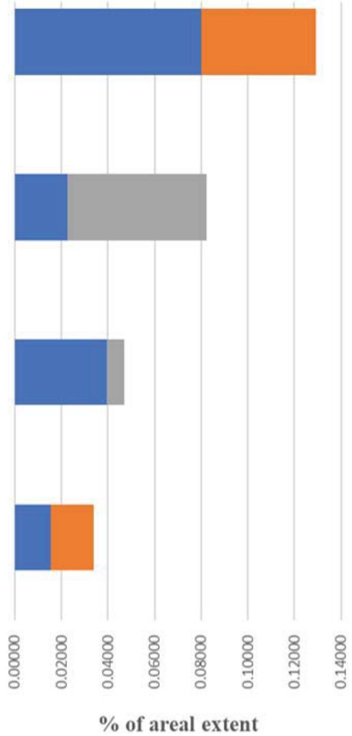

Fig. 10 (b) Hypothetical error of commission/omission

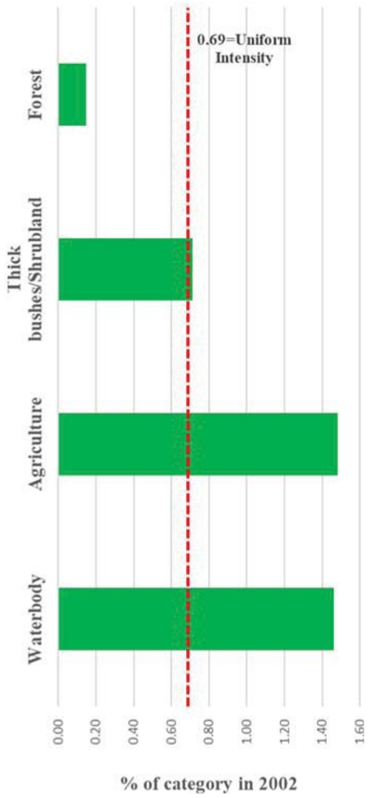

Fig. 11 (a) Transition to Built-up in 2002-2017

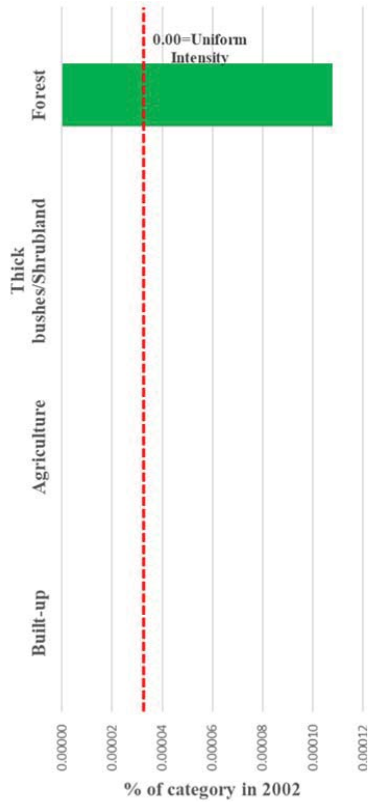

Fig. 12 (a) Transition to waterbody in 2002-2017

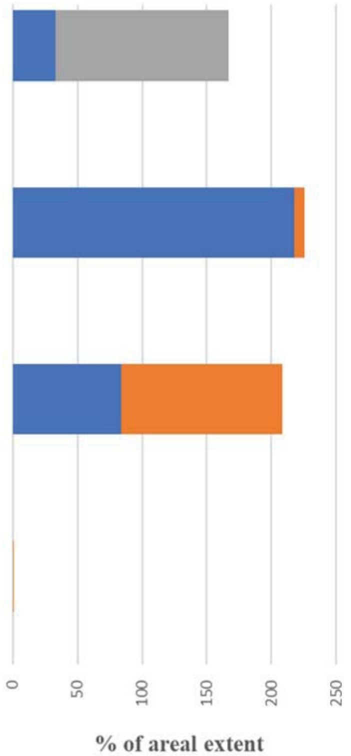

Fig. 11 (b) Hypothetical error of commission/omission

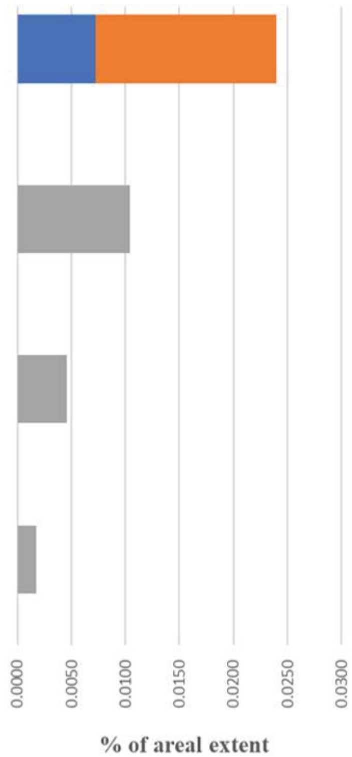

Fig. 12 (b) Hypothetical error of commission/omission

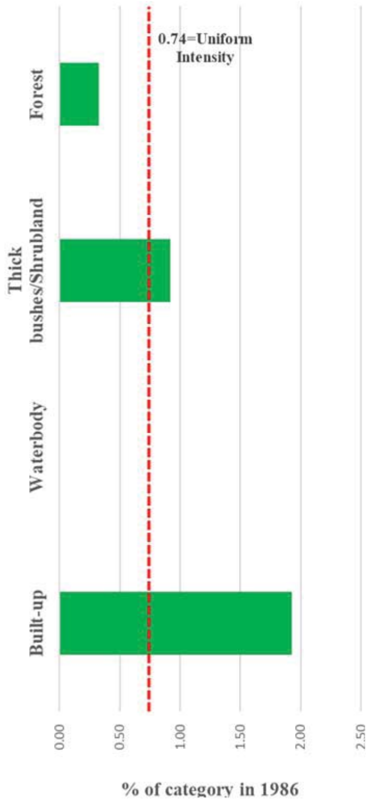

Fig. 13 (a) Transition to Agriculture in 1986-2002

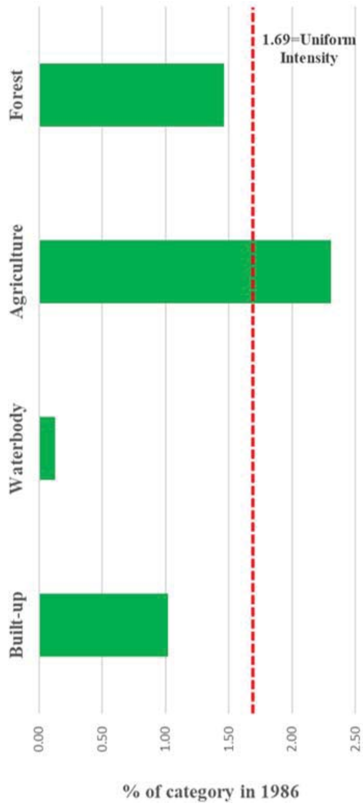

Fig. 14 (a) Transition to Thick bushes/shrubland in 1986-2002

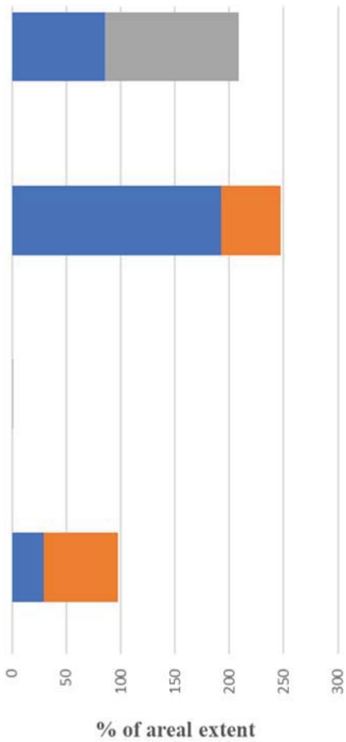

Fig. 13 (b) Hypothetical error of commission/omission

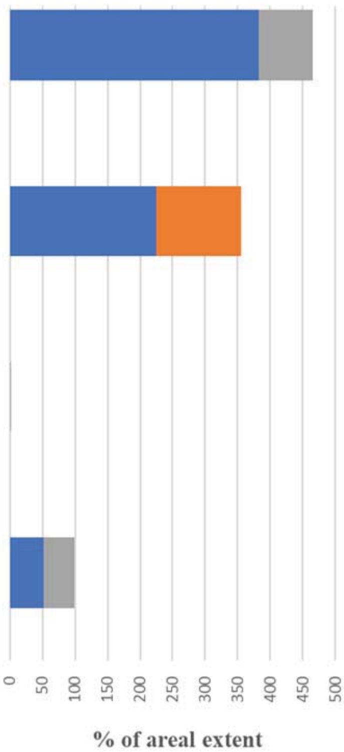

Fig. 14 (b) Hypothetical error of commission/omission

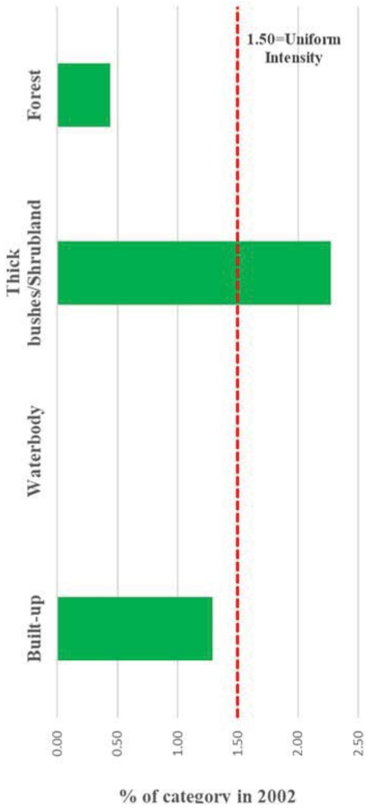

Fig. 15 (a) Transition to agriculture in 2002-2017

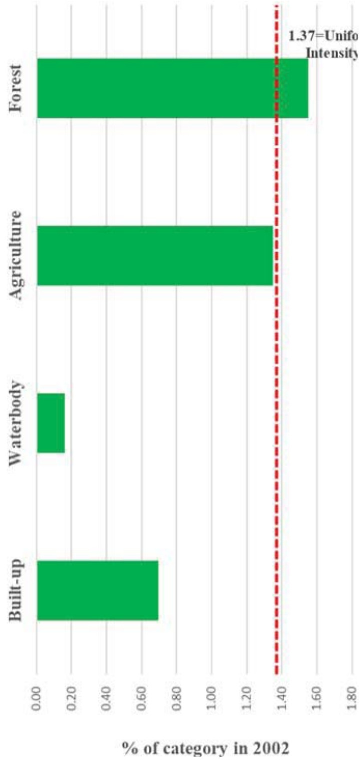

Fig. 16 (a) Transition to Thick bushes/shrubland in 2002-2017

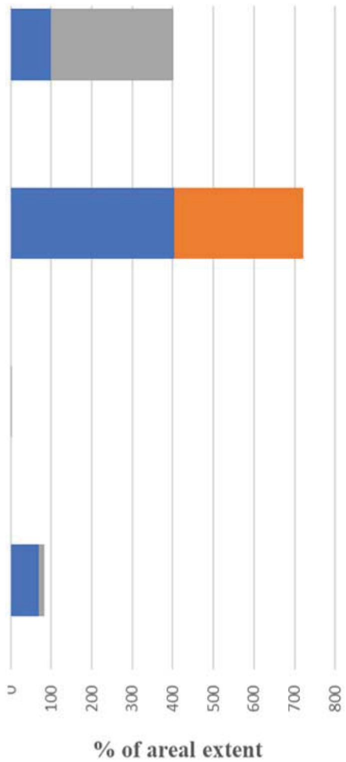

Fig. 15 (b) Hypothetical error of commission/omission

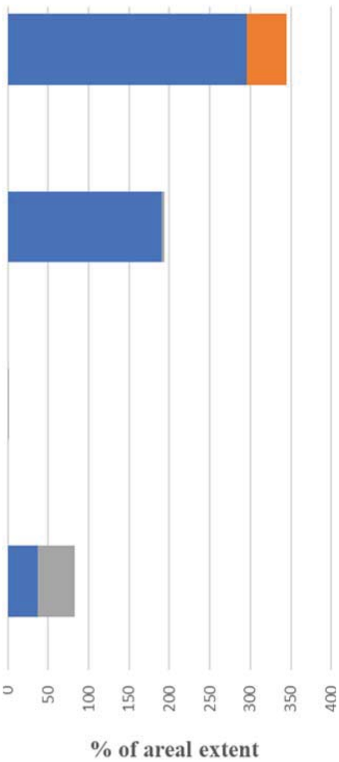

Fig. 16 (b) Hypothetical error of commission/omission

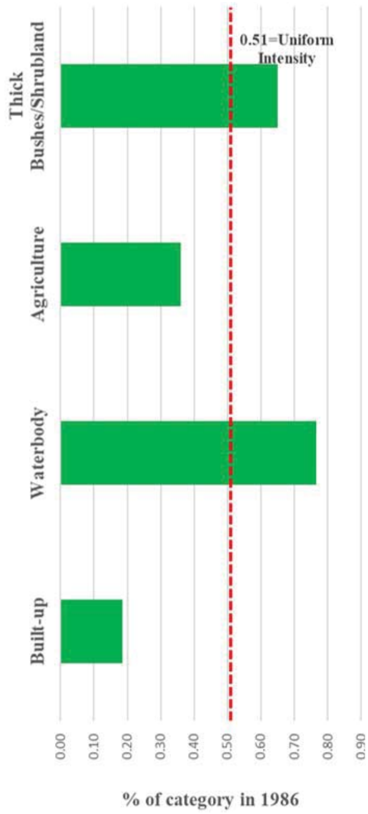

Fig. 17 (a) Transition to forest in 1986-2002

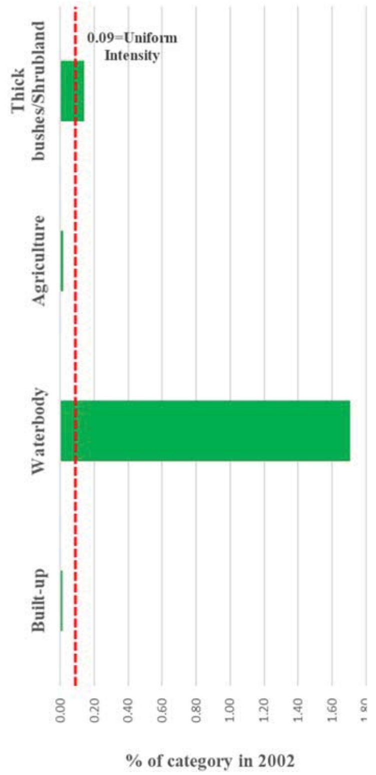

Fig. 18 (a) Transition to forest in 2002-2017

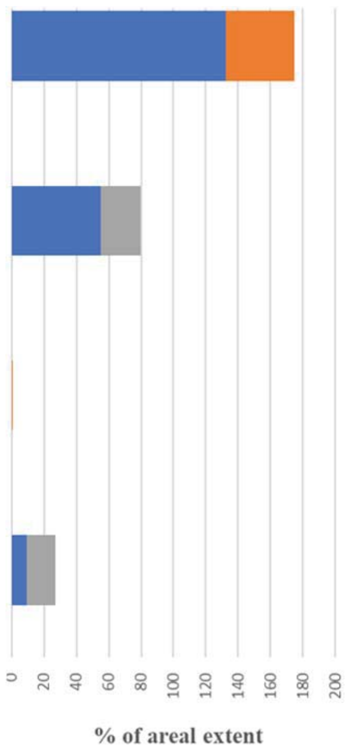

Fig. 17 (b) Hypothetical error of commission/omission

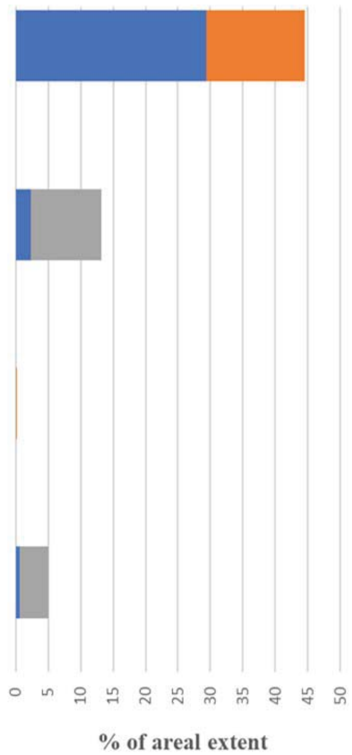

Fig. 18 (b) Hypothetical error of commission/omission

Though agriculture gained from built-up in the first interval, it lost heavily to built-up in the same period, hence, the shrunken of -8.44%. But agriculture recorded 52.07% increase mainly due to transitions from thick bushes, which was large from the initial stage. This explains the 19.78% shrunken of thick bushes at the end of the second period.

The pixel gaining thick bushes/shrubland targeted agriculture and forest in the first and second intervals, respectively. However, it avoided built-up and waterbody in both intervals (Figs. 14 (a), (b) and 16 (a), (b)). Figs. 17 (a), (b) and 18 (a), (b) represent the transitions to the forest category. Forest targeted waterbody and thick bushes/ shrubland in both intervals while avoiding built-up and agricultural lands. This suggests that the transition intensity of waterbody and thick bushes were above the annual uniform intensity.

Forest first targeted waterbody and then moved to target thick bushes in the first interval and largely targeted waterbody in the second period. Built-up also targeted waterbody in the second period as earlier indicated; this explains why waterbody lost 45.12% in the second period. Forest was heavily targeted by thick bushes in the second time interval translating into a loss of 28.93% at the end of 2017.

C. Social Factors Associated with Land-Use Change and Trade-Offs with Ecosystem Services

Ghana has lost its water bodies to illegal mining over the last four decades. Illegal mining in the study area has resulted in the diverting of water bodies in search of the gold and other minerals. The mining activity was intensively carried out in the study area after 2000, leading to a loss and pollution of water bodies [50].

The transition of the forest to thick bushes/shrubland and agriculture was significant. Forest is lost in both periods. Majority of households in the area relies on wood as a source of cooking fuel. The use of charcoal is predominant in both rural and urban areas. MINISTRY of Energy estimated that Accra and Kumasi (the two most populated cities in Ghana) accounted for over 50% of all charcoal usage between 2004 and 2008 [51]. In a more recent study, Abdul-Wakeel Karakara estimated that 45.56% and 31.32% of Ghanaian household adopts wood and charcoal as their main source of cooking respectively, this implies that non-modern fuel is popular [52]. Population increase, therefore, is an important driving force for the decrease in thick bushes and forest and as more mouths need to be fed unsustainable farming practices coupled with bush fires and the current land tenure system [53].

There are trade-offs as forest and thick bushes decrease as they have been used as wood fuel and charcoal. A trade-off between the reduction of the forest cover and thick bushes/ shrubland and ecosystem services as fuelwood species are important sources of construction materials, livestock feed, medicinal substances, and food in the form of fruits [54]. Fuelwood and charcoal wood species have also been identified to be providing regulating services such as windbreaks during a rainstorm, erosion prevention, and shade during sunshine.

Migration in and out of the municipalities as a result of seasonal migration for both non-farm and on-farm jobs also requires that more foods are produced. However, the loss of soil nutrients means that more thick bushes and forest lands are converted to agricultural lands.

D. Implications for Land Management Strategies

The dynamics of environmental change and land-use change in the study area continue as factors that stimulate the changes to remain active. The increase in a built-up area in both time intervals gives reason to be more concerned about the environment because as the population continues to grow, more agricultural lands and thick bushes could be converted into residential and recreational centers.

As a result of the expansion of the built-up area, more mouths must be fed, leading to an expansion of agricultural lands. The rise in the agricultural category in the second time period could be explained by the fact that the built-up area increases and mainly targeted agricultural lands. The expansion of agricultural lands mainly targeted thick bushes. In Ghana, the land tenure system follows the traditional system of land administration where the local chiefs are the custodians of the community lands and are allocated to the indigenes for their survival. However, most of these lands suffer from soil infertility due to years of usage without replenishing the nutrient lost. In this regard, farmers, as a matter of necessity, have to keep expanding their cropland and be able to produce on fertile soil at the expense of the thick bushes, shrublands and forest [55], [56]. Notwithstanding, farmers continue to reap lower yields due to the lack of application of fertilizers. This affects the farmers' well-being as they are deprived of the minimum production to ensure a non-deprived living. Furthermore, the emergent of commercial farming, where a large proportion of available lands are allocated to these large-scale farmers, continues to threaten the livelihood of farmers. This is manifested in their inaccessibility to the scarce natural resources. It has been suggested that the observed LULC changes are disseminated interactively with the local community to raise their environmental awareness level of land conservation [57]. Alongside a proposal made in a similar research in Ghana, we also suggest that without assessing their current level of environmental consciousness, it is impossible to raise their awareness [19].

VII. CONCLUSIONS

The study showed that the forest had changed significantly in both periods at a fast reducing rate. The observed changes could affect the ecosystem's health and those who depend on natural resources for survival. Agriculture is also lost in the first period in response to the cancellation of agricultural subsidies as part of the SAP that relegated agriculture to the bench. However, agriculture expanded rapidly in the second period as the population increases. The rapid increase in population also led to an expansion of the built-up category. The intensification of agriculture could breed soil degradation, which could eventually decrease productivity. The results revealed that the overall change in the 31-year period was greater in the second period (2002-2017). For residents to better mitigate and adapt to the land-use changes, there is the need for an impact assessment to link with their livelihood.

Previous studies show that land-use change is driven by interrelated factors/activities. Therefore, demographic characteristics have a role in land-use change [58]. To help in developing the best land-use strategies/policies further validation of the social factors is necessary.

APPENDIX

TABLE V
ERROR/CONFUSION MATRIX FOR 1986 CLASSIFICATION

	Built-Up	Water body	Agriculture	Thick Bushes/ Shrubland	Forest	Row Total	Error of Comm. (%)	User Accuracy (%)
Built Up	45	1	2	2	3	53	15.09	84.91
Waterbody	0	18	1	1	2	22	18.18	81.82
Agriculture	1	1	42	3	4	51	17.65	82.35
Thick Bushes/Shrubland	1	1	1	44	5	52	15.38	84.62
Forest	1	0	2	2	41	46	10.87	89.13
Column Total	48	21	48	52	55	224		
Error of Om. (%)	6.25	14.29	12.50	15.38	25.45			
Producer Accuracy (%)	93.75	85.71	87.50	84.62	74.55			
	Overall Accuracy		84.82					
	Kappa coefficient		0.81					

TABLE VI
ERROR/CONFUSION MATRIX FOR 2002 CLASSIFICATION

	Built Up	Water body	Agriculture	Thick Bushes/ Shrubland	Forest	Row Total	Error of Comm. (%)	User Accuracy (%)
Built Up	48	1	2	2	4	57	15.79	84.21
Waterbody	1	20	1	2	3	27	25.93	74.07
Agriculture	1	1	45	2	2	51	11.76	88.24
Thick Bushes/Shrubland	1	1	1	42	3	48	12.50	87.50
Forest	1	0	2	1	46	50	8.00	92.00
Column Total	52	23	51	49	58	233		
Error of Om. (%)	7.69	13.04	11.76	14.29	20.69			
Producer Accuracy (%)	92.31	86.96	88.24	85.71	79.31			
	Overall Accuracy		86.27					
	Kappa coefficient		0.83					

TABLE VII
ERROR/CONFUSION MATRIX FOR 2017 CLASSIFICATION

	Built Up	Water body	Agriculture	Thick Bushes/ Shrubland	Forest	Row Total	Error of Comm. (%)	User Accuracy (%)
Built Up	53	0	2	2	3	60	11.67	88.33
Waterbody	1	22	1	1	2	27	18.52	81.48
Agriculture	1	1	51	1	3	57	10.53	89.47
Thick Bushes/Shrubland	1	1	2	49	4	57	14.04	85.96
Forest	2	1	2	2	50	57	12.28	87.72
Column Total	58	25	58	55	62	258		
Error of Om. (%)	8.62	12.00	12.07	10.91	19.35			
Producer Accuracy (%)	91.38	88.00	87.93	89.09	80.65			
	Overall Accuracy		87.21					
	Kappa coefficient		0.84					

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