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Article

Application of Geo-Information Techniques in Land Use and Land Cover Change Analysis in a Peri-Urban District of Ghana

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Abstract: Using Satellite Remote Sensing and Geographic Information System, this paper analyzes the land use and land cover change dynamics in the Bosomtwe District of Ghana, for 1986, 2010 thematic mapper and enhanced thematic Mapper+ (TM/ETM+) images, and 2014 Landsat 8 Operational Land Imager and Thermal Infrared Sensor (OLI/TIS) image. The three images were geo-referenced and processed for classification, using the maximum likelihood classifier algorithm. A *Jeffries-Matusita's* separability check was used in confirming the degree of spectral separation acceptability of the bands used for each of the land use and land cover classes. The best *Kappa hat* statistic of classification accuracy was 83%. Land Use and Land Cover (LULC) transition analysis in Environmental Systems Research Institute ESRI's ArcMap was performed. The results of the classification over the three periods showed that built up, bare land and concrete surfaces increased from 1201 in 1986 to 5454 ha in 2010. Dense forest decreased by 2253 ha over the same period and increased by 873 ha by the 2014. Low forest also decreased by 1043 ha in 2010; however, it increased by 13% in 2014. Our findings showed some of the important changes in the land use and land cover patterns in the District. After the urbanization process, coupled with farmland abandonment, between 1986 and 2010, substantial increments in urban land and clear increments in farmland coverage between 1986 and 2014were found to be the reason for vegetation cover decreases. This suggests that major changes in the socio-ecological driving forces affecting landscape dynamics have occurred in the last few decades.

Keywords: land use/land cover; change detection; accuracy assessment; separability; GIS; peri-urban; Bosomtwe; Ghana

1. Introduction

The dynamics of human land use and land cover (LULC) changes have implications for land use and environmental management and planning in peri-urban areas [1–4]. In view of this, modelling the human land uses and land cover (LULC) change is essential for the assessment of consequent social and environmental impacts of human activities [5]. Globally, quite a substantial amount of research has been done on the use of remote sensing and GIS to model the land use and cover dynamics [6–9] and [10]. In peri-urban areas where demand for land meant for various applications persist, it is imperative to assess the degree of LULC changes. This is so, in order to identify the trends and to ascertain the extent of land use types trade-off among the different LULC applications [11].

Considering the fact that the peri-urban areas are the melting pots of diverse socio-economic undertakings [12], it is imperative to monitor the trends of land use and cover changes to ensure that these are in sync with the available land space and the rate of population growth over time. Theorizing the construction of land surface change dynamics, Prenzel [13], examined configuration of the earth surface, in terms of the spatial and structural landscape dynamics over time. In terms of the spatial and structural landscape dynamics, the landscape configuration dynamics should be seen as structural-temporal occurrence changing over time [7,13,14]. In order to categorically and quantitatively analyze these LULC dynamics, remote sensing applications are imperative. This is apparently because the quantitative changes are amenable to remote sensing and geo-information modelling.

Furthermore, Nagarajan and Poongothai [15] have indicated that human interference and interactions with the land surface result in a variety of outcomes. These varieties of outcomes constitute the LULC change patterns from a complex system [16]. In this regard, considering the rapid changes in the land use and cover driven by population increases and expended demand for land. It is crucial that accurate and up-to-date land use and cover change information is produced for both human society as well as environmental planning purposes [17].

According to Addo [12], the use of remote sensing and GIS tools for the mapping of peri-LULC changes have revealed intriguing results and offered some critical policy recommendations for sustainable land management. In the same vein, Weerakoon [18] studying the suitability of urban agriculture, has also opined that it is extremely difficult to thoroughly appreciate the levels of land use and cover change decision making, from only descriptive perspectives, without quantification. This assertion is in partial support of the submission made by Rounsevell *et al.* [19] that many variables that describe forest land use change, for instance, is qualitative in nature and are difficult or impossible to describe in quantitative form.

However, sometimes the story told by the people from their perceptions requires scientific corroboration, using a "second opinion" from the air using quantitative methodologies. This is important especially in areas where human accessibility is restricted for a fair judgment of results perceived by human interpretations [6]. Assessing LULC changes from a quantitative point of view therefore, provides insights into a decision-making process and complementing those qualitative assessments based on expert opinion.

In his work on the peri-urban land use, Dutta [20] indicated that human activities ranging from agriculture to residential land uses have had considerable impacts on the peri-urban environment. Land use and cover change analysis is therefore crucial in establishing the interactions among the drivers and effects of land use change. This is because these have long-term implications on environmental management [21]. In the Bosomtwe district, urban-peri urban migration from the main city centres in closer proximity to the district have led to the increase in infrastructure of built and bare land and concrete land sue surfaces in the north-western part of the district.

Abbas *et al.*[10], in their study of the urbanization in Katsina, Nigeria, indicated that urban sprawl and its concomitant effects of soil and land degradation resulting from increasing built environments, continues to characterize the peri-urban landscape. Sreenivasulu and Bhaskar [22] have once again supported this assertion by explaining that changes in land use can be due to urban expansion and the loss of agriculture land, changes in river regimes, and the effects of shifting cultivation.

The Bosomtwe district of the Ashanti region is one of such area, which from a cursory observation might suggest some considerable land use and land cover dynamics. Over the years, the district, though predominantly rural, its peri-urban presence leaves much for land use policy implications at least in the next decade. Although some research on LULC dynamics have been done in the district, specific LULC studies employing the tools of remote sensing and GIS, has not been done for the entire district. Modelling of LULC change dynamics require robust approaches, such as geo-information tools which helps in assessing to an appreciable extent, the rate of changes, be it increasing and/or decreasing trends, in general for the Bosomtwe District. The suitability of these techniques has been supported by Addo [12] who indicated that the use of geo-information techniques offer relative advantages of allowing access to areas being used as peri-urban farmlands to be rapidly established at relatively low cost.

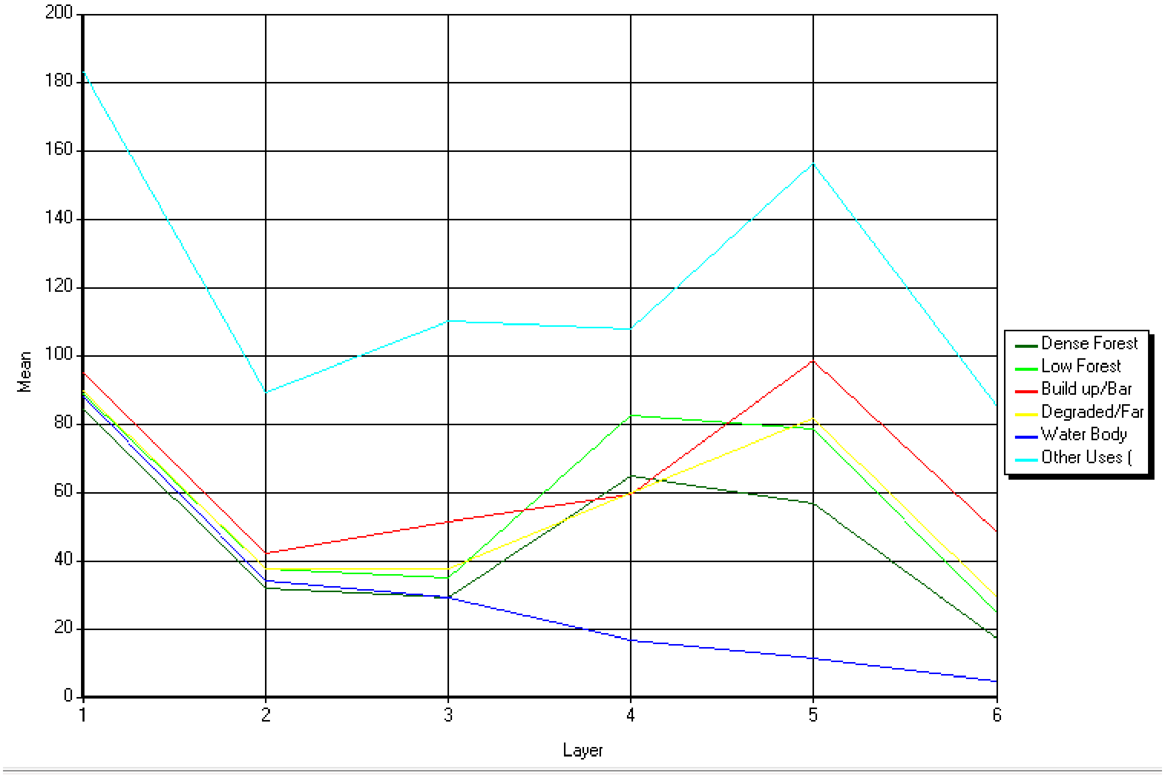
The effort for this work is to corroborate, or otherwise, the earlier results of perception of land use change dynamics by inhabitants of the district derived from a socio-economic survey. In view of this, the justification for the use of the Landsat TM imagery was warranted to explain the actual trends of land use and land cover changes in the district [1]. Accordingly, Manonmani and Suganya [23] have reiterated that GIS and remote sensing have the potential to support decisions by providing data and analytical tools for the study of urban environments. The objective of this paper is to analyze, using geo-information (remote sensing and Geographic Information System) to ascertain the LULC change dynamics in the district, for the past 21 years.

2. Results

This section reports the result of the *Jeffries-Matusita Distance* spectra separability as well as the Kappa hat statistical accuracy assessment of the LULC classification before reportage of the actual change detection results for the various LULC, as well as the land use transitions among the LULC types. Nonetheless, for reducing uncertainty in land cover dynamics, only the most important changes were taken into account in order to clearly separate the true changes from possible misclassification.

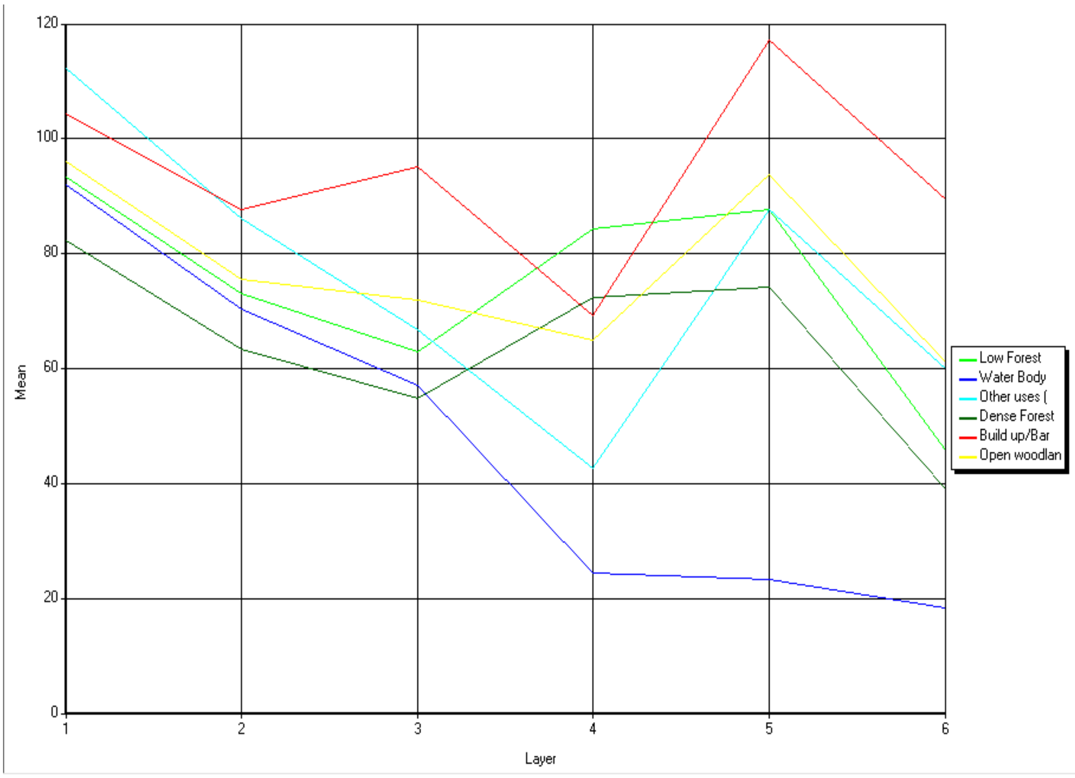
2.1. Interpretation of the Spectral Plots

The signature mean plots (Figure 1a) for the 1986 image yielded a Best Minimum Separability of the Jeffries-Matusita index of 1263.45. It shows that most of the land use classes were moderately separated in the bands, except the band 2, where almost all the classes coincided. This was expected to an extent, considering the level of reflectance characteristics of the images as per the surface configuration of the area at that time. Temporal degradation of the land during this time had exposed a greater percentage of the land to bare and open woodland and farm lands.

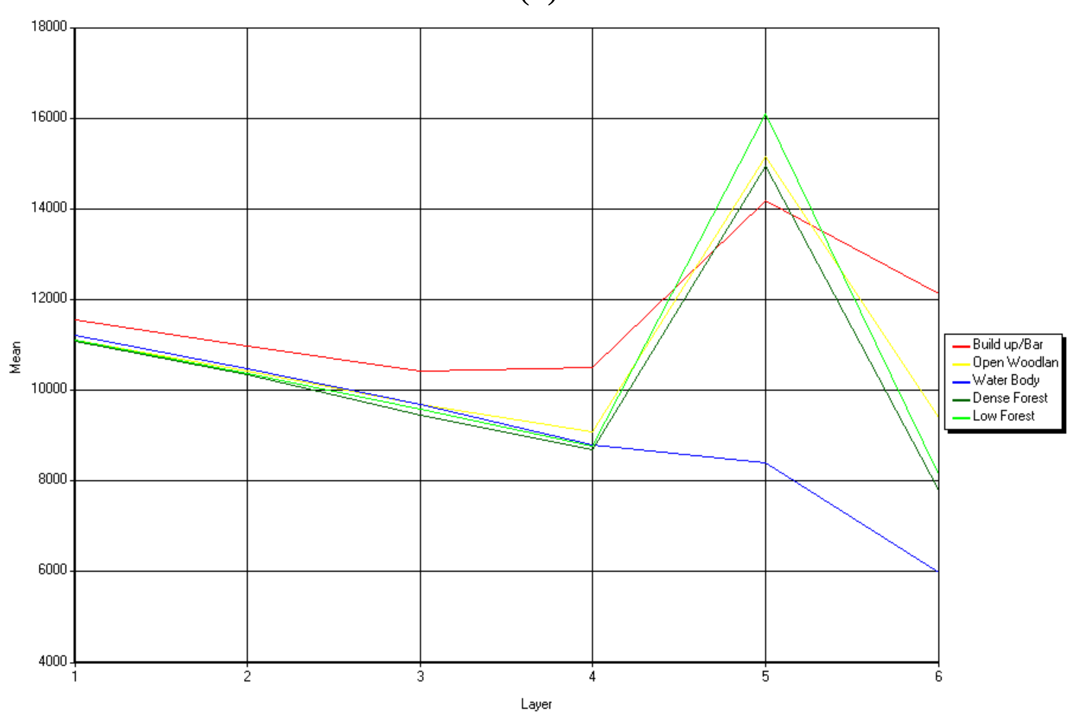


(a)

Figure 1. *Cont.*



(**b**)



(**c**)

Figure 1. Spectoral Separability Plots for LULC Classes for (**a**) 1986 LULC; (**b**) 2010 LULC; (**c**) 2014 LULC.

Separability in the 2010 (Figure 1b) image indicated a Best Minimum Separability of Jeffries-Matusita of 1287.51; thus, almost all the land use classes were from fairly separated to moderately separated. Especially in band 5, all the land use classes, with the exception of low forest and other uses as line stripes, separated well; this was especially so with the water body. In the same light, band 4 was also well separated. However, bands 1 and 2 did not show a better separability among the LULC types. This is an expected outcome since water reflects better in band 7. The signature plot (1c) for the 2014 image also shows that, with the exception of band 4, 5 and 6, which showed a moderate separability of the built up, low forest and water bodies, the rest of the land use classes were fairly separated by the remaining three bands. The Best Minimum Separability of Jeffries-Matusita index is 1072.25.

2.2. Classification Accuracy

In this study, because of the absence of the former land use maps and aerial photographs for the area, which would have been used as reference for accuracy checks, field observations were made and GPS points measured and recorded. This was used to aid in the assessment of the overall Kappa and individual class accuracies for the producer and user accuracies. The Kappa statistic is generally accepted as a measure of classification accuracy for both the model as well as user of the model of classification [24]. Kappa values are characterized as <0 as indicative of no agreements and 0–0.2 as slight, 0.2–0.41 as fair, 0.41–0.60 as moderate, 0.60–0.80 as substantial and 0.81–1.0 as almost perfect agreement [24,25]. The overall classification accuracy of the images yielded a *Kappa hat* statistic of 80.70%, 72.41% and 82.76% for the 1986, 2010 and the 2014 images, respectively. This is an indication of classification accuracy of moderately substantial to almost perfect agreement (Tables 1).

The overall accuracies were very good with the user and producer accuracies also being considerably high for almost all the land use classes. This is an indication of an acceptable LULC classification accuracy for images for which there were no available ground truth data as well as aerial photographs nor a pre-existing land use land cover maps. The high to very high accuracy of classification for the three images, emphasize the precision of the LULC sampled points obtained via the Global Position System (GPS) survey. For the accuracy assessment of the 1986 image, the technique of land use persistency was used and juxtaposed with the current GPS points collected from current field work.

The only limiting factor in the check for LULC accuracies was the absence of reference maps or points, during the accuracy assessment process; this was however fixed by another approach. On the basis of the classification accuracy check for the 1986 image, owing to the absence of pre-existing land use maps or aerial photographs to be used as the base reference map, we resorted to the Google history for the date of 20th April 2003. From the image, we assume that land use/covers such as the lake and towns, as well as some farmland were constantly put to such use over several years' events; therefore, these LULC types do not change position over time. Based on this assumption, we selected the land use and land cover points from the Lake Bosomtwe, and settlements such as *Kuntenase* the district capital, *Abono, Esereso, Nkonwi, Amankwaadei* and New *Brodekwaano, w*hich did not change over the time and their respective coordinates recorded.

Subsequently, other land use types such as the dense forest reserve, near *Aputuogya* and at the southeastern part of the Lake as well as some farmlands visible in the Google image were also selected and their coordinates recorded as well. In all, 57 land use and land cover points were picked for the five land use categories namely the dense Forest, Low Forest, Built up and concrete areas, Open wood and farmlands as well as the Lake (water body).

These ground control points (GCPs) were imported into the ERDAS Imagine software, to compare the signatures of the various land uses to compute the accuracy assessment. At the end of the computation, the percentage accuracy of the classification was considerably improved over the previous value to 80.70%. The overall Kappa accuracy was also 0.764; this is, by far, a more improved accuracy.

Table 1. Classification contingency matrix for 1986, 2010 & 2014 images.

	1986 ERROR MATRIX					
LULC Class	**DF**	**LF**	**BBC**	**OWLF**	**WB**	**Total**
DF	9	1	0	0	0	10
LF	1	6	0	0	0	7
BBC	0	0	10	1	0	11
OWLF	0	2	0	0	12	14
WB	0	0	0	0	9	9
Total	**10**	**9**	**10**	**1**	**21**	**51**
	Reference Totals	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**	***Classification Accuracy***
DF	14	10	9	64.29%	90.00%	
LF	9	7	6	66.67%	85.71%	
BBC	11	11	10	90.91%	90.91%	***80.70%***
OWLF	13	14	12	92.31%	85.71%	
WB	10	9	9	90.00%	100.00%	
	2010 ERROR MATRIX					
LULC Class	**DF**	**LF**	**BBC**	**OWLF**	**WB**	**Total**
DF	1	0	0	0	0	1
F	2	2	2	6	0	12
BBC	1	0	31	0	0	32
OWLF	0	1	4	6	0	11
WB	0	0	0	0	2	2
Total	**4**	**3**	**37**	**12**	**2**	**58**
	Reference Totals	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**	***Classification Accuracy***
DF	4	1	1	25.00%	100.00%	
LF	3	12	2	66.67%	16.67%	
BBC	37	32	31	83.78%	96.88%	***72.41%***
OWLF	12	11	6	50.00%	54.55%	
WB	2	2	2	00.00%	100.00%	
	2014 ERROR MATRIX					
LULC Class	**DF**	**LF**	**BBC**	**OWLF**	**WB**	**Total**
DF	2	0	0	0	0	2
LF	1	1	0	3	0	5
BBC	0	0	34	0	0	34
OWLF	1	2	3	9	0	15
WB	0	0	0	0	2	2
Total	**4**	**3**	**37**	**12**	**2**	**58**

Table 1. *Cont.*

	2014 ERROR MATRIX					
	Reference Totals	**Classified Totals**	**Number Correct**	**Producers Accuracy**	**Users Accuracy**	***Classification Accuracy***
DF	4	2	2	50.00%	100.00%	
LF	3	5	1	33.33%	20.00%	
BBC	37	34	34	91.89%	100.00%	***82.76%***
OWLF	12	15	9	75.00%	60.00%	
WB	2	2	2	100.00%	100.00%	

DF = Dense Forest; LF = Low Forest; BBC = Built up/Bare land/Concrete; OWFL = Open woodland/Farm Lands; WB = Water Body.

3. Analysis of Land Use and Land Cover Types

3.1. Analysis of LULC Classes for the 1986 Image

The land use land cover class statistics were computed by subtracting the component areas covered by clouds and its shadows, over the image. This subtraction was the reason for the reduction in the size of the total area of the district under study. The presence of the cloud cover and shadow for example, reduced the total land area from 32,900 ha to 32,432 and 31,613 ha for the 1986 land areas, respectively. Results for the analysis of the 1986 image shows that the LULC types at that time was a reflection of the incidence of drought and wild fires that characterized the previous year starting from 1983 to 1985. From Figure 2, it can be observed that the vegetation cover of the district was largely degraded temporarily (since the vegetation regenerated in subsequent years).

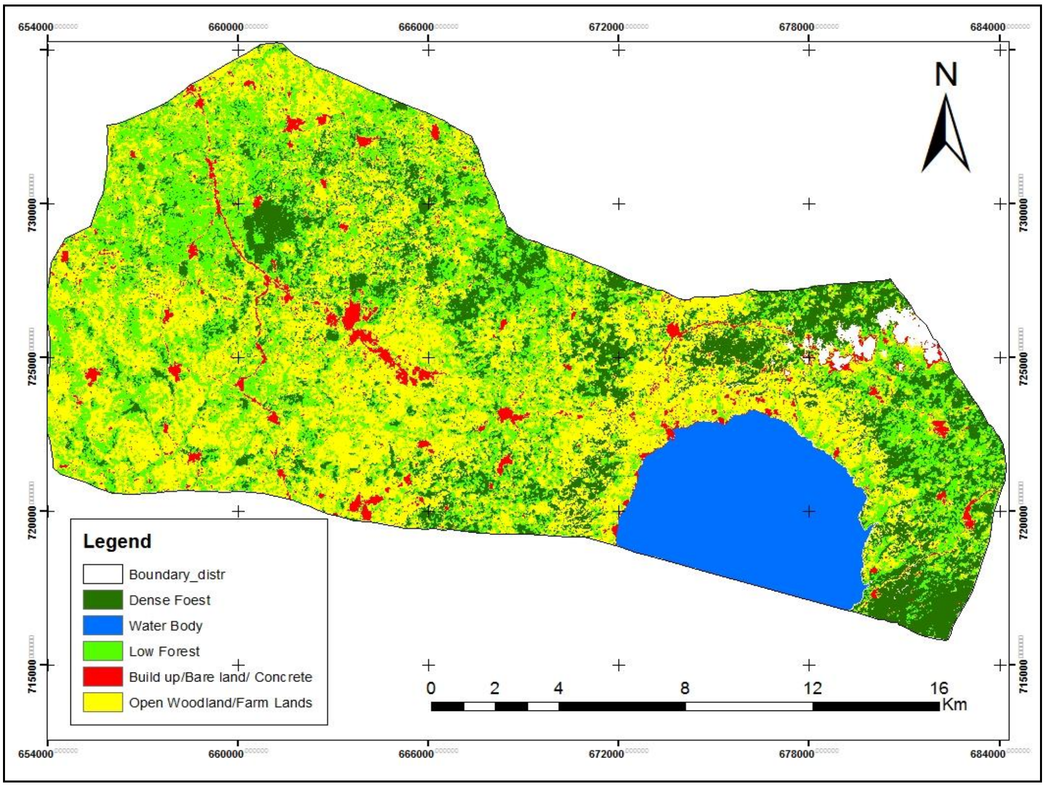


Figure 2.LULC Map of 1986 Landsat 5 TM image.

Results from the classified image shows that open woodlands and farmlands dominated the landscape, with 12,722 hectares (ha), representing 39% of the land area. Next in importance was the low forest, which was the newly regenerating vegetation. This covered an area of 9181 ha with percentage coverage of 28%. Patches of dense forests, that survived the drought and wild fires constituted an appreciable proportion of 5834 ha representing 18% of the total land area. Built up/Bare land and Concrete surfaces at the time was low; it occupied 1201 ha. The only water body that was classified is the Lake Bosomtwe. Other water bodies were not discernible from the images for classification. The lake area was identified to be 3494 hectares.

3.2. Analysis of Land Use Land Cover (LULC) Classes for 2010 Image

By 2010, the LULC classes have shown considerable change dynamics with some profound revelations in terms of the dense forest and low forest cover (Figure 3). The total area of dense forest cover in that year was 3581 ha representing only 10% of the entire district LULC. This deficit in coverage on the dense forest led to the appreciation in land areas of land uses and covers as Open Woodland and farmlands with 11,530 ha, as well as low forest, with 8138 ha, measuring up to about 36 and 25% by proportion respectively. Build up/Bare land and concrete land use and cover, were identified low to be 5454 ha representing 17% of the area coverage. The lake (water body) in that year was 3420 ha representing 11% of the total area.

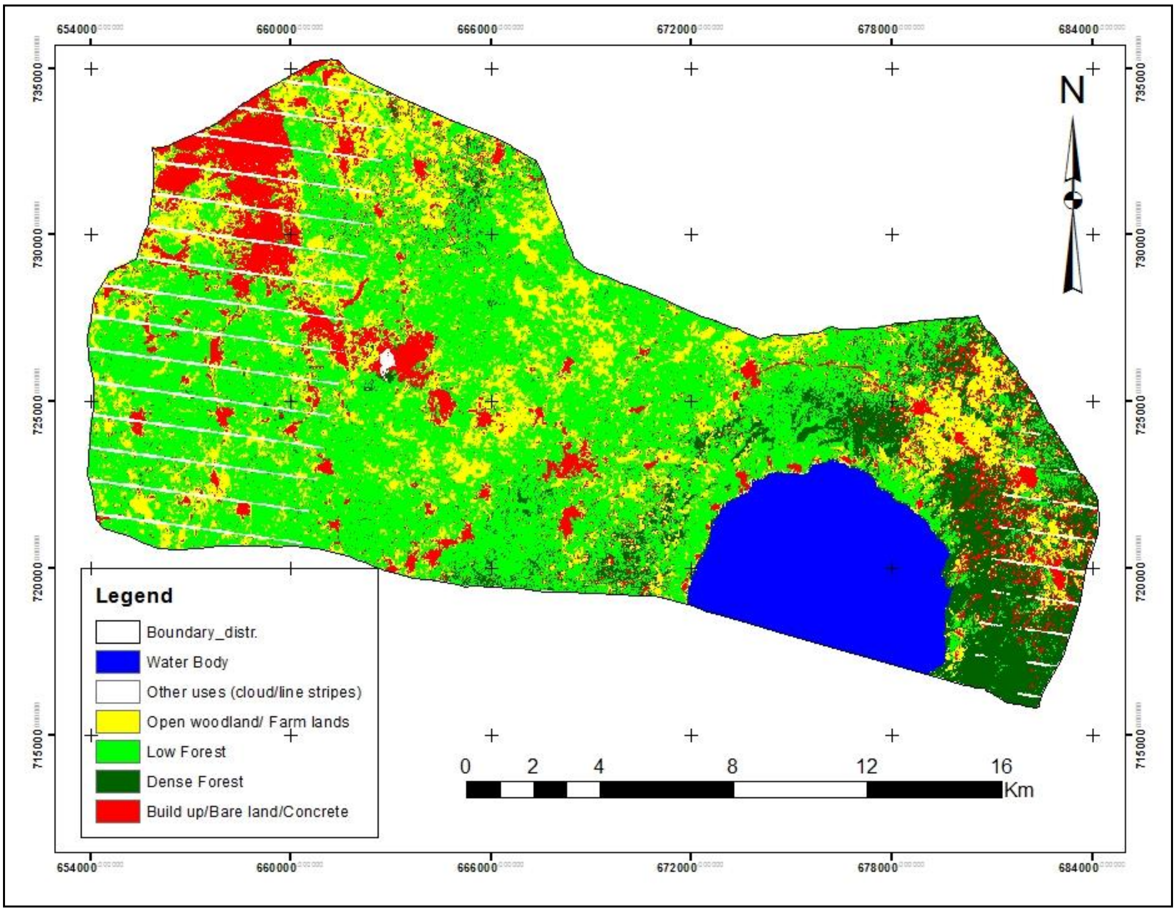


Figure 3. LULC Map of 2010 Landsat ETM+ image.

3.3. Analysis of LULC Classes for the 2014 Image

The 2014 image shows that the district has experienced an appreciable level of cover changes in terms of the increasing build up / bare lands and concrete surfaces. The land use and land cover (LULC) classes showed some startling revelations as far as the area coverage of the respective land uses were concerned.

Low forest cover maintained its high area of coverage with 10,947 ha, representing 33% of the total area of land use and covers. Open wood land and farmlands was also next by area coverage of 9367 ha, with a proportion of 29%. Build up/bare land and concrete surfaces, although showed an increase from the visual observation, the statistics of 4597 ha by area coverage, indicated a decrease in area from the 2010 image, representing 14% of the total land area. The area covered by the lake (water body) was 3424 ha representing about 11% of the total area (Figure 4).

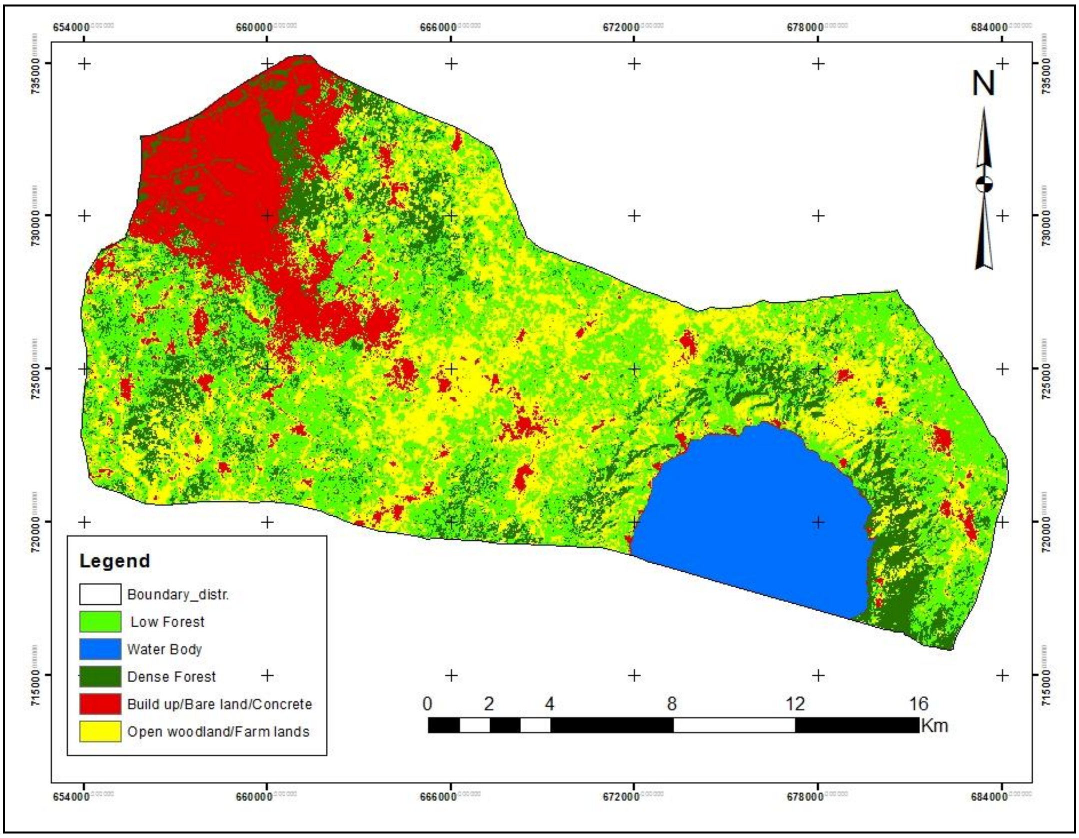


Figure 4. LULC Map of 2014 Landsat 8 OLI/TIS image.

4. Analysis of Land Use and Land Cover Change Trends

4.1. LULC Classes Change Trends between 1986 and 2010

The land use and land cover (LULC) class trend analysis shows the direction in which the various classes are heading using their respective initial years of comparison as the base. Between 1986 and 2010, the 24-year period, dense forest decreased by 2253 ha. Low forest also decreased by 1043 ha, with built up bare land and concrete areas increasing by 4253 ha. The water body (Lake Bosomtwe), also receded its shores by 75 ha. Open wood and farmland increased appreciably 1192 ha, over the period under review (Table 2, Figure 5). This was the case since the district has and continues to recover from the drought and temporal vegetation degradation. By this year, most of the land, particularly, the forest cover had been converted into farmlands.

4.2. LULC Classes Change Trends between 2010 and 2014

The LULC trends between 2010 and 2014 indicated that human activities had begun taking considerable toll on the land use and cover types. Dense forest increased by 873 ha, while open woodland and farmlands also decreased by 2164 ha. Low forest, built up/bare and concrete surfaces increased and decreased by 2810 ha and 857 ha, respectively. The marginal decrease in the Built up areas was due to the component of bare land areas that were re-vegetated by open wood and farmland as well as by low forest covers over the period. Intrinsically, however, the residential and commercial components of the built up class showed an increase in area of coverage. The water body (Lake Bosomtwe), by 2010, had marginally reclaimed its shores by 5 ha over the five-year period (Tables 2 and 3). The differences in the total land areas are attributed to the proportions of line strips and cloud covers that represented noise in the images. These proportions were not included in the overall area estimations.

Considering the predominance of negative trend in the LULC classes, it was obvious that certain land use classes especially low forest cover and farmland areas, had transition into other uses by the year 2014. It is pertinent to note that the built up, bare land and concrete surfaces in the previous years could be converted to other uses such as low forest and open woodland and farmland. This is because most of the bare land areas included the bare school parks (e.g., *Onwe No. 2*), the illegal gold mining (also known as *"galamsey"* in local parlance) pits between *Beposo* and *Amakom* communities and sand winning sites that dotted the district. All these bare areas have conversional abilities to other uses as indicated at a certain conversion probabilities.

Table 2. Composite table of area statistics in Hectares.

Year	**1986**		**2010**		**2014**	
LULC	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
DF	5834.15	18.0	3581.37	10.4	4454.46	13.6
LF	9180.62	28.3	8137.62	46.8	10,947.33	33.4
BBC	1201.00	3.7	5454.36	11.9	4596.93	14.0
OWFL	12,722.35	39.2	11,530.26	20.1	9366.75	28.5
WB	3494.23	10.8	3419.64	10.7	3424.32	10.5
Total	**32,432.35**	**100**	**32,123.25**	**100**	**32,789.79**	**100**

Table 3. Land use and land cover (LULC) change trend from 1986 to 2014.

LU Classes	**1986 to 2010**		**2010 to 2014**	
	Area (ha)	**% Change**	**Area (Ha)**	**% Change**
DF	−2253	−63	873	+20
LF	−1043	−13	2810	+26
BBC	4253	+78	−857	−19
OWFL	−1192	−10	−2164	−23
WB	−75	−2	+5	0

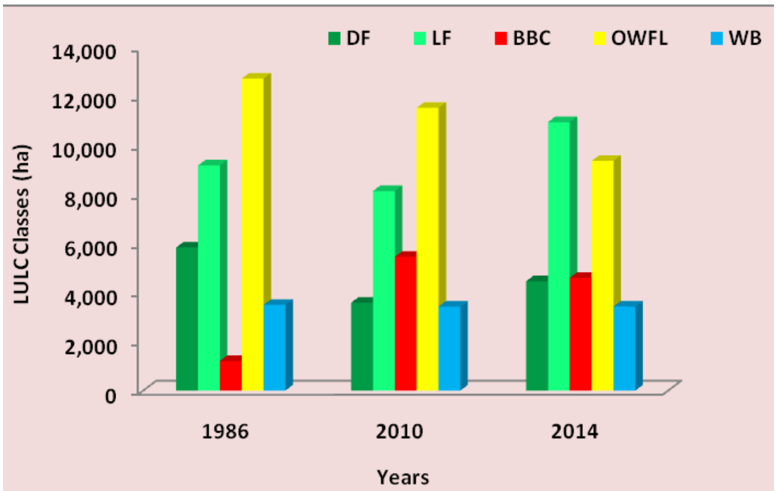


Figure 5. Grouped bar graph of the LULC Area (Ha) for 1986, 2010 and 2014.

5. Land Use and Land Cover Change Transition between the Years

This section analyses the land use and land cover change transitions from one year to the other. This is done to ascertain the degree of change and the intensity of change transitions from one class of land use and land cover to the other, over the period spanning between the two image years. This analysis was aided by the cross-tabulation algorithm of the ArcMap software.

5.1. Land Use and Land Cover Change Transition from 1986 to 2010

The land use and land cover change (LULCC) matrix was used to analyze the rates of land use type conversions from one land use class type (i) to another type (j), between the various years intervals of analysis. These were the co-transitions occurring between 1986 and 2010 as well as 2010 and 2014. Their corresponding probabilities of change were also determined and displayed in the appropriate tables following the matrix tables. This was to measure the rate of change as well as to facilitate the use of the Markov chain modeling to predict the changes in land use types into the future. The various LULC transitions have been presented in the appropriate transition matrices in tables.

Between 1986 and 2010, the area of LULC retention, constituted a total of 1294 ha representing about 42% of the total area. The most land use land cover conversion occurring within this period is the conversion of low forests into open woodland and farm lands (OWFL) a total conversion area of 3360 ha. As seen in Table 4, there was a substantial increase in built up, bare and concrete surface land uses by 3806 ha, representing 78% change over the period. This was gained from the conversion of open woodland and farm lands as well as dense forest by 2059 ha and 637 ha, respectively. The former LULC change was represented by an overall percentage decrease by 62% during this period.

There is a net negative change in the forest cover both dense and low forest covers by a total of 2818 ha representing a total change of decrease by 73%. As a result, some of the bare areas identified as a component of the (built up/bare land and concrete lands) was actually re-vegetated into low forest over the 24 years; the net effect on the forest regeneration did not show any significant improvement. The available statistical data from population census for the study district suggest some proximate answers that confirm the classification results for increased built up. For instance, in 2000, the population was

67,494. This increased to 93,910 in 2010 and a projected figure of 104,470 people was estimated for 2014 [26]. In actual fact, peri-urban residential and commercial built up land uses have increased tremendously over the period, also with evidence from ground truth experiences.

Table 4. Land use class transition matrix from 1986 to 2010.

	LULC Classes	2010 Image					1986 Total
		DF	**LF**	**BBC**	**OPWL**	**WB**	
1986 Image	Dense Forest	**1158**	2017	637	1378	0	5190
	Low Forest	819	**2205**	1657	3360	0	8042
	Built Bare/Conc.	36	142	**501**	367	4	1051
	Open Wood/Farm Lands	1155	2842	2059	**5151**	1	11,207
	Water Body	28	9	2	30	**3079**	3148
	2010 Total	3196	7215	4856	10,286	3084	**28,638**
	Change (ha)	−1994	−827	3805	−921	−64	
	Change (%)	−62	−11	+78	−9	−2	

All other land use transitions did occur marginally including the Lake Bosomtwe water body which was converted to open woodland and farmlands along its fringes through agriculture activities closer to the banks of the lake.

On the basis of the conversion probabilities, between 1986 and 2010, the water body, built up area and the open woodland and farmlands had land use probability persistence rates of more than 30%with the forest covers having rates less than 30% (Table 5). There is a 42% likelihood that most of the open woodland and farmlands were created from the conversion of low forest covers.

Table 5. Land use transition probability matrix from 1986 to 2010.

	LULC Classes	2010 Image					
		DF	**LF**	**BBC**	**OPWL**	**WB**	**1986 Total**
1986 Image	Dense Forest	**0.22**	0.39	0.12	0.27	0.00	1.00
	Low Forest	0.10	**0.27**	0.21	0.42	0.00	1.00
	Built Bare/Conc.	0.03	0.14	**0.48**	0.35	0.00	1.00
	Open Wood/Farm Lands	0.10	0.25	0.18	**0.46**	0.00	1.00
	Water Body	0.01	0.00	0.00	0.01	**0.98**	1.00

5.2. Land Use Class Transition Matrix from 2010 to 2014

The land use land cover matrix from 2010 to 2014, portrayed major land use conversions/transitions from one land use class to another. At this time, the various land use class types were in real transition of change after the base year's land use cover anomalies. This was particularly so for the diagonal matrix of land uses that maintained their types in the following reference years by an increase over the previous reference year at a total of 17,340 ha. This was about 54% of the total land area. The highest conversions from one type to another, however, was from open woodland to low forest cover and to build up with 3068 ha and 2027 ha respectively in 2014 (Table 6).

Table 6. Land use class transition matrix from 2010 to 2014.

	LULC Classes	2014 Image					
		DF	**LF**	**BB/Conc.**	**OW/FL**	**WB**	**2010 Total**
2010 Image	Dense Forest	**1525**	1518	34	501	4	**3581**
	Low Forest	1324	**4732**	75	2006	0	**8138**
	Build Bare/Conc.	514	1435	**2218**	1288	0	**5454**
	Open Wood/Farm Lands	981	3068	2027	**5450**	3	**11,530**
	Water Body	0	0	5	0	**3415**	**3420**
	2014 Total	**4344**	**10,753**	**4359**	**9245**	**3422**	**32,123**
	Change (Ha)	+763	+2615	−1095	−2285	+2	
	Change (%)	+18	+24	−25	−25	0	

Furthermore, there was a conversion of dense forest to low forest by 1518 ha while 2006 ha of low forest were converted into open woodland and farmland. Up to 1435 ha of built up bare land and concrete surfaces were covered up by low forest. There were marginal conversions of the lake by an area of 5 ha to build up bare land and concrete areas. By 2014, the proportion of dense forest has increased by a percentage gain of 21%. However, of very significant increase in land use proportion was the low forest, with an approximate percentage of 32%. The probability of land use conversion from other land uses to build up, bare land and concrete was again less that 20%, while the probabilities for the transition from other land uses into forest and low forests were 42 and 58%, respectively (Table 7).

Table 7. Land use transition probability matrix from 2010 to 2014.

	LULC Classes	2014 Image					
		DF	**LF**	**BB/Conc.**	**OW/FL**	**WB**	**Total**
2010 Image	Dense Forest	0.43	0.42	0.01	0.14	0.00	1.00
	Low Forest	0.16	0.58	0.01	0.25	0.00	1.00
	Build up/Bare/Concrete	0.09	0.26	0.41	0.24	0.00	1.00
	Open Wood/Farm ands	0.09	0.27	0.18	0.47	0.00	1.00
	Water Body	0.00	0.00	0.00	0.00	1.00	1.00

The tables of rate of change and trend are a furtherance of the explanations offered to the LULC change and transitions occurring within the classes over the periods of time, according to the Markov chain approach. This approach explains the probability of change from one class to another class or the probability of same LULC retention of class according to their relevant proportions. These explain the potentials and the conversion possibility of the LULC from one time to another according the laws of cellular automata conversion principles from one cell state (i,j) to another after time t.

6. Discussions

The seeming improvement in the vegetation cover was obtained from the open and bare land areas which were re-vegetated over the 24 year period. Explicitly, residential and commercial built up land uses were actually increasing. What presented the false impression was the composite built up-bare-concrete land use, part of which (bare areas) were covered in subsequent images. This trend of the LULC dynamic notwithstanding, there is a considerable reduction and transition from dense forest cover into low forest, which in itself also contains some human land use *i.e.*, plantation agriculture. Again the fact that open woodlands are increasing indicates that the level of agriculture based and other vegetation reduction based activities that emit carbon dioxide would continue to increase and consequently increase the local atmospheric greenhouse gas (GHG) loading [21]. The increasing concentrations would have implications for “local warming” with variable impacts on the local climate, especially temperature and rainfall patterns.

The results obtained and analyzed, from the land use classes for the various years indicated that the district is experiencing appreciably rapid urbanization as the study conjectures and to a large extent corroborated by the socio-economic survey [27]. Areas that exhibited peri-urban to urban land uses are concentrated mostly in the northwestern part of the district. Communities occupying this sub-section of the district include; *Esereso*, *Sawua*, *Jachie*, *Pramso* and *Aputuogya*. The remaining communities in the district remain predominantly rural. The expansion rate in the growth of built up bare land and concrete surfaces area concurs with Acheampong and Anokye [28] that population pressure and associated demand for residential accommodation are usually anticipated phenomena in peri-urban areas. The trending of this growth is seen in the typical “funnel-shaped” pattern from the main city centers towards the Bosomtwe District.

Clearly, land use and cover trends are largely inconsistent with increasing built up/bare land and concrete surfaces, as the classification results depict. In consonance with ground truth and population information, built up areas have increased to such an appreciable extent. This finding reinforces the general argument that areas of perceived urbanization tend to demonstrate rapid growth in residential and built up land uses [29].The trends identified are characteristic of peri-urbanization to a possible urbanization.

Although the dense forest increased marginally in 2010, the low forest cover continued to increase considerably. In classifying the land uses and covers, some of the land use types were identified from ground truth. However, these were embedded in the low forest vegetation cover, with plantation farms of oil palm and some citrus fruits that dominate some areas in the district. This point to the fact that forest cover invariably loses quality in abundance whenever there is competition for the land use cover, in proportion to the other land uses, comparatively [30]. Open woodland and farmlands are created during the clearing and burning of the vegetation, in preparation for cultivation. As far as forest cover as a sink to carbon dioxide is concerned, the enhanced emissions of anthropogenic sources could increase the carbon dioxide loads in the immediate local atmosphere [31]. The consequences of these on local climate variability and change are imminent in the district.

The pointers show that land use in the district, though originally rural and agricultural, has been changing from the more agriculture and forest land uses (AFOLU) to peri-urban residential and commercial land uses, though at moderate rates of conversion. This is arguably an encouraging land use trend that needs to be promoted in order to reduce forest degradation and agriculture based greenhouse gasses emissions. The foregone analysis of the result shows that LULC transition in the district has been in the direction of built up/bare areas and concrete. There may be other extraneous factors responsible for this trend. This is because while low forest decreases in one year, there is a marginal transition from other land use classes into low and dense forest covers in subsequent years. This fluctuating trend in land use, however, is more in favour of built up bare and concrete areas, at the expense of forest land use and cover types over the entire periods under analysis. This situation according to Peng *et al* [32], is usually attributable to the rural land uses that change in response to the drivers of economic changes occurring as a result of modernization of the rural landscape and gradually replaced by the urban landscape characteristics.

7. Materials and Methods

7.1. Profile of the Study Area

The Bosomtwe District is located in the central part of the Ashanti Region. It lies within Latitude 6°28′N–Latitude 6°40′N and Longitudes 1°2′W–Longitude 1°37′W. *Kuntenase* is the District Capital. It spans over a land area of 330 km^2 (Figure 6). The District is bounded to the North by *Atwima Nwabiagya* and theKumasi Metropolis as well as to the East by *Ejisu-Juaben* Municipal. The southern section is bounded by *Amansie* West and East Districts, all in the Ashanti Region of Ghana.

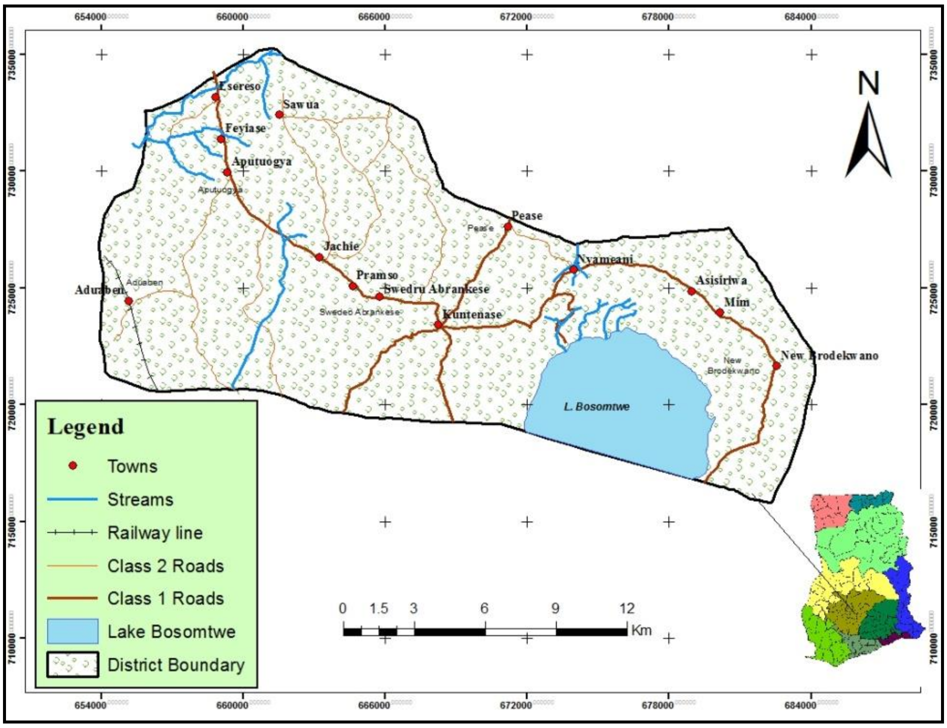


Figure 6. Map of the Bosomtwe District showing the study communities in Ghana.

Lake Bosomtwe, the largest natural (crater) lake in Ghana is located in the district. With the exception of the lake which has an outer ridge that maintains a constant distance of 10 km from the center of the lake and stands at an elevation of 500 to 1500 m, the rest of the district has other varying unique topographical features. The drainage pattern of rivers and streams draining the Bosomtwe District is dendritic and centripetal in outlook. Around Lake Bosomtwe, there is an internal drainage where the streams flow from surrounding highlands into the lake in a centripetal fashion. The streams form a dense network due to the double maxima rainfall regime. Notable rivers in the district are rivers *Oda*, *Butu*, *Siso*, *Supan* and *Adanbanwe*.

The district falls within the equatorial zone of climate with a rainfall regime typical of the moist semi-deciduous forest zone of the country. There are two well-defined rainfall seasons. The main season occurs from March to July and September to November with mean annual rainfall of about 1900 mm. The mean monthly temperature is about 36 ℃ with a relative humidity of between 60 and 85%.

The district falls within the Moist Semi-Deciduous Forest zone where different species of tropical hard woods with high economic value can be found. Species of trees found in the district include Wawa *(Triplochiton scleroxylon)*, Mahogany *(Khaya ivorensis)*, and *Onyina (Ceiba pentandra)* among others. In certain parts of the district, however, the original forest cover has been turned into secondary forest and grassland through indiscriminate exploitation of timber and inappropriate farming practices such as the slash and burn system and illegal gold mining activities.

The physical growth of settlements in the district is influenced by distance between the settlement and the Kumasi Metropolis. Further, the presence of infrastructure, socio-economic activities, the tourism sector improvements are all value additions to various land uses and cover. These make the district one of the potentially boisterous in the Ashanti Region.

7.2. Data and Software

The classification and analysis of the various LULC classes were done using three Landsat satellite images covering the Landsat 5 TM for 1986 acquired on the 29th December 1986, Landsat 7 ETM+ for 2010 acquired on 6th February and Landsat 8 OLI/TIS for 2014 was acquired on the 8th January, respectively (Table 8 and Figure 7 a–c). The choice for the selection of the three dates was influenced by the image quality in terms of those with limited or low cloud cover. The years with considerable evidence of vegetation regeneration after the 1980s forest fires due to prolonged drought conditions; and the need to ascertain the LULC trends over the 24 year period was considered long enough to generate adequate changes. The Garmin Global Position System (GPS) receiver was used to pick some 58 coordinates of selected land use land covers as ground control points from the field. The locations of these reference data were determined at random by identifying and locating the land use classes of interest in the field and their GPS points and coordinates picked and recorded. The instrument accuracy was determined at ±3m. The field surveys were conduction in early part of February 2013. The accuracy of the 1986 image was determined to form expert knowledge of the study district. The 2010 accuracy were determined using co-ordinate points of land uses obtained from the Google Earth image. The 2014 classification was assessed using the GPS points of selected land uses and land cover types collected in the field. These were used in the accuracy assessment procedure.

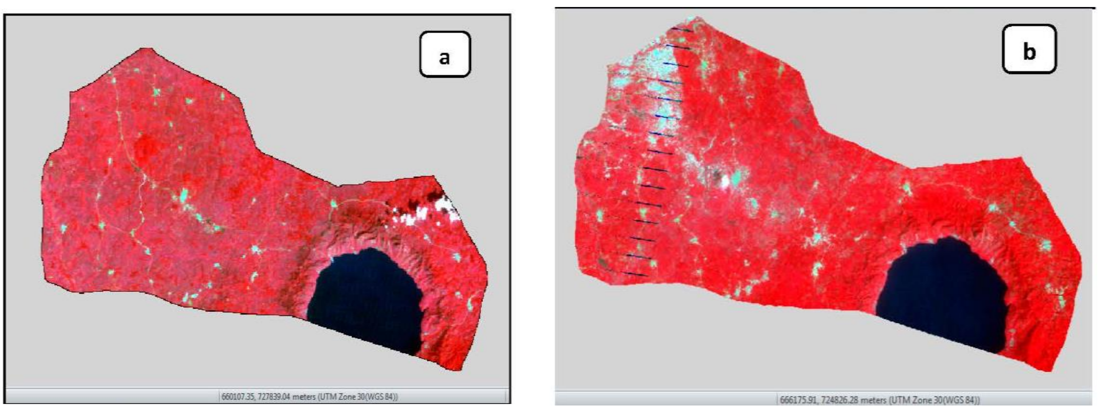


Figure 7. *Cont.*

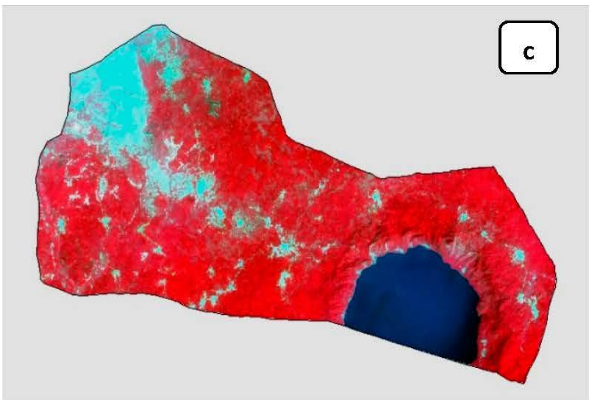


Figure 7. The Landsat ETM/ETM+ Satellite Images for (**a**) 1986, (**b**) 2010 and OLI/TIS Image of (**c**) 2014 respectively, used in the classification of the LULC types.

Table 8. Satellite images characteristics.

Year	Satellite Sensor	Date Acquired	Spatial Resolution	Bands Used	Solar Elevation
1986	Landsat 5 TM	1st of November	30m × 30m	1, 2, 3, 4, 5 & 7	45.06
2010	Landsat 7 ETM+	6th of February	30m × 30m	1, 2, 3, 4, 5 & 7	2010
2014	Landsat 8 OLI/TIS	8th of January	30m × 30m	1, 2, 3, 4, 5 & 7	2014

The image analytical software used and detailed in the methodological flow diagram, were *Hexagone Geospatial's ERDAS Imagine13* and *ESRI's ArcGIS v.10.1* (Figure 8). Based on the field experience and familiarity of the study area as well as the spectral characteristics of the images, the land use and cover classes identified were: Dense Forest cover (DF), Low Forest cover (LF), Built up/Bare lands and Concretes (BBC), Open Woodland and Farm lands (OWLF), Water Body (WB). Other phenomena such as cloud cover and line strips on the images were classified but were not used in the land use matrix analysis (Table 9).

Table 9. LULC classification scheme.

LULC Classes	Descriptions of Land Use Land Cover Classes
Dense Forest (DF)	Deciduous and semi-deciduous forest tree cover with canopies typical of the tropical rainforest biome. Mostly restricted to the upper elevations of mountains ranges of the area including along the rims of Lake Bosomtwe.
Low Forest (LF)	Vegetative communities dominated by evergreen trees, with mean heights usually between 6 and 15 m. Also included in this class is the plantation agriculture such as oil palm and citrus.
Built Up/Bare Land/Concrete (BBC)	This is a land-use dominated by urban, peri-urban to rural settlements including bare, tarred and un-tarred roads as well as other concrete surfaces.
Open Woodlands/Farm Lands (OWFL)	Actively cultivated and fallow lands and prepared lands for cultivation. Vegetative communities dominated by perennial and annual grasses with occasional herbaceous species presence.
Water Body (WB)	The only water body classified is the Part of the lake Bosomtwe which falls in the study area.
Other Uses	These refer to the other uses identified as image noise such as cloud cover and shadows.

Adapted from Kepner *et al.* [33].

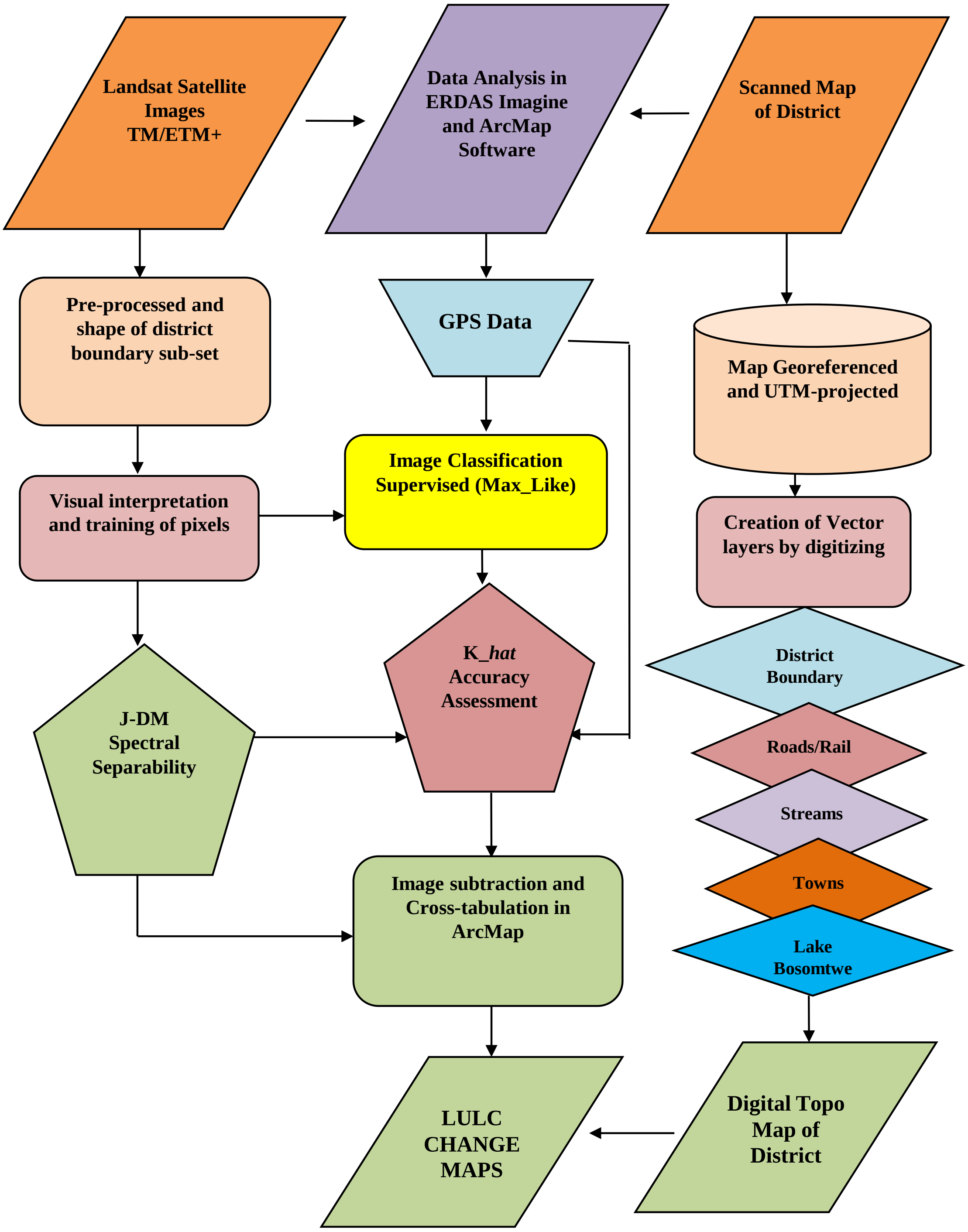


Figure 8. Methodological work flow in ERDAS Imagine and ArcGIS.

7.3. Jeffries-Matusita Distance Separability and Accuracy Assessment

A spectral separability was also done to ascertain the degree of separation of each of the six (one, two, three, four, five and seven) bands from the other. This was also to appreciate the relative separability performance of each band according to the land use classes and to show the performance of the user in assigning certain pixel to a land use and land cover class. The separability criteria were assessed using *Jeffries-Matusita index* and compared with the divergent index [33]. In combination with the classification accuracy assessment, the quality of the results was checked. As reported in the appropriate sections, the results accuracy ranged from moderate to almost perfect agreement.

7.3.1. Spectral Separabilty

A spectral separability was done after classification, to ascertain the degree of separation of each of the six (one, two, three, four, five and seven) bands, from the other. This was also to appreciate the relative separability performance of each band according to the land use classes they reflected. This was to show the performance of the user in assigning certain pixel to a land use and land cover class. The separability criteria were assessed using Jefferies-Matusita and compared with the divergent indices [34]. The separability listing also contains the average divergence and the minimum divergence for the band set. These numbers can be compared to other separability listing (for other band combinations), to determine which set of bands is the most useful for classification.

The *Jeffries-Matusita* distance has upper and lower bounds (JM is between zero and 1414). If the calculated divergence is equal to the appropriate upper bound, then the signatures can be said to be totally separable in the bands being studied. A calculated divergence of zero means that the signatures are inseparable. That is, the *JM* values that ERDAS Imagine reports are those resulting from multiplying the values in the formula times 1000. A separability listing is a report of the computed divergence for every class pair and one band combination (Figures 1–5).

7.3.2. Classification Accuracy Assessment

Classifying LULC maps from satellite images, require a quality check on the acceptability of the results of the classes that have been trained and assigned to each pixel in the image. The use of aerial photographs and previous LULC classes as well as the use of Global Position System (GPS) shows identified ground control points (GCPs), which are, in most instances land use types. The area of interest has invariably been used to corroborate the accuracy of LULC classification [32]. In the absence of base maps and aerial photographs of the study area, GPS points of 58 LULC types were selected as ground controls points (GCPs) to ascertain the accuracy of the classification. This was done using the Kappa hat statistical analysis.

7.4. Image Classification and Change Detection

The LULC classes were assigned with the help of the classifier based on the user defined classification schema [33]. This scheme was based on the visual interpretation of the images coupled with the user's familiarity of the study area. In view of the relatively low spatial resolution of 30m × 30m, some of the classes have been combined for interpretation convenience. The scheme adopted is, described in Table 9. This scheme formed the basis for the creation of the training areas which also contained the sampled LULC types from the field as GCPs in the image for the picking up of spectral signatures for the various LULC classes.

The classification algorithm used in the ERDAS Imagine software was supervised maximum likelihood classifier (MLC). Image differencing was performed in ArcGIS to ascertain the levels of change from one land use type to the other and by how much in terms of area in hectare. The rate of change (r) was calculated using the formula:

$$r = 1 - \left[1 - \left(\frac{A_2 - A_1}{A_1}\right)\right]^{1/t} \tag{1}$$

where, A_1, A_2, and t are the LULC map of previous year, the current year and the time in years as duration between the two years respectively [35].

7.5. Land Use Land Cover Change Transition

The analysis of the results from the image years between 1986 and 2002 and 2002 and 2007, LULC types were cross-tabulated for their transitional matrix shows that the land use classes transited from one type to another according some degree of proportions. Using the Markov transition matrix approach, we determined the transition rates from one land use type to another under certain intrinsic conditions. This was executed in ArcGIS *cross-tabulation* tool functionality.

This is because land use transitions follow rules that determine the change of a cell's state during a subsequent iteration, according to Samat *et al.* [36]. These have cellular automata (CA) tendencies, which are based on the cell conversion probability, also called the likely rate of transition from one cell state (*i*,*j*) to another after a time *t*. These five land use classes represent main land use activities in the district as per the classification. The transition of cells from time *t* to *t+1* is determined by a function of its state, cell suitability and its transition probability rule.

This is given by equation below:

$$^{t+1}LU = f\left({}^{t}(LU)x\,{}^{t}(S_{i,j})x\,{}^{t}(P_{x,y;i,j})\right) \tag{2}$$

where,

$^{t+1}LU_{i,j}$= the potential of cell i,j to change at time t+1,
$^{t}LU_{i,j}$= current land use type of cell i,j at time t,
$^{t}S_{i,j}$ = states of cell i,j at time t,
$^{t}P_{x,y,i,j}$ = probability of cell i,j to change from state x to state y at time t+1.

The diagonals of the matrix, in Tables 4 and 6, indicate, for instance, the land use types in area per hectare that was remained without any conversions of LULC class over the time period [7,37].

8. Conclusions and Recommendations

The LULC trends from 1986 through to the years 2010 and 2014 are consistently in favour of built up/bare land and concrete surfaces, as well as the open woodland and farmlands, to an appreciable extent. These trends are certainly the characteristics of peri-urbanization and a possible urbanization, consequently. This result largely implies that the Bosomtwe district is rapidly peri-urbanizing as the study conjectured, based on the earlier increasing urbanizing trend from the 1980s to the early 2000s.

In any case, the general observations from the field work, coupled with the classified images, show that plantation agriculture and food subsistent crop farming, dominate the landscape in terms of land use and cover in the District from 1986 to 2014. However, the pointers show that the land is put more to the use of residential and commercial purposes than agriculture and forest land uses (AFOLU).

In general terms, however, the probability of other land use types changing into other LULC types is highly in favour of built up and concrete land uses. According to the Markov chain transition reaction of proportions, the land use activities could lead to the general reduction in the vegetation cover in the district consequently over the next 24 years projected into the future. In comparing the vegetation and non-vegetation covers of the district, it can be observed that LULCs other than built up areas (which rapidly increased) are slightly increasing at the expense of forest covers. As low forest and dense forests reduce in size, particularly from 1986 to 2010, it is an indication of the reduction in agriculture and forest land use activities in the district. Conservation and protection of forest land use and cover are still imperative to ensure that forest based carbon emissions are controlled from unsustainable land use practices at the local scale [38,39].

The study findings have shown important changes in the land use and land cover patterns in the district. After an urbanization process, coupled with farmland abandonment between 1986 and 2010, substantial increments in peri-urban to urban land uses and clear increments in farmland coverage were found between 2010 and 2014. This suggests that major changes in the socio-ecological driving forces affecting landscape dynamics have occurred in the last two decades or so. In addition, this Landsat data-based study has provided insight into the dynamics of peri-urban landscapes, within the context of urban planning science.

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Author Contributions

The scheme of work was performed according to task-sharing among co-authors. Divine Odame Appiah first conceptualized the paper and was fine-tuned in accordance with the data by Dietrich Schröder and John Tiah Bugri, Eric Kwabena Forkuo and Divine Odame Appiah designed the study, and performed the classification and statistical analysis. Divine Odame Appiah and Dietrich Schröder wrote the first draft of the manuscript. Divine Odame Appiah, John Tiah Bugri, and Eric Kwabena Forkuo conducted the literature survey. All four authors managed the analyses and discussions of the data. All contributing authors read, corrected and approved the final manuscript before submission. Divine Odame Appiah served as the lead and corresponding author.

Conflicts of Interest

The authors declare no conflict of interest.

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