Research Article

Predictive Land Use Change under Business-As-Usual and Afforestation Scenarios in the Vea Catchment, West Africa

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Abstract This study aimed to assess the historical Land use/land cover (LULC) changes and project the future (2025) LULC pattern in the Vea catchment based on Business as Usual (BAU) and afforestation scenarios of land use. Landsat Imagery of 1990, 2001, 2011 and 2016 were classified at overall accuracy assessment of 82%, 86%, 85% and 88% respectively. Major transitions were modeled using the Multi-layer Perceptron Neural Network algorithm, and the future scenarios maps of LULC were projected based on the Markov chain after validation of the Land Change Modeler. The results indicate the conversion of forest/mixed vegetation (23.1%) and grassland (76.9%) to cropland as the dominant LULC conversion from 1990 to 2016. An increase in cropland, built-up areas, and water bodies were observed while grassland and forest/ mixed vegetation decreased over the last 27 years. The 2025 LULC simulation indicates continuous expansion of cropland at the expense of forest/mixed vegetation which is projected to decrease by 4.5% in 2025 for the BAU scenario. Under afforestation scenario, where forest/mixed vegetation and grassland are expected to increase, cropland is projected to decrease by 20% in 2025. These findings set a reference ground for sustainable land use governance through responsible planning and management of land and water resources by considering trade-offs between cropland expansion and ecosystems' preservation in the Vea catchment.

Keywords *Cropland; Land change modeler; land use/land cover change; Vea catchment*

1. Introduction

In the past decades, research has revealed unprecedented rates of land use/land cover (LULC) change which can be attributed to many factors including but not limited to overgrazing and rapid socio-economic development (WRC, 2008; Gyasi et al., 2011). These changes are responsible for the increasing land degradation and declining soil productivity (Braimoh and Vlek, 2004; Biro et al., 2013). According to the World Atlas of Desertification (WAD), over 75% of the Earth's land area is already degraded, and about 90% could become degraded by 2050 (Cherlet et al., 2018). Globally, Africa

accounts for 65% of the total extensive cropland degradation of the world (Thiombiano and Tourino-Soto, 2007) and the situation is not different in the White Volta Basin (WVB) where the Vea catchment in Ghana is located.

In the WVB, the issue of LULC change has been addressed by several studies (Daudze, 2004; Mahe et al., 2005; Abagale et al., 2009; Agyemang, 2009; Gyasi et al. 2011, Batuuwie, 2015). For example, Abagale et al. (2009) showed that the Nasia basin within the WVB has undergone considerable LULC change between 2000 and 2008 with a loss of 10% closed savannah, a decrease of 3.2% in open savannah woodland and an increase in built up areas from 2.7% to 11.4%. Similar observation was also made by the study of Baatuuwie (2015) that observed a decrease in the forest/dense woodland areas and an increase in settlement and cropland (46.5% to 49.2%) between 1990 and 2015 when they used a multidimensional approach to assess land degradation at Nawuni (a sub-basin within the WVB). However, these studies on LULC change in the WVB have been conducted on a scale which may ignore or over-simplify landscape features due to the coarse resolution of the underlying data (e.g. 250 m MODIS). Consequently, spatial details at local (watershed) scale are missing. Understanding spatial patterns of LULC at local scale is important for local level management and decision making, which is normally not possible with coarse regional scale products. By using a higher spatial resolution (30m) satellite image, this study seeks to provide future LULC information which will be relevant for improving land management at the Vea catchment due to the findings of earlier research reporting continuous degradation.

In the Vea catchment, there are limited studies on LULC changes as well as projection of the future LULC specific to the catchment. Apart from broader scale studies (Daudze, 2004; Mahe et al., 2005; Batuuwie, 2015) covering the WVB, only Forkuor (2014) studied LULC changes in the catchment and revealed that the catchment is dominated by agricultural land, which occupied about 52% of the Vea catchment. Little effort has been made in projecting future LULC patterns which is essential for: (1) devising effective national land use plans and policies for sustainable development and (2) improving water and land management for effective implementation of the sustainable development goals (eg., SDG 15), in the context of climate change and climate variability. As LULC data are essential input to a number of biophysical and economic models, knowledge of future LULC patterns will be necessary in knowing the plausible state of our natural resources (e.g., water, land) in the future and devise appropriate strategies to avert calamity. The most widely used technique in obtaining this information is through the analysis of remotely sensed data in conjunction with ground data (Braimoh and Vlek, 2004; Daudze, 2004).

This study assessed the historical (1990 to 2016) LULC changes and projects the future (2025) LULC patterns in the Vea catchment based on Business-as Usual (BAU) and afforestation scenarios. The study provides the basis for understanding the past, present and future LULC patterns, and information to decision makers for sustainable land management in the Vea catchment.

2. Materials and Methods

2.1. Study Area

The study area is the Vea catchment located between latitudes 10°30'- 11°08' N and longitudes 0° 59'-0° 45'W (Figure 1). The Vea catchment is a sub-catchment of the White Volta Basin (WVB) with an area of about 308 km^2 and covers mainly the Bongo and Bolgatanga districts in the Upper East Region of Ghana with a small portion in the south-central part of Burkina Faso. The climate of the catchment is controlled by the movement of the Inter-Tropical Discontinuity (ITD) over the West African region (Obuobie, 2008). Located in a semi-arid agro-climatic zone, the catchment crosses three agro-ecological zones: the Savanna and Guinea Savanna zones in Ghana, and north Sudanian Savanna zone in Burkina Faso (Forkuor, 2014). The catchment is characterized by a uni-modal rainfall regime from May to October with a mean annual rainfall of about 956 mm which normally peaks in August (Larbi et al., 2018). The temperature is uniformly high with a mean annual value of 28.9^{o}C and

potential evapotranspiration exceeds monthly rainfall for most part of the year, except the three wettest months of July, August and September (Limantol et al., 2016). The catchment is characterized by fairly low relief with elevation ranging between 89 m and 317 m (Figure 1) whereas the LULC is mainly dominated by cropland followed by grassland interspersed with shrubs and trees. Agriculture, which includes the cultivation of annual crops such as *Vigna unguiculata* (cowpea), *Oryza sativa* (rice), *Sorghum bicolor*, (sorghum) *Pennisetum glaucum* (millet), and *Arachis hypogaea* (groundnuts), is the main activity of the people in the catchment.

2.2. Landsat Data Processing

2.2.1. Landsat Images

The 30m resolution Landsat Images for the years 1990, 2001, 2011 and 2016 (Table 1) covering a period of 27 years, were downloaded for two scenes based on availability and seasonal compatibility from the United States Geological Survey (USGS) GLOVIS website (USGS, 2017). A cloud cover criterion of less than 10% was used. In all cases, end of growing/harvest season (October and November) images were used to reduce the confusion between natural vegetation and agricultural lands, and to minimize interference due to cloud cover (Ruelland et al., 2008; Zoungrana et al., 2015).
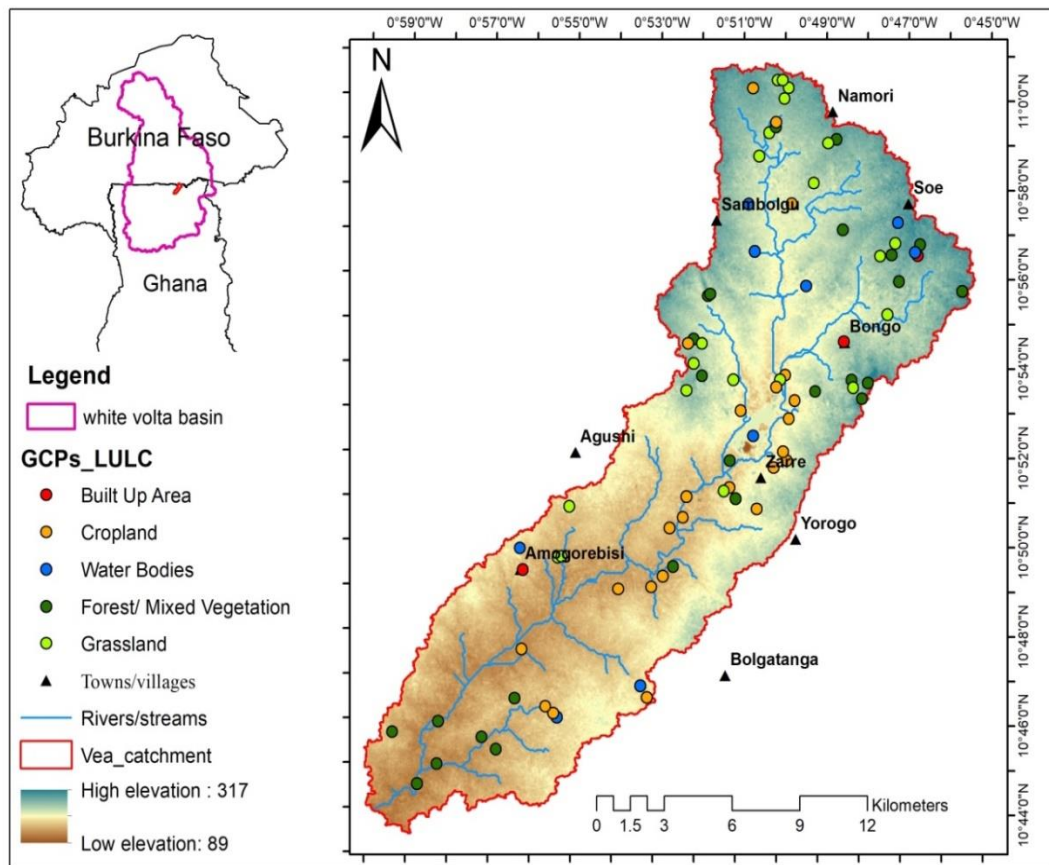

Figure 1: *DEM map of Vea catchment with LULC ground truth data*

Table 1: *General characteristics of landsat images*

Date of acquisition	Platform (sensor)	Scene path and row (p, r)	No. of bands
2016-10-24	Landsat 8 (OLI /TIRS)	p194r052; p194r053	11
2011-10-24	Landsat 7(ETM+)	p194r052; p194r053	8
2001-10-27	Landsat 7(ETM+)	p194r052; p194r053	8
1990-11-02	Landsat 4/5(TM)	p194r052; p194r053	7

OLI: Operational Land Imager; ETM+: Enhanced thematic mapper, Thematic Mapper (TM); Bands used: 5, 4, 3 and 2.

2.2.2. Reference Data

Reference data used for the classification and accuracy assessment were obtained from high-resolution images of Google Earth, previous 2013 LULC map of the Vea catchment (Forkuor, 2014) and a field campaign using Global Positioning Systems (GPS). The google earth imagery is provided by digital globe and SPOT satellite over the study area with resolution between 10 m to 1.5 m. These datasets were collected to serve as a basis for image classification and accuracy assessment. The field campaign was conducted within the same dry season (January to March 2017) for best correlation between the 2016 Landsat image and the ground features. In all, a total of 250 reference points from both 2017 field campaign (150 points) and Google Earth Image (100 points) of the year 2016 were collected. Sixty percent of the collected data were used for training and the remaining for validation. With the help of a handheld GPS device, a total of 150 polygons were created for five LULC types during the field survey. The polygons were created from 30 m X 30 m plots of a particular LULC type (eg. Cropland). Two hundred reference points from 2011 Google Earth Image and previous 2013 LULC map of the catchment were used for the classification (58 points) and validation (142 points) of the 2011 image. The year 2001 Landsat image was classified (65 points) and validated (135 points) based on 200 points selected from Google Earth Image. Also, 215 points were collected for the year 1990 of which 56 were used for classification and 159 points for validation. The samples were picked from areas that remained unchanged after loading the samples of the year 2001 on the 1990 Landsat image.

2.3. Mapping and Accuracy Assessment

2.3.1. Image Classification

The LULC maps were produced based on the methodology outlined in Figure 2 by considering five LULC classes (Table 2) based on previous studies in the study area and the LULC classification scheme of the study by Forkuor (2014). A supervised image classification based on maximum likelihood algorithm - a statistical decision criterion that assigns pixels to the class of the highest probability was performed (Chander et al., 2009; Ahmad, 2012). The Landsat images of 1990, 2001, 2011 and 2016 were classified based on training data obtained from both onscreen digitization of various LULC classes and part of the reference data collected for the various LULC classes.

Table 2: *Land use/land cover classification scheme modified from Forkuor (2014)*

LULC categories	Description
Water body	Areas permanently covered with standing or moving water such as inland waters, waterlogged areas, wetlands, dams, dugouts and streams.
Grassland	Mainly the mixture of grasses and shrubs with or without scattered trees (<10 trees per hectare) and areas covered with only grasses.
Built-up areas	Areas of human settlements, roads, artificial surfaces etc.
Cropland	Areas used for crop cultivation (irrigated and rain-fed agriculture), harvested agricultural land and bare soil.

Mixed vegetation/ Forest	Areas with dense trees usually over 5 m tall, riparian vegetation, shrubs and trees.

2.3.2. Accuracy Assessment

The aim of accuracy assessment is to quantitatively determine how effectively pixels were grouped into the correct feature classes in the area under investigation. Accuracy assessment of the classified image of the year 1990, 2001, 2011 and 2016 were performed using reference data. An error or confusion matrix which is one of the most widely used accuracy assessment method (Congalton and Green, 2009) was generated for all the LULC classes. The error of omission or producer's accuracy, error of commission or user's accuracy, overall accuracy and the Kappa value were determined for each classified LULC map.

2.4. Scenarios Development

Developing scenarios of future LULC conditions is important for a variety of research themes, including hydrologic change and water availability (Wilk and Hughes, 2002). In developing countries such as Ghana, due to the complex land tenure systems, land use change is a relatively uncontrolled process compared to developed countries. In this study, two different LULC change scenarios, i.e., Business-as-usual (BAU) and afforestation scenarios (Table 3) were considered. The afforestation scenario was created by altering the probability matrices for cropland, grassland and forest/mixed vegetation produced from the Markov chain analysis by limiting the probability that grassland and forest/mixed vegetation would be converted to cropland.

Table 3: *Land use/land cover change scenarios*

Scenarios type	Description
Business- -as-usual	The future 2025 LULC map is produced based on the historical trend of LULC transitions (expansion in cropland at the expense of natural vegetation) from 1990 to 2016.
Afforestation	Increase in natural vegetation (forest/mixed vegetation and grassland) by 15% in the future 2025 by limiting the expansion of cropland.

2.5. Change analysis and modelling

2.5.1. Post Classification Change Analysis using the Land Change Modeler

Diverse modelling tools have been applied to analyse LULC dynamics over the past years with each tool producing different degrees of accuracy (Wu and Webster, 2004). Embedded in IDRISI software are various land use modelling tools such as the Land Change Modeler (LCM), Cellular Automata (CA), CA_Markov, GEOMOD, and STCHOICE which are commonly used (Eastman, 2006). For short-term projections, mostly ten years or less, LCM has been noted to provide good projection accuracy in LULC change analysis (Roy et al., 2014). Moreover, compared to other models that project LULC change based on supervised classifications, the LCM produces more accurate output due to the robust nature of the Multi-layer perceptron (MLP) neural network used in LCM (Vega et al., 2012). These reasons guided the choice of the LCM to project the LULC changes in the Vea catchment for the 2025 horizon.

The LULC change analysis and the scenarios maps for the Vea catchment were produced in the LCM using the following procedure: change analysis, transition potential modelling, model validation and change projection (Figure 3). The model evaluates LULC change between two sets of images of different dates, same legend, and spatial characteristics, and presents the change results in graph and map forms (Megahed et al., 2015). In this study, the LULC changes for the four time periods (1990 to

2001, 2001 to 2011, 2011 to 2016 and 1990 to 2016) were performed by post-classification comparison technique, a widely used approach for LULC change detection (Mahmoud et al., 2016). The LULC change analysis was performed using the change detection module in the LCM which provides information on; gains and losses of each LULC class, the net change which is the difference between the gains and losses of each class, contributors to the net change experienced by each class, and the transition of areas among each LULC class that has occurred between two different dates (Eastman, 2006).

2.5.2. Transition Potentials Modelling using the Multi-layer Perceptron Neural Network

The LULC maps of the year (2001t_1 – 2011t_2 and 1990t_1 – 2016t_2) were used as inputs to produce the transitions. The change analysis module was used to identify the most dominant transitions (grassland to cropland, forest/mixed vegetation to cropland and forest/mixed vegetation to grassland) which were used to create transition potential maps required for modelling by setting a threshold of 1000 hectares. The likelihood of transformation from other classes to cropland (Evidence likelihood image) was created using the change maps. The LCM employs logistic regression, SimWeight and Multi-Layer Perceptron (MLP) neural network as modelling algorithms to model transition variables. The MLP neural network was employed in this study to produce the transition potential maps. The MLP is extensively enhanced and requires no user intervention, with the ability to model several transitions at a time, and also capable of modelling non-linear relationships (Eastman, 2006). The MLP neural network operates as a feedforward artificial neural network (ANN) model with uni-directional data flow through hidden layers in between (Nazzal et al., 2008). The neural network training is based on a supervised training algorithm which is a common method of training ANN. The transition potential maps for the LULC changes were produced with MLP accuracy rate (85%) which is within the acceptable range (Eastman, 2006).
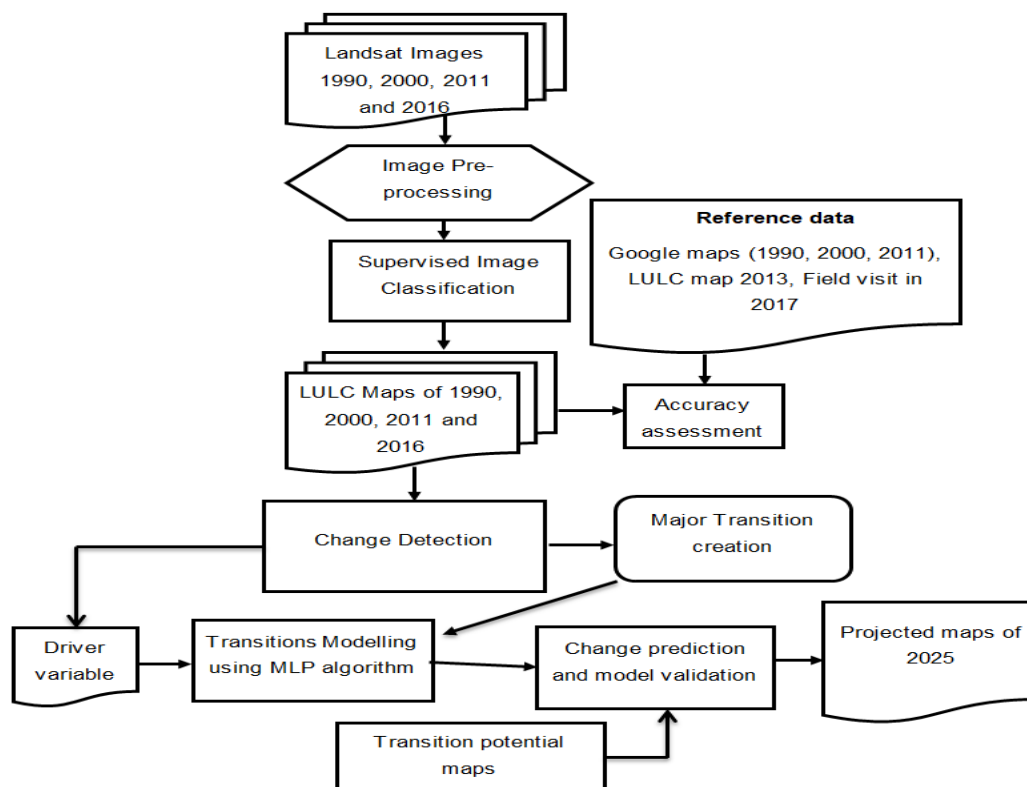

Figure 2: *Flowchart of LULC mapping, change analysis and modelling*

2.5.3. LCM Validation and Change Projection

The LCM model projective power was assessed using the Cramer's V by modelling the transitions from 1990-2001 using the transition sub model after setting the driver variable (Evidence likelihood variable) which is obtained from the historical changes between 1990 and 2001), to produce the transition potentials required to project the 2011 LULC map using the Markov chain. The Markov chain calculates how much land transition from one class to another from time t_o to t_1 in each transition based on the historical rate of LULC changes (Eastman, 2006; Olmendo et al., 2015). To validate the LCM, the statistical approach which examines the agreement between a pair of maps that show any categorical variable, and can have any number of categories was used (Pontius and Chen, 2008). The output of the simulated 2011 map was compared with the real or classified map of 2011 using the validation module to evaluate the accuracy of the model through the application of Kappa Index (Pontius, 2000; Langley et al., 2001) which includes; overall accuracy of simulation run (K_{no}) and the level of agreement of location ($K_{location}$). The Kappa value ranges from -1 which indicates no agreement to 1 which indicates perfect agreement (Pontius, 2000). This is done to ascertain the quality of the projected map and the actual LULC map. Comparison between changes indicated by the real map to the change shown by the simulated map over the validation period was made. After validation and assessment of the model, the LCM was used to project the future LULC scenarios maps for the year 2025 based on the same driving variable and the historical LULC change between 1990 and 2016 by going through the procedure defined in Figure 2.

3. Results

3.1. Accuracy Statistics and LULC Change Analysis

The accuracy assessment results of the classified LULC maps indicate overall classification accuracies of 82% (1990), 86% (2001), 85% (2011), 88% (2016) and Kappa statistics above 0.8 (Table 4a - 4d).

Table 4: *Accuracy statistics of the classified land use/land cover maps*

(a) Year 1990; Overall accuracy = 82.3%; Kappa = 0.8

LULC	Reference image					Reference totals	User accuracy (%)	Producer accuracy (%)
	1	2	3	4	5			
Cropland	31	5	3	0	0	39	79.5	77.5
Grassland	4	30	6	0	0	40	75.0	75.0
Forest/mixed vegetation	3	5	32	0	0	40	80.0	78.0
Built-up Areas	2	0	0	28	0	30	93.3	100.0
Water bodies	0	0	0	0	10	10	100.0	100.0
Classified total	40	40	41	28	10	159		

(b) Year 2001; Overall accuracy = 85.9%; Kappa = 0.84

LULC	Reference image					Reference total	User accuracy (%)	Producer accuracy (%)
	1	2	3	4	5			
Cropland	30	3	1	0	0	34	88.2	78.9
Grassland	4	27	3	1	0	35	77.1	81.8
Forest/mixed vegetation	1	3	26	0	0	30	86.7	86.7
Built-up Areas	3	0	0	22	0	25	88.0	95.7
Water bodies	0	0	0	0	11	11	100.0	100.0
Classified total	38	33	30	23	11	135		

(c) Year 2011; Overall accuracy = 84.5%; Kappa = 0.82

LULC	Reference image					Reference total	User accuracy (%)	Producer accuracy (%)
	1	2	3	4	5			
Cropland	31	4	3	1	0	39	79.5	83.8
Grassland	3	24	5	0	0	32	75.0	77.4
Forest/mixed vegetation	1	3	30	0	0	34	88.2	78.9
Built-up areas	2	0	0	23	0	25	92.0	95.8
Water bodies	0	0	0	0	12	12	100.0	100.0
Classified total	37	31	38	24	12	142		

(d) Year 2016; Overall accuracy = 88%; Kappa = 0.86

LULC	Reference image					Reference total	User accuracy (%)	Producer accuracy (%)
	1	2	3	4	5			
Cropland	26	2	1	0	0	29	89.7	83.9
Grassland	3	22	1	0	0	26	84.6	81.5
Forest/mixed vegetation	1	2	20	0	0	23	87.0	90.9
Built up areas	1	1	0	14	0	16	87.5	100.0
Water bodies	0	0	0	0	6	6	100.0	100.0
Classified total	31	27	22	14	6	100		

The LULC classification results of the year 1990, 2001, 2011, 2016 and the area under each LULC type are shown in Figure 3 and Table 5 respectively. Cropland was found to be dominant in the LULC maps of the year 2001 (40.62%), 2011 (54.09%) and 2016 map (56.64%) with the southern part of the catchment mostly dominated by natural vegetation (forest/mixed vegetation and grassland) as shown in Figure 4. The changes in LULC from 1990 to 2001, 2001 to 2011, 2011 to 2016 and 1990 to 2016 in terms of the net change of the LULC classes which were analyzed by the LCM are shown in Figure 4 and Table 5. The most dominant LULC change was the conversions of grassland to cropland, followed by the conversion of forest/mixed vegetation to cropland within the last 27 years. Between 1990 and 2001, cropland increased by 22.87% followed by built-up areas (22.46%) while grassland decreased by 25%. Between 2001 and 2011, cropland continued to increase by 24.9% together with built- up areas (25.3%) while grassland and forest/mixed vegetation decreased by 34.6% and 20.7% respectively. During the last five years (2011 to 2016), built-up areas continued to increase by 39.14%, followed by water bodies (12.87%) and cropland areas (4.50%), while grassland and forest/mixed vegetation decreased further (Table 6). Between 1990 and 2016, forest/mixed vegetation and grassland decreased by 20.8% and 44.9% respectively, while cropland, water bodies and built-up areasshowed an increase. The results of the rate of change (Table 6) of the LULC types showed that built- up areas, cropland and water bodies increased at an annual rate of 0.04, 3.0 and 0.01 km^2 respectively while grassland and forest/mixed vegetation cover decreased at an annual rate of 2.6 and 0.45 km^2 respectively within the last 27 years.

Table 5: *LULC classification statistics with area in km^2 (%) from 1990 to 2016*

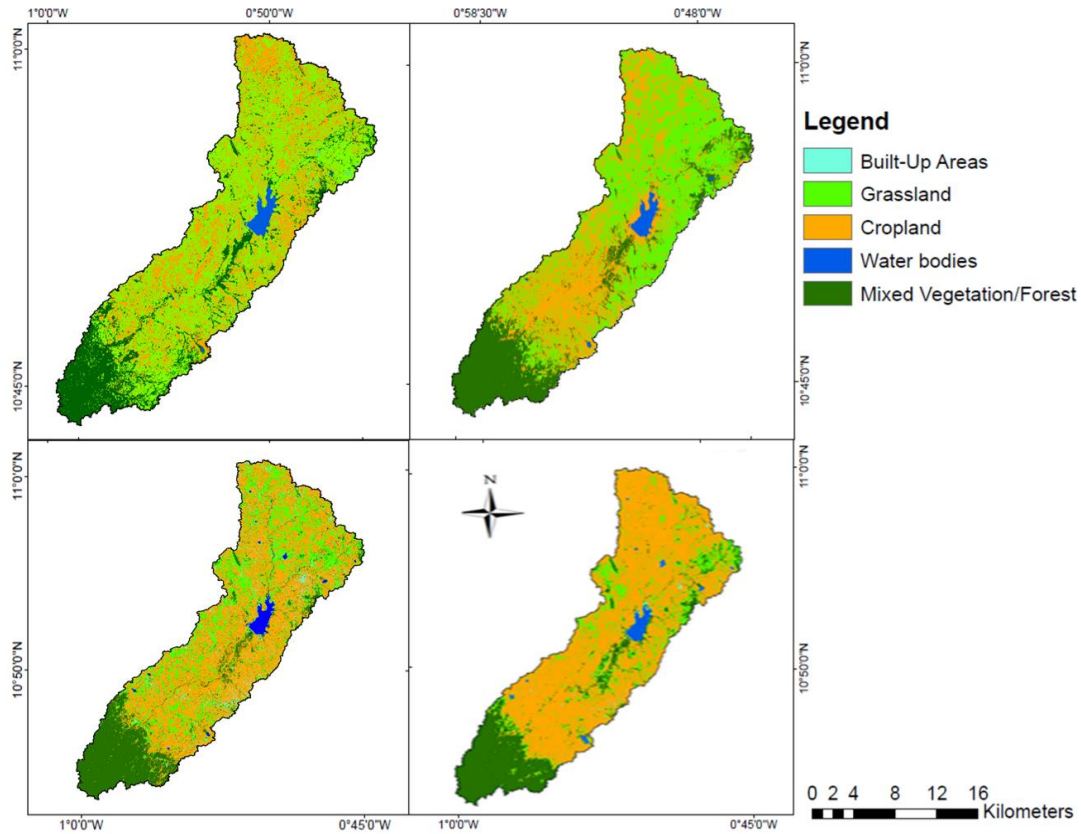| LULC Class	1990	2001	2011	2016	Area coverage (%)			
					1990	2001	2011	2016
Cropland	96.53	125.15	166.64	174.50	31.33	40.62	54.09	56.64
Grassland	150.33	120.26	89.38	82.72	48.80	39.04	29.01	26.85
Built-up areas	0.69	0.89	1.02	1.67	0.22	0.29	0.33	0.54
Water bodies	4.56	5.35	4.27	4.90	1.48	1.74	1.39	1.59
Forest/mixed veg.	55.96	56.42	46.76	44.28	18.17	18.31	15.18	14.37

Figure 3: *Spatial distribution of land use/cover maps of the Vea catchment for 1990, 2001, 2011 and 2016*

Table 6: *Change statistics and rate of change of LULC type from 1990 to 2016*

LULC Class	Area change (km²)				Rate of change (km²) per year			
	1990-2001	2001-2011	2011-2016	1990-2016	1990-2001	2001-2011	2011-2016	1990-2016
Cropland	2862 (22.8%)	4149 (24.9%)	786 (4.5%)	7797 (80.7%)	2.60	4.15	1.57	3.00
Grassland	-3007 (-25%)	-3088 (-34.6%)	-666 (-8.1%)	-6761 (-44.9%)	-2.73	-3.09	-1.33	-2.60
Built-up areas	20 (22.4%)	13 (25.3%)	66 (39.1%)	98 (58.6%)	1.8	0.01	0.13	0.04
Water bodies	79 (14.7%)	-108 (-12.3%)	63 (12.8%)	34 (6.9%)	0.07	-0.11	0.13	0.01
Forest/mixed vegetation	45 (0.8%)	-966 (-20.7%)	-248 (-5.6%)	-1168 (-20.8%)	0.04	-0.97	-0.50	-0.45

NB: Percentage change in LULC type is found in the bracket.

3.2. Contributors to the Changes in Land Use/Land Cover

In order to observe the transformations from all other LULC classes to cropland, charts of contributors (LULC types which are converted to other LULC type) to cropland area dynamic over the 27 year period expressed in hectares were produced (Figure 4). The main contributing factor to the expansion in cropland within the last 27 years was grassland followed by forest/mixed vegetation. From 1990 to 2001, grassland contributed about (20%) to the increase in cropland followed by forest/mixed vegetation (14%). Similar observations were made from the year 2001 to 2011, and 2011 to 2016,

where grassland and forest/mixed vegetation were the main contributors to the increase in cropland in the Vea catchment.
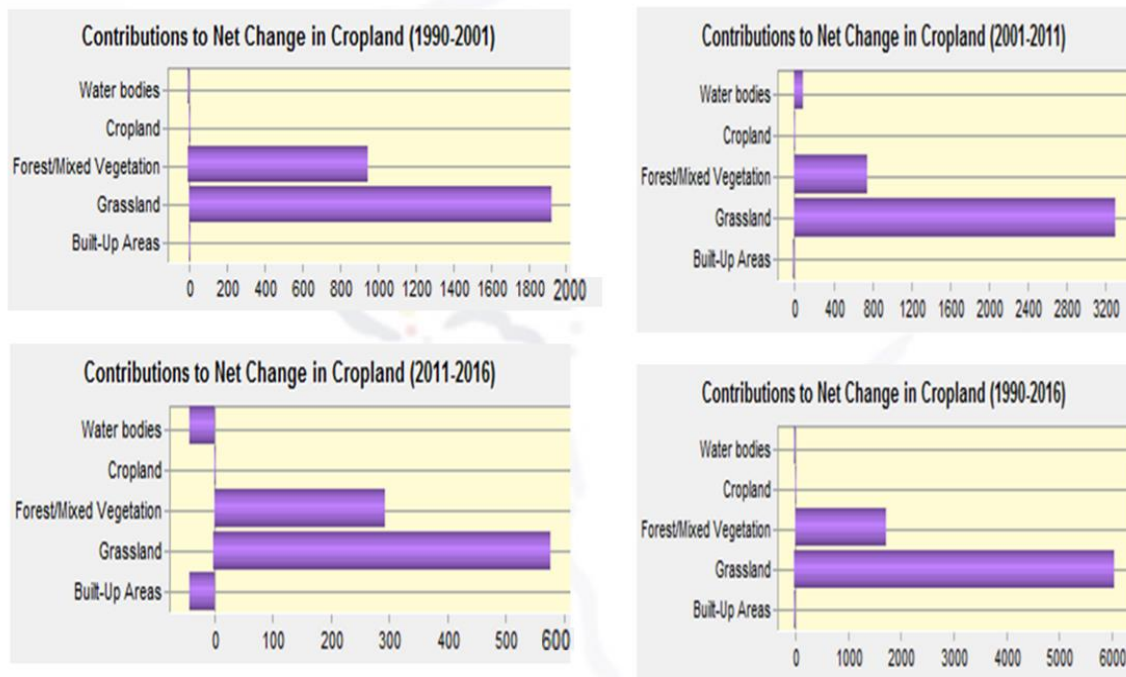

Figure 4: *Contribution to net change in cropland (in hectares) by forest/mixed vegetation and grassland for 1990-2001, 2001-2011, 2011-2016 and 1990-2016*

3.3. Model Validation

The results of the overall Cramer's V test of projective power of the LCM as presented in Table 7 indicate Cramer's V value greater than 0.4. Comparison of the modelled and classified LULC maps of 2011 (Figure 5 and Table 8) showed minor differences between the simulated and actual maps. In the simulated map (Figure 5), the area for cropland was a little underestimated while grassland was a little overestimated especially in the northern part of the catchment. The statistical validation of the simulated change in 2011 and the corresponding error is shown in Table 8. A simulated change of 29.22 km^2 of cropland which is less than the actual change of 41.49 km^2 was observed with an error of 7.3%. The Kappa value which is related to the location and quantity of the image was observed to be high when the modelled and classified LULC maps were compared. The overall accuracy of simulation run (K_{no}) and the level of agreement of location ($K_{location}$) values were found to be 80.47% and 78.35% respectively. This indicates that the LCM was capable of projecting the 2011 LULC map by simulating the historical changes that occurred from the year 1990 to 2001, hence is capable of projecting a reasonable result for the year 2025. Between 1990 and 2016, the contribution from grassland and forest/mixed vegetation to cropland were 76.9% and 23.1% respectively.

Table 7: *Cramer's V test for each LULC*

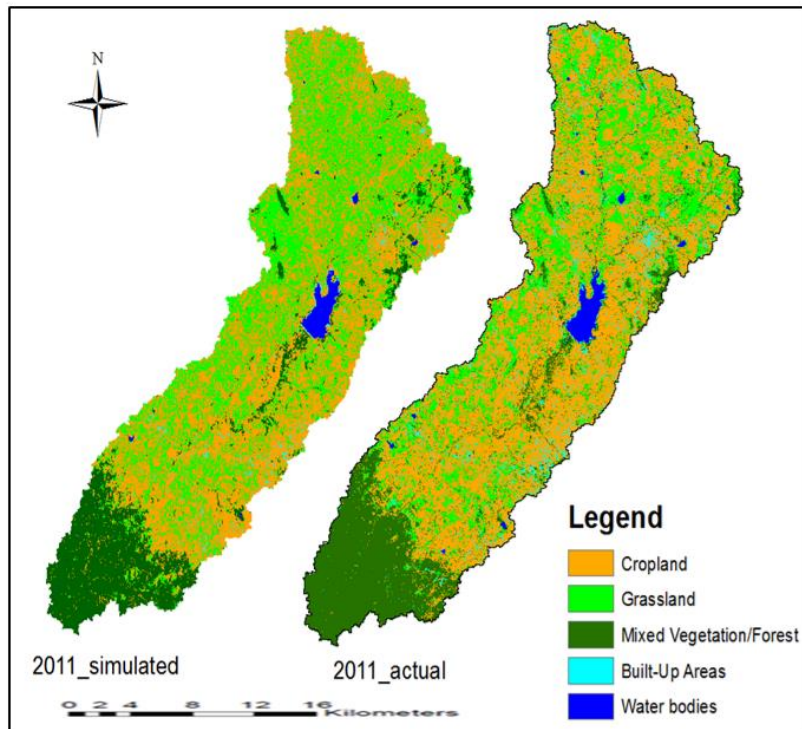| Evidence likelihood variable	Overall Cramer's V	Water bodies	Cropland	Forest/mixed vegetation	Grassland	Built-up areas
(1990-2001)	0.5549	0.2155	0.9042	0.6393	0.3351	0.0577
(1990-2016)	0.4668	0.2726	0.6180	0.2334	0.0474	0.00

Figure 5: *Simulated and actual LULC maps of 2011*

Table 8: *Comparison between actual and simulated LULC area statistics (in km^2) for the year 2011*

LULC Class	2001	Area coverage (km^2)		Simulated-Actual or error (km^2)
		Actual 2011	Simulated 2011	
Cropland	125.15	166.64 (41.49)	154.43(29.28)	-12.21(7.3%)
Grassland	120.26	89.38(-30.88)	97.97(-22.29)	8.59(9.6%)
Built-up areas	0.89	1.02 (0.13)	0.95(0.06)	-0.07 (6.7%)
Water bodies	5.35	4.27 (-1.08)	4.35(-1.0)	0.08 (1.9%)
Forest/mixed veg.	56.42	46.76 (-9.66)	50.42(-6.0)	3.66 (7.8%)

NB: Values in the bracket indicate simulated change and actual change in km^2 during the validation period.

3.4. Simulation of LULC Changes

The outputs from the Markov chain projection of the future 2025 LULC maps for the two LULC change scenarios are shown in Figure 6. In BAU scenario, as shown in Table 9, there is an evidence of potential increase in cropland at the expense of natural vegetation (grassland and forest/mixed vegetation) from 56.6% in 2016 to 57.5% in 2025. Grassland is projected to increase from 26.8% to 28.5% which can be attributed to the projected decrease in forest/mixed vegetation from 14.4% to 11.8% by the year 2025. There were no changes in water bodies and built-up areas due to the fact that the model considered the major transitions that occurred over the past years. In the case of afforestation scenario, which considers limitation in cropland expansion by promoting vegetation growth while ensuring food security, there would be a potential increase in forest/mixed vegetation from 14.4% in 2016 to 15.3% in 2025. Grassland is projected to increase from 26.85% in 2016 to 31.3% in 2025, while cropland decreased from 56.6% to 51.3% by 2025.
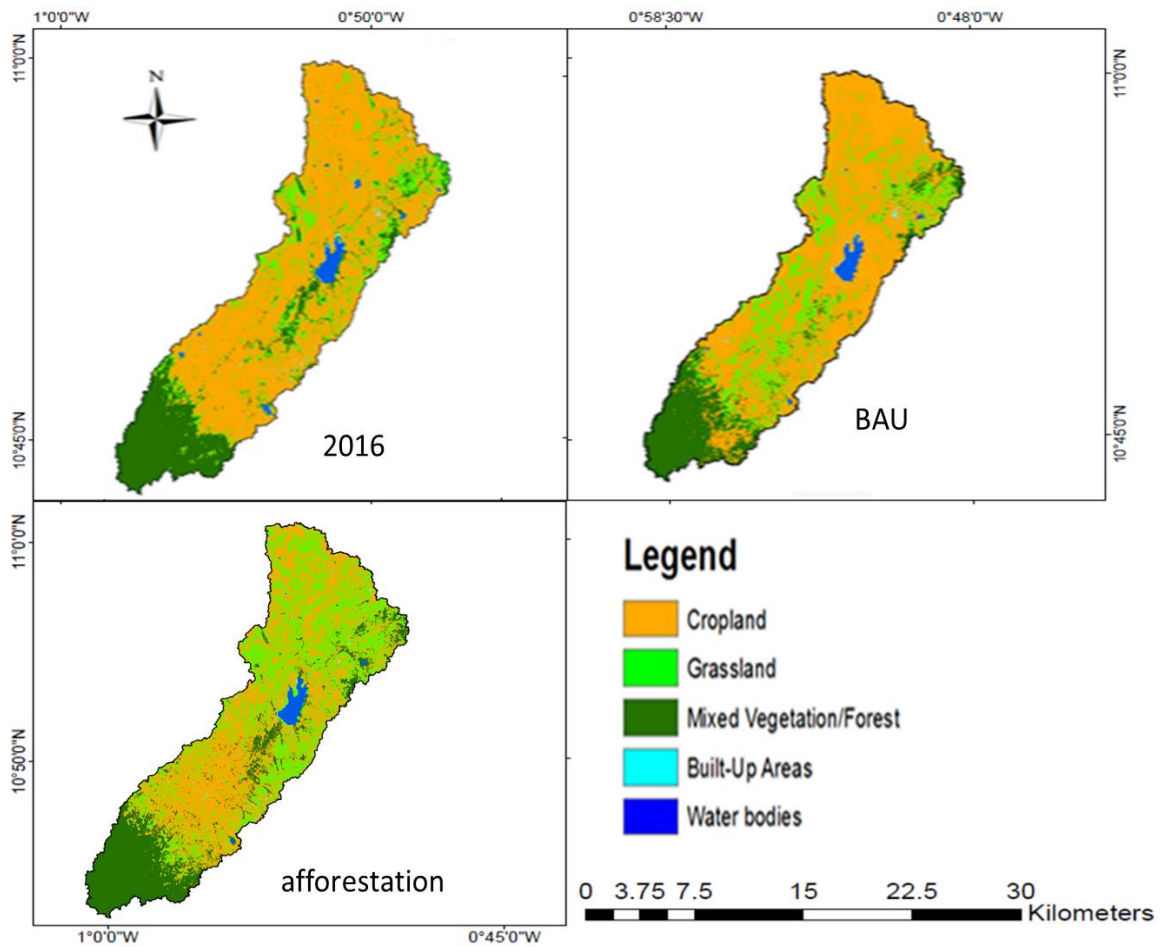
Figure 6: *LULC maps for the year 2016 and for the two 2025 scenarios (BAU and afforestation)*

Table 9: *Projected LULC area statistics (in km^2) for the year 2025 relative to baseline (2016)*

LULC Class	Baseline 2016	Future 2025 scenarios	
		BAU	afforestation
Cropland	174.50 (56.6%)	177.04 (57.5%)	155.5 (51.3%)
Grassland	82.72 (26.8%)	88.06 (28.5%)	94.55 (31.3%)
Built-up areas	1.67 (0.5%)	1.67 (0.5%)	1.02 (0.5%)
Water bodies	4.90 (1.6%)	4.90 (1.6%)	4.90 (1.6%)
Forest/mixed vegetation	44.28 (14.4%)	36.40 (11.8%)	46.66 (15.3%)

4. Discussion

4.1. Classification Accuracy, LCM Model Projection and Validation

This study assessed the changes in LULC over period 27 years and modelled the changes to produce the future 2025 scenario maps of LULC conditions in the Vea catchment using the LCM. The accuracy of the LULC classification observed in this study can be attributed to the heterogeneity of the study area and the likely confusion between grassland and cropland due to the mono-temporal data used. This is in line with the observation made by Zoungrana et al. (2015) that the confusion between natural vegetation and agricultural lands are minimized when late-season images (eg. October images) are classified. However, Forkuor (2014) noted that the heterogeneity of the Vea catchment whereby grasses and trees are intermixed with harvested croplands can be seen as a major contributing factor to the spectral confusion between grassland and cropland. In terms of the model projection accuracy,

an overall Crammer's V value of 0.55 (1990-2001) and MLP neural network accuracy rate of 85% were achieved and according to Eastman (2006), a Cramer's V value above 0.4 and accuracy rate of about 80% is acceptable in modelling.

The model validation results based on the comparison between the actual and simulated 2011 LULC map obtained from this study can be attributed to the nature of the model. It was noticed that the simulation in our study shows less change than the actual change (Table 8) during the validation period (2001-2011). Also, some LULC changes were not relatively well simulated by the model during the validation period which according to Olmendo et al. (2015) can be attributed to the acceleration of changes that occurs in the reference year which does not show during calibration period. According to Robertson and Swinton (2005), if the changes during the calibration interval which in this case 1990-2001 are not stationary with the changes during the validation interval (2001-2011) as shown in Table 6, then an extrapolation from the calibration interval to the validation interval will probably have systematic errors which will affects the accuracy of projection. Moreover, the differences between the simulated and actual LULC maps and the reported Kappa statistics can be attributed to the fact that Land changes involve complex processes that are shaped by dynamic, non-linear human-nature interactions, which can be difficult for the available variable and algorithm to capture (Perez-Vega et al., 2012; Kolb et al., 2013).

4.2. Spatio-Temporal Analysis of Historical LULC Changes

The historical LULC change analysis indicated a loss of vegetation in the southern part of the Vea catchment in the year 1990 which can be attributed to deforestation (cutting down of trees for charcoal production and timber) and agricultural expansion. Between 1990 and 2016, forest/mixed vegetation area which consist of forest, riparian vegetation, shrubs and closed woodland were found to have decreased due to cropland expansion over the past 27 years. However, in 2001, there was an increase in vegetation at the southern part of the catchment and this can be attributed to measures such as the enforcement of the forest protection laws put in place to protect the area and the creation of forest reserves. The observed decrease in natural vegetation is similar to the results obtained by Daudze (2004), who found a decrease in woodland and mixed vegetation in the same region from 1986 to 2000 due to an increase in agricultural area and bare land. The LULC change dynamics mainly the conversion of natural vegetation to cropland observed over the last 27 years have also been reported by other studies such as Braimoh and Vlek (2004); Mahe et al. (2005) in the same region. These changes in LULC can be attributed to human activities such as farming in this region. Farming in this region is characterized by low inputs i.e little or no amendment, continuous cropping, with farms usually expanded and scattered across the landscape to increase yield (Boateng, 2013). Apart from farming activities, overgrazing by cattle, firewood or charcoal production are all contributory factors to the loss of natural vegetation in this region (Gyasi et al., 2011; Agyemang, 2007).

The revealed expansion in cropland over the past 27 years confirms the results obtained by studies such as Forkuor (2014); Boateng (2013); Ruelland et al. (2010); Brinkmann et al. (2012) in similar regions. For example, a study by Baatuuwie (2015) found an increase in settlement/cropland from 46.1% to 49.2% between 1990 and 2013 at the Nawuni basin, for which Vea is a sub-catchment. Similarly, Awotwi et al. (2014) also observed an expansion in agricultural land from 1990 to 2006 as a result of clearing of savannah and grassland in the White Volta basin where the Vea catchment is located. The expansion in cropland in the Vea catchment can be attributed to numerous factors such as; increase in socio-economic activities of the area and construction of a number of small dams together with the Vea dam over the last 27 years for irrigation, which as a result has increased the cultivation of crops such as cereals (maize and rice) and legumes in the area. In terms of built-up areas, an increase from 0.22% (1990) to 0.54% (2016) was noticed, which is a sign of an increase in population and socio-economic development at the catchment. Although the number of dams increased between the year 2001 and 2011, the decrease in water bodies from 1.74% to 1.39% is possibly due to severe siltation of the Vea dam during that period. Also, Conventional tillage and

continuous cropping and grazing practiced by the majority of farmers along the steep slope upstream of the Vea dam induces erosion and hence siltation of the reservoir (Baatuuwie, 2015). Between 2011 and 2016, the water body increased from 1.39% to 1.59% and this can be attributed to the increase in mean annual rainfall of the Vea catchment over the period observed by the study of Larbi et al. (2018).

4.3. Relevance of Results to achieving National and International Goals

The results obtained in this study, though at local scale, are essential for (1) the formulation and implementation of national developmental policies (e.g., the Ghana Shared Growth and Development Agenda II - GSGDA II) (FAO, 2017); (2) attainment of United Nation's sustainable development goals (SDGs) and (3) input to biophysical and economic models for decision making.

The GSGDA II outlines the policies and strategies to be adopted by the Government of Ghana (GoG) to combat the negative effects of climate change on socio-ecological systems. Ghana has a local government structure which permit local scale implementation of national policies through local government institutions (e.g. metropolitan, municipal and district assemblies - MMDAs) and ministries (e.g. Food and Agriculture; Environment, Science, Technology and Innovation; lands and forestry). As the Vea catchment forms a substantial part of two local government divisions, i.e. Bongo district and Bolgatanga Municipal, results obtained can contribute to achieving local scale objectives/targets in land use planning and climate change adaption. Due to the country's abundant endowment of natural resources, the GSGDA II identifies the following, amongst others, as some of the broad areas for policy intervention in a bid to develop the country and attain economic prosperity: (1) natural resource management and minerals extraction, (2) biodiversity management, (3) protected areas/forest management and (4) land management and restoration of degraded forests. In this regard, the objectives and results of this study, especially the projected patterns of LULC, will enable the relevant national authorities to formulate future-relevant natural resource policies needed for the sustainable use of resources and achievement of economic prosperity. For example, based on the results presented in section 3.4, the scenario selected by decision makers will be key to determining which land management policies should be pursued to ensure environmental sustainability and food security.

On one hand, pursuit of results of BAU scenario, which projected further increase in cropland area, will mean the promotion of agricultural management practices/policies that reduce GHG emissions, such that the projected increase in cropland area will not necessarily lead to increasing GHG emission and subsequent negative climate change repercussions. Previous studies in Ghana have shown how cropland expansion, coupled with unsustainable agricultural practices increase CO_2 emissions (Asumadu-Sarkodie and Owusu, 2016). On the other hand, selection of results of afforestation scenario, which projected an increase in natural/semi-natural vegetation, will mean the formulation and promotion of sustainable agricultural intensification and modernization programs. Chartres and Noble (2015) observed that a reduction in cropland area will not lead to food insecurity even if GHG emissions are significantly reduced through afforestation. Food demand is bound to increase in the near future due to the continuous rise in population. This requires the formulation and promotion of policies that will increase agricultural productivity while maintaining ecological integrity (Robertson and Swinton, 2005). In addition to considering results of the two scenarios separately, policy makers also have the option of considering different aspects of the two in formulating appropriate national policies.

Apart from its usefulness for formulating and implementing national policies and programs, the results of this study can contribute to assess and monitor progress towards attaining SDGs (e.g., 2, 6, 13, 15). In the case of SDG 15 (life on earth), for example, information on historical, present and future patterns of LULC are essential data for the derivation of indicators needed to monitor relevant targets. The continuous reduction of forest land in the study area (past and future) as found by this research is important information for the derivation of indicators 15.1.1 and 15.2.1 (FAO, 2017), which can be used to access the progress a country is making towards achieving SDG 15. Specifically, comparison of calculated indicators (e.g. Forest area as a proportion of total land area) based on the projected

LULC (up to 2025) and the present state (e.g. 2016), can assist policy makers to formulate appropriate forest management policies that will ensure the attainment of the targets by 2030. Similarly, using results of this study in biophysical models will generate results that will help in achieving other SDGs. For example, previous studies have showed that LULC changes affect the quality and quantity of surface runoff and therefore availability of water resources. Using a physically-based hydrological simulation model and land use scenarios, Yira et al. (2017) found that land use changes such as cropland expansion and savanna degradation increases peak discharge and alters the flood risk of populations. The future LULC patterns projected by this study, when used as input to such simulation models, can provide useful insights into future changes in water availability and an appreciation of whether or not SDG 6 can be achieved. Climate change related risks such as floods and droughts, which have been found to be increasing in recent years (Sylla et al., 2015), can also be minimized when appropriate measures are taken based on results of such simulations.

5. Conclusion

This study analyzed the historical (1990-2016) LULC changes in the Vea catchment and used the Land Change Modeler to project LULC up to 2025 LULC based on two scenarios. The outputs from Maximum likelihood classification of the Landsat images show an expansion in cropland at the expense of natural vegetation (forest/ mixed vegetation and grassland) for the period under consideration. The study also found out that cropland expansion over the past years in the catchment will become the main feature of LULC change especially in forest/mixed vegetation areas under BAU scenario. However, the area covered with vegetation showed an increase in the future under the afforestation scenario. The study demonstrated the ability of the LCM in projecting the future LULC condition of the study area with accuracy above 80% minimum acceptable degree of accuracy without considering exogenous factors (eg. socio-economic data, land policy and biophysical factors). The study recommends in future integration of these factors if possible and the application of other land use change models to improve the accuracy of the future projection. The future LULC condition under BAU scenario calls for the need to make a reasonable land use plan with an emphasis on controlling cropland expanding into forested and water bodies areas in the catchment. Furthermore, Sustainable Agriculture Land Management (SALM) practices must be adopted to intensify production without necessarily converting the remaining land cover of the catchment. The outcome of this study is promising for West Africa where information on historical, present and future patterns of LULC is essential for the mitigation and adaptation strategies in the context of climate change. Results of this study will contribute to devising effective land use plans and policies for climate change adaption, support progress monitoring and attainment of UN SDGs and improve climate, water and land simulation models for effective decision making.

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Conflicts of Interest

The authors declare no conflict of interest.

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