



Land use and land cover change detection and prediction based on CA-Markov chain in the savannah ecological zone of Ghana

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ABSTRACT

Environmental problems have accompanied the accelerated land use and land cover change (LULCC), yet few local level studies make an attempt to assess the dynamics of LULCC. This work employed GIS and remote sensing to quantify the past and predict future dynamics of LULCC based on the synergy Cellular Automata (CA) - Markov Chain Model (MCM). The results revealed that agricultural land in the Bongo district witnessed the greatest expansion from 10.03% to 27.17% of total area from 1990 to 2019, while wooded savannah area witnessed the greatest decline from a share of 42.26% to 15.51% of total area from 1990 to 2019. In the Kassena-Nankana West (KNW) district, shrub and tree savannah and agricultural land expanded from 32.91% to 54.2% and 9.44% to 18.16% of the total area, respectively, at the expense of wooded savannah area (-32.9% of total area) between 1990 and 2019. Future predictions based on prevailing socio-economic development demonstrate that the observed trend would continue till the 2050 period. In the Bongo district, the settlement area will witness the highest proportion of net increase in total area (5.63 km²) at the expense of wooded savannah (-11.26 km²) between 2019 and 2050. Conversely, in the KNW district, the shrub and tree savannah area will experience the highest proportion of net gain in total area (156.02 km²) at the expense of wooded savannah area (-111.49 km²) between 2019 and 2050. This result is an indication that the synergy CA-MCM have effectively captured the spatiotemporal trend in LULCC in this study.

1. Introduction

For a very long time, humanity has transformed landscapes in their efforts to enhance the quantity, quality, and security of environmental resources vital to human well-being, such as medicinal products, food, fibre and freshwater (Potts et al., 2016; Wang et al., 2021). Through the increased use of technology and innovation, human populations have, slowly at first, and at a progressively rapid pace, later on, increased their capacity to obtain diverse services from the ecosystem and expand its territory (Song et al., 2018).

The magnitude and rate of anthropogenic activities on the land surface have accelerated during the last 300 years (Potts et al., 2016). More land has been converted for human use than before, and already converted land in the earlier times was managed more intensively to increase the yields of agricultural and forest products. The phenomenon of landscape change has also shifted spatially over time. While Europe, Asia and America experienced significant landscape change in time past (around the 20th century) and have now witnessed a steady trend in forest land cover, Africa and other developing countries (e.g. Latin Amer-

ica, Southeast Asia) are currently witnessing an exponential shift in landscape and associated ecosystem depletion (Ellis et al., 2013; Peng et al., 2017; Wang et al., 2021).

The accelerated landscape changes have been accompanied by local and global environmental problems (Meyfroidt et al., 2013), raising fears that the sustainable limits of the planet earth to support the human population without causing irreparable damage has reached its tipping point and threshold (Meadows & Randers, 2012). Various reports of the Millennium Ecosystem Assessment team have added further credibility to the indications of apparent global landscape changes (MA, 2003, 2005). The key underlying trigger of past and recent global environmental changes has been anthropogenic activities on the land surface (Meyfroidt et al., 2013).

In the context of this paper, land cover denotes the physical and biological attributes of the land surface. Land use on the other hand denotes any human management activity associated with the land. Land-use change therefore implies a shift from one land use to another or the intensification of the existing land use (Kleeman et al., 2017). Land use and land cover change (LULCC) directly mirror the utilisation of land

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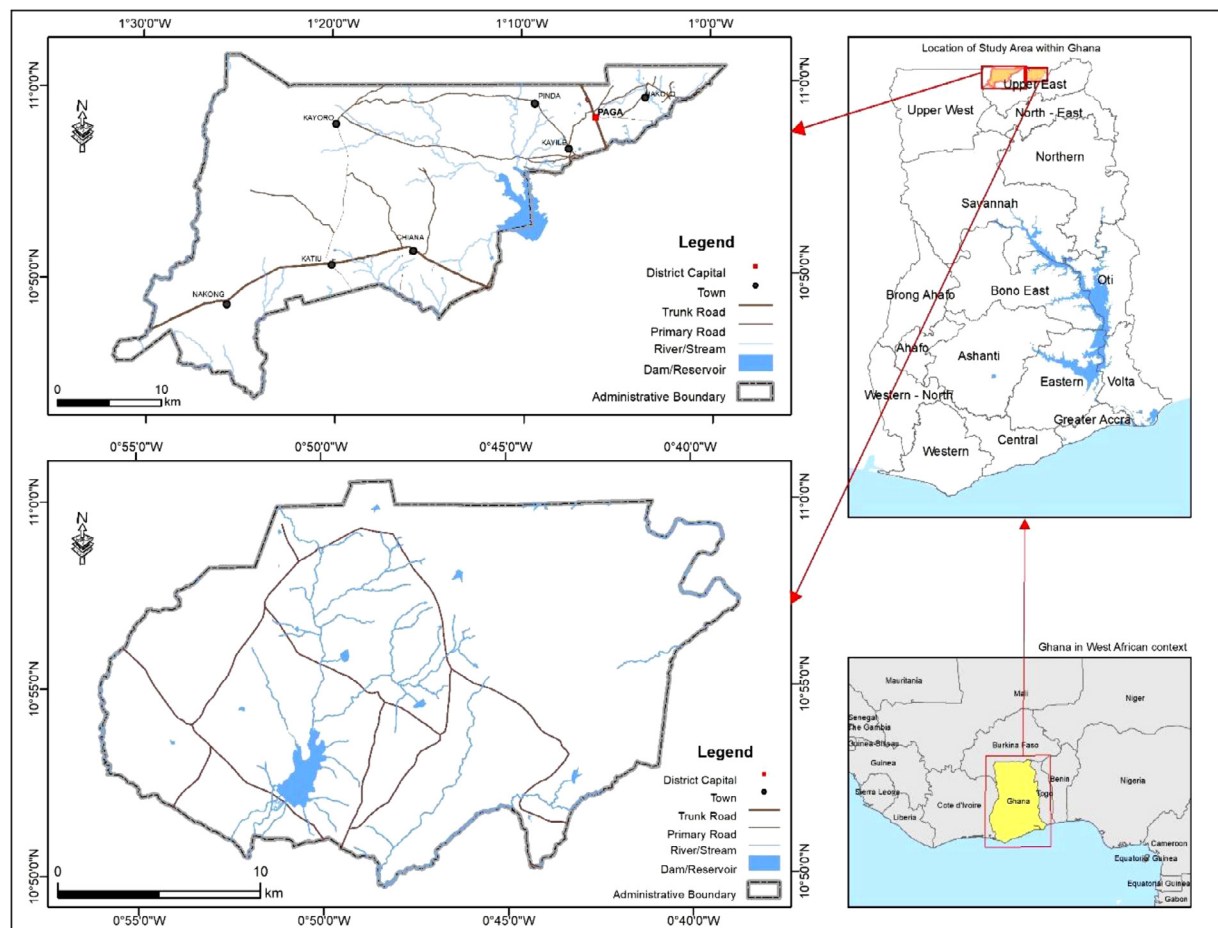


Fig. 1. Location of the study areas.

resources in an area and is an important component of the environmental systems (Kleeman et al., 2017). LULCC has emerged as a threat to social and ecological systems (Lambin and Meyfroidt, 2010) and can cause many ecological crises at various spatial scales such as shortages in natural resources, widespread and irreversible losses of biodiversity (Tolessa et al., 2017; Karki et al., 2018; Bounoua et al., 2018; Lu et al., 2019).

Generally, several studies on LULCC dynamics in Africa have been carried out (Brandt et al., 2016; Greiner, 2016; Koranteng et al., 2016; Tolessa et al., 2017; Timm-Hoffman et al., 2018). For instance, documentation of LULCC using satellite data have been carried out in Africa by Mohajane et al. (2018) and Tavares et al. (2019). Despite the many studies on LULCC dynamics in Africa, information about LULCC dynamics in the savannah ecological zone of Ghana remains scanty. Other studies on LULCC in Ghana (e.g. Basommi et al., 2015; Kleeman et al., 2017; Antwi-Agyei et al., 2019; Osumanu et al., 2019; Larbi et al., 2019; Tuffour-Mills et al., 2020; Osumanu & Akomgbangre, 2020) have been conducted on a broader scale with a larger spatial recommendation domain, and usually do not differentiate between vulnerable and resilient zones. Thus, there is the need to conduct location-specific and local level landscape change assessments to fill this gap. Such information would be useful in managing landscapes and resources and inform future local level policies required for addressing peculiar local socio-ecological needs.

Therefore, this paper seeks to fill this research gap by analysing and predicting LULCC dynamics from 1990 and 2050 in the two distinct study sites within the Savanna ecological zone. Following the presentation of the introduction in Section 1, Section 2 provides a brief profile of the study area and the methodological approaches employed in this

paper. Section 3 provides results and discussion. Section 4 presents conclusion of the study.

2. Methodological approaches

2.1. Study area

This study was conducted in the Upper East Region (UER) in the savannah ecological zone of Ghana. The extension of the study area lies between longitude 0° and 1° West, and latitudes $10^{\circ} 30'N$ and $11^{\circ}N$ (GSS, 2021). Two case study districts (Bongo and Kassena-Nankana West (KNW) districts) were selected (Fig. 1). Due to the semi-arid and physical features of the zone, it is extremely vulnerable to climate and ecological changes (GSS, 2021). The increasing effects of environmental and socio-economic factors, such as LULCC, climate and ecological change, drought, floods, and bushfires (Klutse et al., 2020) presents severe effects on the livelihoods of rural dwellers most especially rain-fed agriculture dependant households (Boafo et al., 2020). The primary reason underlying the selection of the study region (UER) and districts is the depiction of typical cases of LULCC through a Normalized Difference Vegetation Index (NDVI) analysis of the UER. Bongo District is selected because it is the most vulnerable area in the UER to severe LULCC since the 1980s. Conversely, KNW District is the area in the UER that largely contains very high amounts of vegetated cover in the form of gallery and riparian forest, and was therefore selected as a resilient district to LULCC (Fig. 1). KNW District's population density of $97.64/km^2$ is the lowest compared to Bongo District's density of $289.8/km^2$ and the regional (UER) density of $129/km^2$.

Table 1
Details of remote sensing data used in this study.

Bongo					
Year	Satellite	Sensor	Date	Bands used	Spatial Resolution
1990	Landsat 4	MSS	30/11/1990	2,3,4	30m
2000	Landsat 7	ETM	09/11/2000	2,3,4	30m
2010	Landsat 5	TM	29/11/2010	2,3,4	30m
2019	Landsat 8	OLI	22/11/2019	3,4,5	30m
KNW					
Year	Satellite		Date	Bands used	Spatial Resolution
1990	Landsat 4	TM	13/11/1990	2,3,4	30m
		TM	22/11/1990	2,3,4	30m
2000	Landsat 7	ETM	09/11/2000	2,3,4	30m
		ETM	09/11/2000	2,3,4	30m
2010	Landsat 5	TM	29/11/2010	2,3,4	30m
		TM	20/11/2010	2,3,4	30m
2019	Landsat 8	OLI	22/11/2019	3,4,5	30m
		OLI	29/11/2019	3,4,5	30m

2.2. Acquisition of satellite imagery

Landsat Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper (ETM+) and Operational Land Imager (OLI) satellite data were used in this study. These were downloaded from the USGS Global Visualization Viewer website (Table 1). To better visualise roads and rivers, Google Earth was used to create an overlapping vector layer of existing roads and rivers for use in the display of the results.

2.3. Data pre-processing and classification

To achieve accurate surface information from satellite data, it is essential to apply radiometric and atmospheric corrections. Radiometric and atmospheric corrections were performed using the ENVI 5.2 platform prior to the classification. The imagery scenes were then mosaicked, and the study area extracted. Our study combined various bands such as RGB 5, 4, 3 for OLI and RGB 4, 3, 2 for TM to facilitate the gathering of training data required for the classification of the images. Also, in describing the feature classes, we made use of historical and existing expert knowledge on the physical patterns of the study sites and other relevant supplementary data we deemed useful were incorporated (Khwarahm et al., 2021).

The Random Forest Algorithm (RFA), a non-parametric supervised classification method was employed in our study. The RFA produces several classification trees that makes contribution through a voting system for classification of data. RFA can produce moderate accuracy land cover maps even when employed with coarse data (Breiman, 2001; Abdullah et al., 2019; Santos et al., 2022). Our study employed the RFA package in R to classify LULCC maps for 4 years (1990, 2000, 2010 and 2019) for the 2 study sites. Six (6) LULCC classes were identified based on researchers' prior local knowledge, physiographical knowledge of the study areas, visual interpretation using google earth historical function and supportive supplementary data. The Google Earth images were employed to extract reference data and a random sampling technique was used to gather 150 ground control points. The data were divided into test (70%) and training (30%) datasets. The RFA was fitted on the training data for every study year using the number of decision trees (ntree) = 600 and the number of input features (mtry) = 3 (Santos et al.,

2022). We employed fixed mtry. The preference of avoiding the possibility of overfitting the trained model was the key guiding principle that informed our choice of the hyperparameters. The trained model was subsequently employed to predict LULCC classes in the test datasets. The RFA performance was examined by employing the user accuracy values and the kappa coefficients (Congalton, 1991; Hayes et al., 2014). A separate RFA classification was undertaken on the same dataset to further assess the performance of the RFA classifier. Several trials with different mtry (e.g. 3, 6, 9) and ntree (e.g. 200, 700, 900) parameterizations were undertaken to assess out-of-bag (OOB) error levels.

Lastly, the RFA was trained at ntree value of 600 with a default setting for mtry and this helped produce a low OOB error level. We then employed the trained model to predict the 6 LULCC classes based on the test datasets for every study year. To determine genuine LULCC from likely inaccurate changes due to errors in classification, per class accuracy indices and error matrices were calculated. We employed Google Earth images to randomly sample 150 points for every study year and their equivalent LULCC classes were determined. The validated classes were employed to assess producer and user accuracy (Abdullah et al., 2019; Santos et al., 2022). The following LULCC classes were identified: settlement, agriculture, bare soil, water bodies, shrub and tree savannah, and wooded savannah. Four LULCC maps were then generated for each of the 2 study sites with a spatial resolution of 30 m.

2.4. Accuracy assessment

It is important to perform an accuracy assessment between reference data and classified data. The accuracy of 1990, 2000, 2010 and 2019 LULCC maps were assessed by independent datasets. The kappa coefficient, overall accuracy and producer's and user's accuracy were calculated from the error matrix. The dynamics of LULCC for each target year 1990, 2000, 2010 and 2019 was determined by calculating the quantity of each specific class category per time window (Butt et al., 2015) after we performed the accuracy assessment for the generated LULCC maps between 1990 and 2019. Cross-tabulation matrices were performed for change detection.

Table 2 illustrate the overall accuracy, and the kappa statistics for the years 1990, 2000, 2010 and 2019 for the Bongo and KNW districts. The results revealed that the overall accuracy and kappa statistics for the 1990, 2000, 2010 and 2019 images were 85% (0.7984), 78% (0.7098), 84% (0.7990) and 91% (0.8838), respectively for the Bongo district (Table 2). The overall accuracy and kappa statistics for the KNW district for the years 1990, 2000, 2010 and 2019 were 82% (0.7569), 87% (0.8317), 87% (0.8356) and 90% (0.8664), respectively (Table 2).

2.5. Markov chain model, cellular automata (CA) model and CA-Markov models

The CA methods are tools for imitating complex spatial processes founded on simple decision rules. The Markov Chain model (MCM) explains and reveals the quantification of conversion states and the transfer rate between different land-use types (Khwarahm et al., 2021). The MCM, which depends on the stochastic process, has been widely accepted to stimulate and predict LULCC over time (Guan et al., 2011). LULCC prediction normally depend on the transition probability and the transition area matrixes from time one (t0) to time two (t1) as well as the generated LULCC maps (Guan et al., 2011; Khwarahm et al., 2021). The CA model, which consist of even grid-cells with each single grid-cell

Table 2
Accuracy assessment for Bongo and KNW Districts for the years 1990, 2000, 2010 and 2019 classification.

	Bongo district				KNW district			
	1990	2000	2010	2019	1990	2000	2010	2019
Overall accuracy	85.0	78.0	84.0	91.0	82.0	87.0	87.0	90.0
Kappa Statistic	0.7984	0.7098	0.7990	0.8838	0.7569	0.8317	0.8356	0.8664

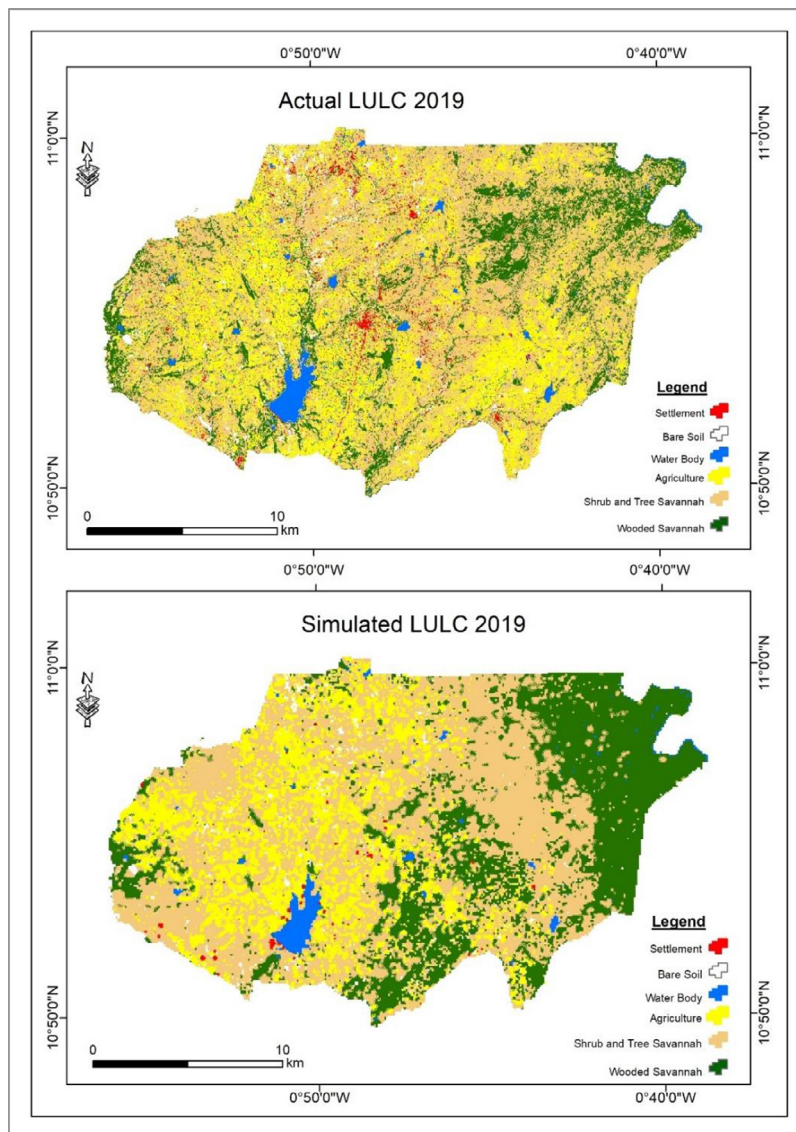


Fig. 2. Simulated and actual LULCC maps for Bongo District.

in a fixed number of positions, is capable of characterizing non-linear spatially distributed LULCC class categories (Mishra & Rai, 2016). The main principle of the CA model is that changes in cell condition can be described by current condition and changes in adjacent cells based on the previous condition (Mitsova et al., 2011; Liping et al., 2018). Combining the MCM with the CA methods solves the limitation of the MCM by adding a spatial dimension to the CA model (Mitsova et al., 2011; Khwarahm et al., 2021). The CA–Markov chain model is an effective combination between the MCM and the CA model for prediction of spatial LULCC. Therefore, the integrated CA–Markov chain model can be used to effectively predict spatiotemporal changes in LULCC (Halmy et al., 2015). Transition suitability images and Markov transition parameters which determines probability of change and the filter contiguity description (kernel size 4 4, 6 6, 8 8) as well as number of iterations (about 600 iterations) were used (Arsanjani et al., 2011; Guan et al., 2011). Many categories of filter contiguity and several iterations were assessed to obtain the best kernel dimension (6 6) and the iterations number (400 iterations). The simulated LULCC map for 2019 was compared with the actual LULCC map of 2019. Kappa index was employed to validate the accuracy of the simulated maps. The CA–Markov model was employed to predict the LULCC in the years 2030, 2040 and 2050 for the Bongo and KNW districts based on 1990, 2000, 2010 and 2019 LULCC maps.

2.6. Model validation

Model validation is a critical step in evaluating the accuracy of predicted data. In this paper, the kappa coefficient was calculated, and the model was validated after simulating the 2019 LULCC conditions using 1990, 2000, 2010 and 2019 LULCC maps. The accuracy of the simulated 2019 LULCC map was assessed by estimating the degree of agreement between modelled and reference map of 2019 using the Kappa Index of Agreement. The Kappa indices (Kappa for no information (Kno), Kappa for location (Klocation), and Kappa for standard (Kstandard) as expressed in Eqs. (1) to (3) determine the overall success rate of the results. A Kappa coefficient of between 0.75 and 1 implies a high agreement while a Kappa coefficient greater than 0.5 but less than 0.75 falls within the medium agreement range. However, if Kappa coefficient is less than 0.5, it implies there is rarely any agreement. After obtaining successful Kappa values, the CA–Markov model was employed to simulate the LULCC maps of 2030, 2040, and 2050. The equations below express the summary statistics for the Kappa variations according to Omar et al. (2014).

$$K_{no} = \left(\frac{M(m)N(n)}{P(p)} - N(n) \right) \quad (1)$$

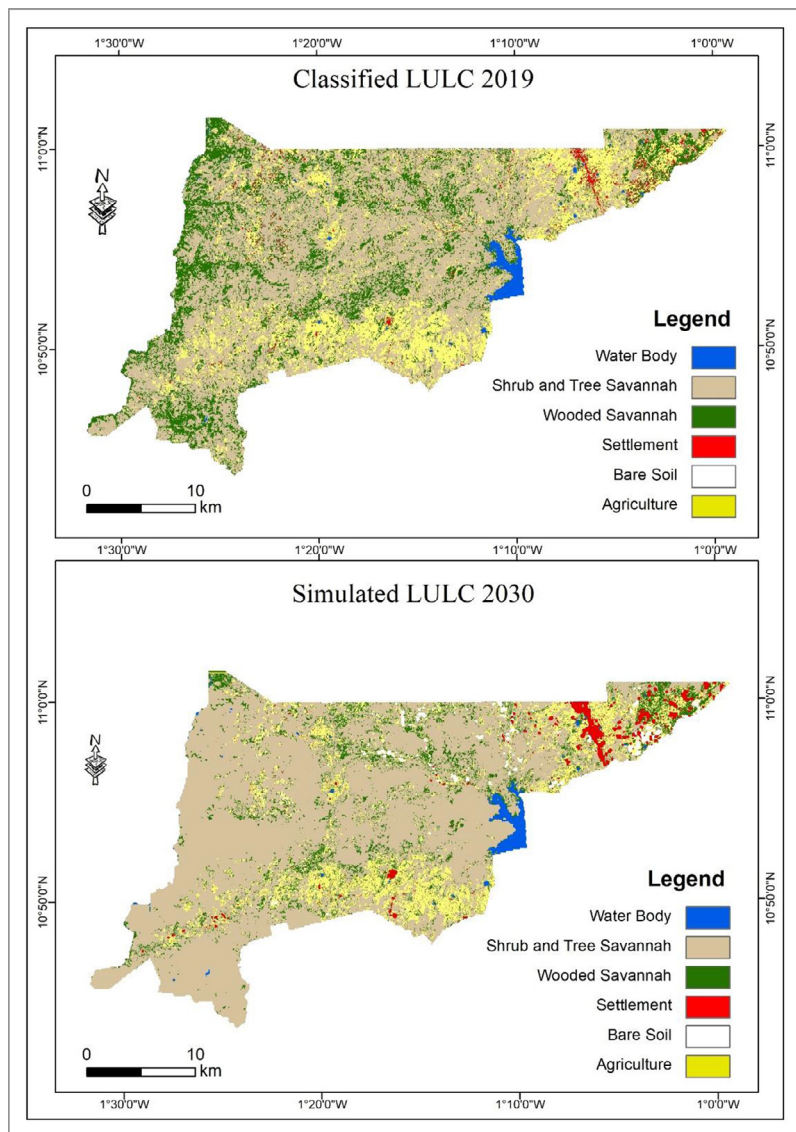


Fig. 3. Simulated and actual LULCC maps for KNW District.

$$K_{location} = \left(\frac{M(m)N(n)}{P(p)} - N(n) \right) \quad (2)$$

$$AndK_{standard} = \left(\frac{M(m)N(n)}{P(p)} - N(n) \right) \quad (3)$$

where no information is defined by $N(n)$, medium grid cell-level information by $M(m)$, and perfect grid cell-level information across the landscape by $P(p)$.

3. Results and discussion

3.1. Classification accuracy

Figs. 2 and 3 show a comparison of the simulated and actual maps in 2019 for both Bongo and KNW Districts. In the simulated map for the Bongo District, the kappa values of $K_{no} = 0.7794$, $K_{location} = 0.7903$, and $K_{standard} = 0.7409$ illustrate a good performance of the model. Similarly, In the simulated map for the KNW District, the Kappa coefficients of $K_{no} = 0.7331$, $K_{location} = 0.6823$, and $K_{standard} = 0.6247$ also demonstrate good performance of the model. The good agreement of all Kappa values confirm that the model has enough ability to forecast future LULCC dynamics soundly.

3.2. Dynamics in LULCC in Bongo and KNW Districts

The total land area of Bongo District is about 41,647.53 Ha. Around the year of 1990, shrub and tree savannah (45.88%) and wooded savannah (42.26%) areas occupied the greatest portion of the total land area (Fig. 4). Agriculture land was the third greatest land use and cover form (10.03% of total area). By the turn of 2019 as shown in Fig. 4, agriculture land witnessed the greatest expansion (27.17%) at the expense of wooded savannah (15.51% of total area) between 1990 and 2019. Settlement, bare soil, and water bodies increased by about three-fold.

Conversely, the total land area of KNW District is approximately 83,992.85 Ha. Wooded savannah and shrub and tree savannah constituted 56.16% and 32.91% of total area, respectively in 1990 (Fig. 5). Agriculture area occupied 9.44% (7,931.61 Ha) of the total land area while settlement, bare soil, and water bodies (0.35%, 0.45% and 0.69%, respectively) each occupied less than 1% of the total land area in 1990. However, by the 2019 period, Wooded savannah area significantly declined to 23.26% of total land area (net loss of 32.9%). Conversely, shrub and tree savannah area expanded to 54.2% of the total area, while agricultural area expanded to 18.16% of total land area. Similar trends have been observed in previous studies (Osumanu et al., 2019; Larbi et al., 2019; Tuffour-Mills et al., 2020; Osumanu and Akomgbangre, 2020). Declines in wooded savannah areas is more noticeable in

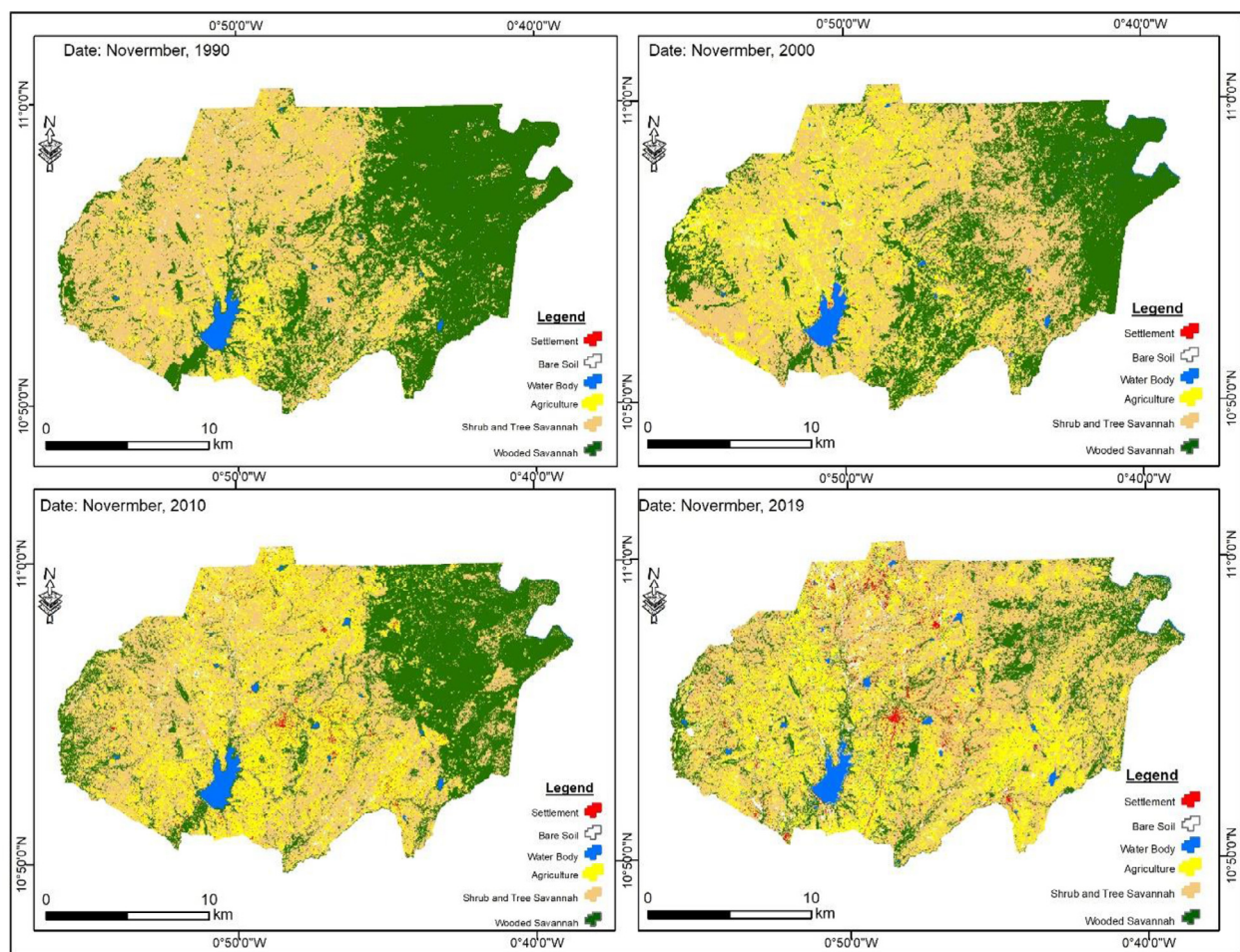


Fig. 4. LULCC map of Bongo District (1990-2019).

Table 3

Class percentage change for 1990-2019 in Bongo and KNW districts.

LULCC Type	Bongo District						KNW District					
	1990-2000		2000-2010		2010-2019		1990-2000		2000-2010		2010-2019	
	Change (Ha)	Percent Change	Change (Ha)	Percent Change	Change (Ha)	Percent Change	Change (Ha)	Percent Change	Change (Ha)	Percent Change	Change (Ha)	Percent Change
Settlement	61.56	0.15	540.99	1.31	385.83	0.93	401.49	0.48	573.03	0.68	69.3	0.08
Agriculture	3398.94	8.16	2449.81	5.88	1289.6	3.10	3900.29	4.64	1951.3	2.32	1472.9	1.75
Bare Soil	264.24	0.64	148.05	0.36	754.11	1.81	-98.91	-0.12	-63.9	-0.08	907.83	1.08
Water Body	158.4	0.38	9.9	0.02	630	1.51	167.22	0.20	455.04	0.54	16.02	0.02
Shrub and Tree Savannah	-416.7	-1.00	-1680.9	-4.04	3148.9	7.56	-3303.9	-3.93	12707.5	15.13	8479.9	10.10
Wooded Savannah	-3466.5	-8.32	-1467.8	-3.52	-6208.49	-14.91	-1067.2	-1.27	-15621.9	-18.61	-10945.9	-13.03

Bongo District than KNW District, owing to land use intensification, high population density and smaller total land area compared to KNW District (Larbi et al., 2019). The findings of this study also mirror that of Wardell et al. (2003) and Kleemann et al. (2017) which disclosed declining trends in wooded savannah areas and marked expansion in agriculture and settlement areas since the 1980s in the UER. The minimal regeneration of fallow areas to wooded savannah area occurred around river blindness-endemic areas along the sissili river in the KNW District.

3.3. Land use and land cover class percentage change for Bongo and KNW Districts between 1990 and 2019

Table 3 presents LULCC in hectares and percentage change for Bongo and KNW Districts between 1990 and 2019. In Bongo District, the set-

tlement area increased by 0.15% between 1990 and 2000, by 1.3% from 2000 to 2010 and by 0.93% from 2010 to 2019. The settlement area in KNW District increased by 0.48% between 1990 and 2000. Settlement area in KNW District continued to expand from 2000 to 2010 and 2010 to 2019 by 0.68% and 0.08%, respectively. Distinct expansion in settlement area occurred in Bongo District than KNW District from 2000 to 2019.

Agricultural area in Bongo District witnessed significant expansion of 8.16% (representing 3398.94 Ha) of total land area between 1990 and 2000. From 2000 to 2010 and 2010 to 2019, agriculture area in Bongo District increased by 5.9% (2449.81 Ha) and 3.1% (1289.6 Ha) of total land area, respectively. Similarly, in KNW District, the mainstream LULCC class expansion was seen in agricultural land, which expanded by 4.6% of the total land area (3900.3 Ha) from 1990 to 2000 and by

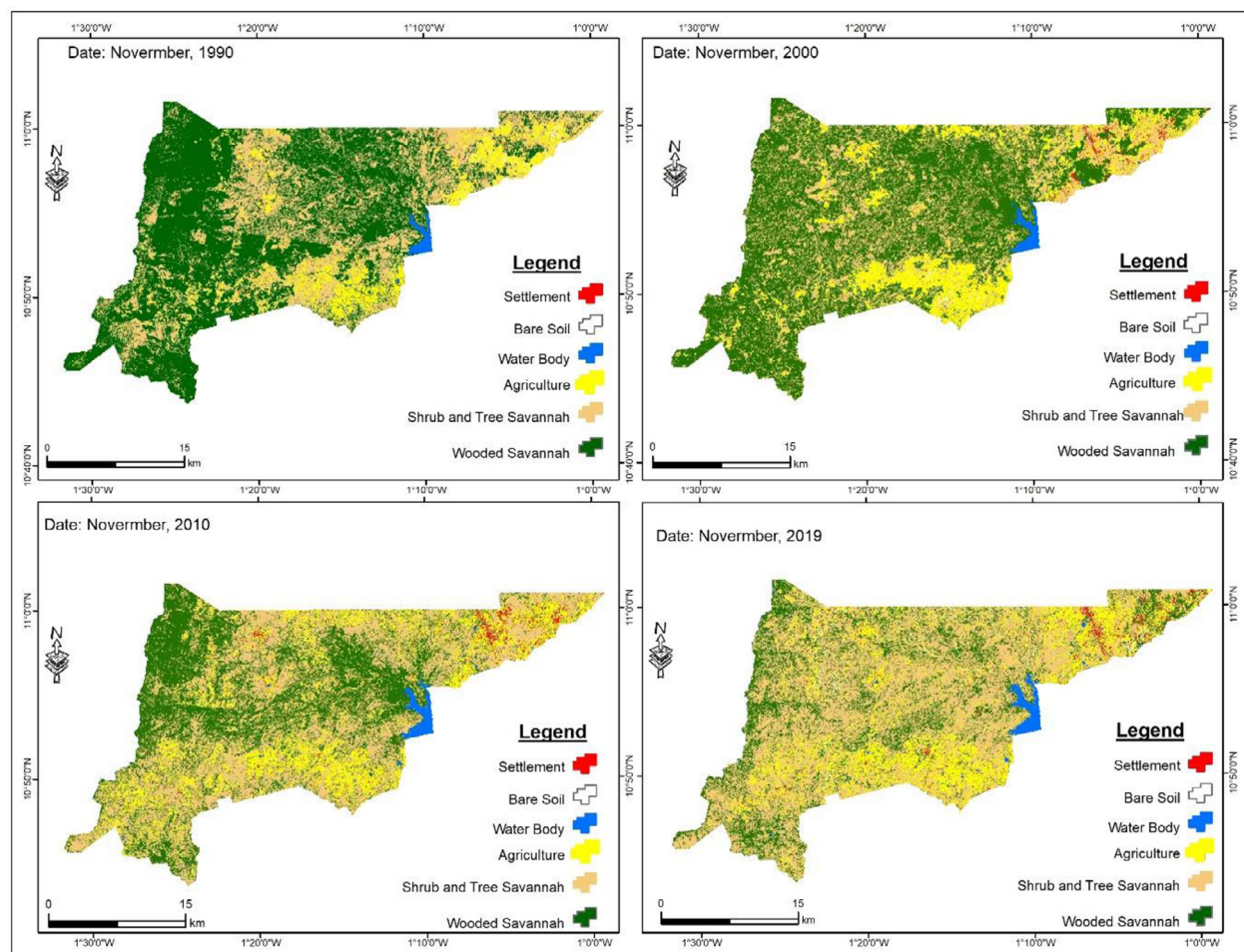


Fig. 5. LULCC map of KNW District (1990-2019).

2.3% (1951.3 Ha) between 2000 and 2010. From 2010 to 2019, the agriculture area increased by 1.8% of the total land area. Although the agriculture area witnessed the highest expansion relative to other land use and cover types in both study districts, Bongo District witnessed a higher expansion of agricultural land area relative to the total land area of Bongo District than KNW District between 1990 and 2019.

Bare soil and water bodies increased by less than 1% between 1990 and 2010 in Bongo District. However, both bare soil and water bodies increased by 1.8% and 1.5%, respectively, between 2010 and 2019. Bare soil in KNW District decreased by -0.12% and -0.08% between 1990-2000 and 2000-2010, respectively, but increased by 1.1% between 2010 and 2019. Water bodies marginally increased by less than 1% from 1990 to 2019 in KNW District. Whereas bare soil consistently increased between 1990 and 2019 in Bongo District, bare soil decreased in KNW District. The increases in bare land areas in Bongo District are attributable to increased use of agrochemicals and bad farming practices, which exacerbate land degradation, while increases in water bodies are attributable to past and present Government irrigation programs. Shrub and tree savannah declined for the periods 1990 to 2000 and 2000 to 2010 by -1% (-416.7 Ha) and -4% (-1680.9 Ha), respectively, in Bongo District. Along the same period in Bongo District, the wooded savannah area also declined considerably by -8% (-3466.5 Ha) and -3.5% (-1467.8 Ha), respectively. From 2010 to 2019, while the wooded savannah area decreased considerably by -14.9% (6208.5 Ha), shrub and tree savannah increased by 7.6% (3148.9 Ha). In KNW District however, apart from 1990 to 2000, in which shrub and tree savannah decreased by -3.9%, shrub and tree savannah areas significantly increased by 15% and 10.1% from 2000 to 2010 and 2010 to 2019, respectively, owing

to significant declines in wooded savannah -18.6% (-15621.9 Ha) from 2000 to 2010 and -13% (-10945.9 Ha) from 2010 to 2019.

Analogous to this present study, Ruelland et al. (2010) observed that wooded savannah and shrub and tree savannah areas declined from 34% and 18% of total land area in 1967 to 11% and 6%, respectively, of total land area in 2003 in the UER. Agriculture and degraded areas increased from 11% to 23% of total land area and 9% to 27% of total land area, respectively, between 1967 and 2003 in the UER (Ruelland et al., 2010; Larbi et al., 2019). This findings further confirm the widespread deforestation and loss of forest cover in the UER (Yiran et al., 2012; Boateng, 2017; Larbi et al., 2019). The remaining areas in the UER with substantial forest cover are uninhabited areas along the Red, Black and White Volta Rivers (Yiran et al., 2012; Boateng, 2017). The relative stability of the shrub & tree savannah areas in Bongo and KNW Districts in the UER is attributed to the gradual degradation of wooded savannah areas (Gessner et al., 2015; Dimobe et al., 2017; Larbi et al., 2019).

3.4. Projected LULCC patterns and trends in Bongo and KNW districts between 2019 and 2030

In Bongo District, the CA-Markov model based on business-as-usual scenarios (in which poverty levels will keep rising, population growth will continue unabated, and inhabitants will continue to collect firewood and produce charcoal) forecast that between 2019 and 2030, settlement area will increase by 7.30 km² at the expense of other land use and cover forms, which represents a change of 24.48% of the total area (Table 4). Overall, the net change in settlement area is 3.26 km². In KNW District, settlement and bare lands will witness net gains of

Table 4
Projected LULCC in Bongo and KNW Districts between 2019 and 2030.

LULCC class	Bongo District				KNW District			
	loss km ²	gain km ²	net change km ²	% change	loss km ²	gain km ²	net change km ²	% change
Settlement	-4.04	7.30	3.26	24.48	-2.04	10.23	8.19	38.25
Agriculture	-26.67	44.88	18.21	14.00	-54.32	7.01	-47.31	-45.35
Bare land	-7.03	2.59	-4.43	-46.24	-4.20	8.66	4.47	28.64
Water Body	-2.05	1.18	-0.87	-46.24	-0.95	0.76	-0.20	-1.73
Shrub and tree Savannah	-2.05	1.18	-0.87	-7.67	-12.25	162.85	150.60	24.97
Wooded Savannah	-29.32	13.37	-15.95	-33.90	-117.06	1.31	-115.75	-148.74

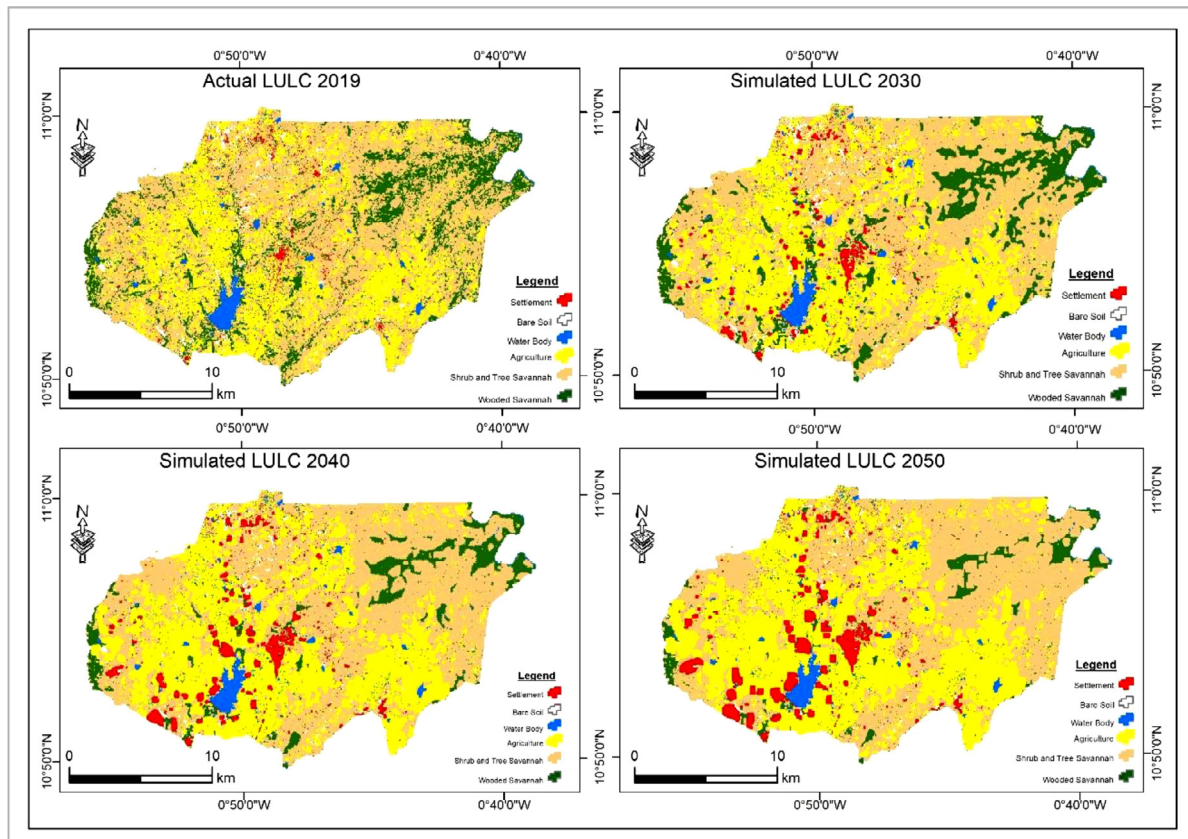


Fig. 6. Projected LULCC maps for Bongo District between 2019 and 2050.

8.19 km² and 4.47 km², accounting for 38.25% and 28.64% of the total area, respectively.

In Bongo District, a net change of 18.21 km² is expected to occur in agriculture areas, signalling a 14% change in the total area. The remaining land use and cover classes such as bare land, water body, shrub and tree savannah and wooded savannah are projected to decline by net losses of -4.43 km², -0.87 km², -0.21 km², and -15.95 km², respectively between 2019 and 2030 in Bongo District. These net losses in bare land, water body, shrub and tree savannah and wooded savannah represent declines in total area by -46.24%, -46.24%, -7%, and -33.90%, respectively (Table 4).

In KNW District, agriculture and wooded savannah areas are predicted to witness significant net decreases of -47.31 km² and -115.75 km² accounting for -45.35% and -148.74% of total area change, respectively. The highest proportion of net gain in land area between 2019 and 2030 is shrub and tree savannah, with a net gain of 150.60 km² and this net gain accounts for 24.97% of total land area.

3.5. Projected LULCC in Bongo and KNW Districts between 2030 and 2040

From 2030 to 2040 in Bongo District, settlement area and agriculture lands are projected to increase by net gains of 5.44 km² and

22 km², respectively, accounting for 29.01% and 14.47% of the total area, respectively. Bare land, water bodies, shrub and tree savannah and wooded savannah areas in Bongo District are expected to decline considerably by -7.34%, -1.88%, -1.63%, and -73.26% of total area, respectively (Table 5). The decline in shrub and tree savannah between 2030 and 2040 in Bongo District will constitute the highest proportion (21.82 km²) due to expansion in agriculture and settlement area. The net change of -19.90 km² in wooded savannah areas will be the greatest proportion of net change in a particular land use and cover type between 2030 and 2040. Although the highest proportion of loss is in shrub and tree savannah area, the net change in shrub and tree savannah area (-3.15 km²) is considerably low compared to the net change in wooded savannah areas (-19.90 km²) because the shrub and tree savannah area will gain a significant amount (18.67 km²) of the total area at the expense of the wooded savannah area. Bare lands are projected to decrease by a net change of -4.18 km² due to the implementation of sustainable land-use practices, reclamation, and regeneration efforts in Bongo District.

In Kassena Nankana West District however, between 2030 and 2040, agriculture, bare land, water bodies, and wooded savannah areas are expected to witness a net change of -6.17 km², -0.84 km², -0.24 km², and -3.84 km², respectively, which translate to -6.14%, -5.71%, -2.15%

Table 5
Projected LULCC in Bongo and KNW Districts between 2030 and 2040.

LULCC class	Bongo District				KNW District			
	loss km ²	gain km ²	net change km ²	% change	loss km ²	gain km ²	net change km ²	% change
Settlement	-0.62	6.06	5.44	29.01	-2.94	3.69	0.76	3.41
Agriculture	-3.39	25.38	22.00	14.47	-12.68	6.51	-6.17	-6.14
Bareland	-4.21	0.03	-4.18	-7.34	3.72	2.88	-0.84	-5.71
Water Body	-0.21	0.00	-0.21	-1.88	-0.51	0.27	-0.24	-2.15
Shrub and tree Savannah	-21.82	18.67	-3.15	-1.63	-7.03	17.36	10.34	1.69
Wooded Savannah	-20.85	0.95	-19.90	-73.26	-8.12	4.28	-3.84	-4.76

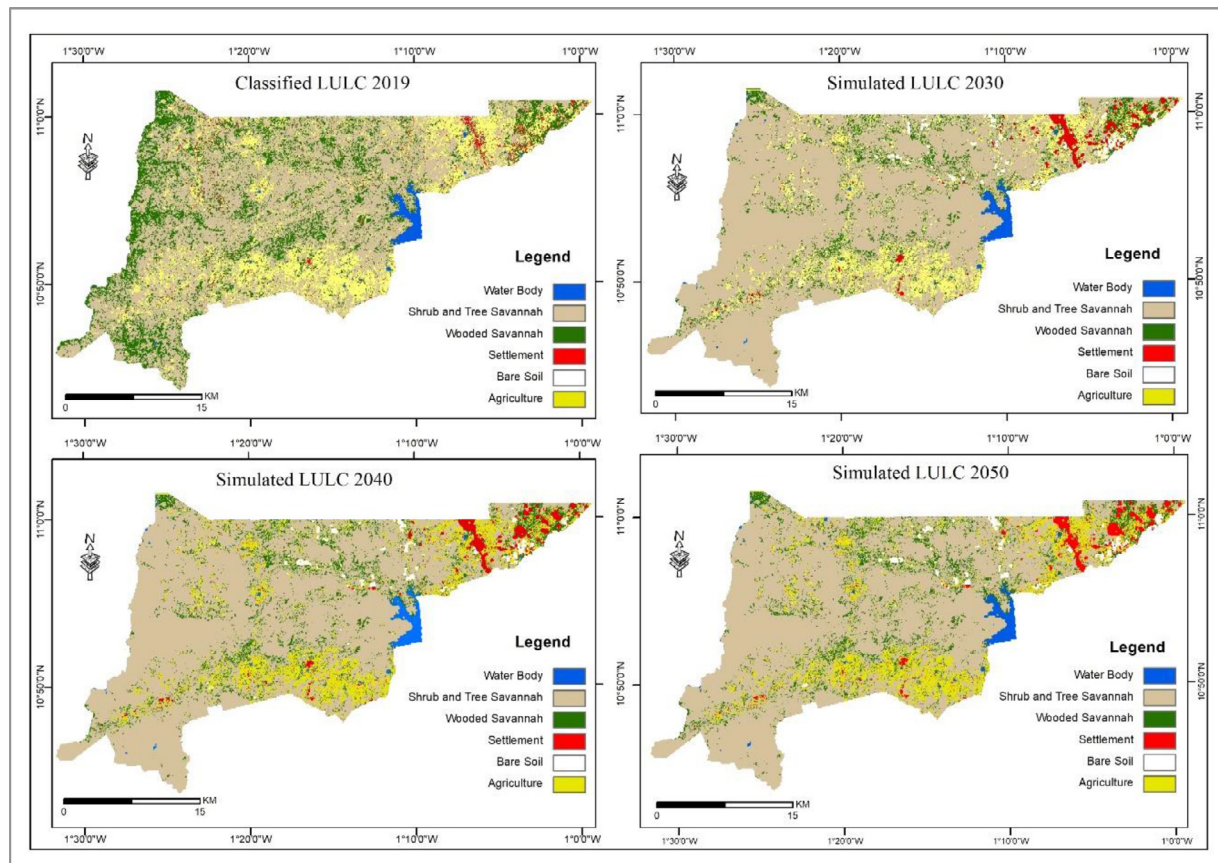


Fig. 7. Projected LULCC maps for KNW Districts between 2019 and 2050.

and -4.76% of total area change, respectively (Table 5). The only areas expected to witness significant expansion in KNW District are shrub and tree savannah and settlement, with the net change of 10.34 km² and 0.76 km², respectively, accounting for 1.69% and 3.41% of the total land area change.

3.6. Projected LULCC in Bongo and KNW Districts between 2040 and 2050

Similar dynamics observed over the period 2019 to 2040 in Bongo District are expected to continue through to the 2050 period. Settlement area and agricultural land is projected to increase at the expense of other land use and cover forms at 23.1% and 10.97% of total area, respectively. Bare land, water bodies, shrub and tree savannah and wooded savannah areas are equally projected to decline by -86.73%, -1.89%, -5.68% and -70.83% of total area, respectively (Table 6). Conversely, in KNW District, between 2040 and 2050, agriculture, wooded savannah and bare land are expected to expand with a net change of 2.19 km² (2.20%), 3.12 km² (3.73%) and 0.14 km² (0.94%), respectively (Table 6). Shrub and tree savannah will decrease by a net change of -4.92 km² (-0.18%).

3.7. Projected LULCC Maps for Bongo and KNW Districts between 2019 and 2050

Fig. 6 presents LULCC maps for Bongo District between 2019 and 2050. It can be observed that the highest proportion of net loss in the area is wooded savannah, with a net decrease of -11.26 km² (-70.83% of the total area) between 2019 and 2050. The second highest proportion of net decrease in area is shrub and tree savannah, which accounts for a net decrease of -10.39 km² (-5.68%) of total area between 2019 and 2050.

Bare land will witness a net decrease of -2.51 km² between 2019 and 2050. Settlement and Agriculture lands will witness net increases of 5.63 km² (23.10%) and 18.73 km² (10.97%) of the total area in Bongo District between 2019 and 2050 (Fig. 6).

In KNW District, Shrub and tree savannah area will witness a net gain of 156.02 km² (25.64%) while settlement and bare land areas will increase by a net gain of 8.60 km² and 3.77 km² of the total area change (Fig. 7). Wooded savannah will decrease at a net loss of -111.49 km² (-135.83%) of total area change. Likewise, the agriculture area will decrease by a net loss of -56.25 km² (-58.99%) of total area change at the expense of settlement area between 2019 and 2050. This finding is

Table 6
Projected LULCC in Bongo and KNW Districts between 2040 and 2050.

LULCC class	Bongo District				KNW District			
	loss km ²	gain km ²	net change km ²	% change	loss km ²	gain km ²	net change km ²	% change
Settlement	−0.23	5.86	5.63	23.10	−2.43	2.09	−0.35	−1.58
Agriculture	−3.00	21.73	18.73	10.97	−2.85	5.05	2.19	2.20
Bare land	−2.52	0.00	−2.51	−86.73	−2.17	2.31	0.14	0.94
Water Body	−0.21	0.00	−0.21	−1.89	−0.39	0.19	−0.20	−1.80
Shrub and tree Savannah	−20.68	10.29	−10.39	−5.68	−9.23	4.32	−4.92	−0.81
Wooded Savannah	−11.77	0.51	−11.26	−70.83	−3.64	6.77	3.12	3.73

contrary to previous studies which project significant increases in agriculture area by the 2050 period in Ghana (Aduah et al., 2018). The findings however confirm the forecast that wooded savannah area will decline considerably by the 2050 (Larbi et al., 2019) as well as likely increases in settlement area (Ackom et al., 2020).

4. Conclusions

Analysing and predicting past and future land use dynamics and land cover changes have become a prerequisite for sustainable landscape governance, particularly in the drylands. Geospatial data in combination with land surface modellers (e.g. CA-Markov chain) are effective tools in providing valuable information on the dynamics of LULCC over space and time. Understanding the dynamics of LULCC offers guidance in policy formulation in sustainable landscape governance. Agriculture and settlement areas in both study districts have expanded at the expense of wooded savannah and shrub and tree savannah areas between 1990 and 2019. Future predictions point to a continuous trend (i.e. from 2019 to 2050), in which substantial expansion of agriculture and the settlement area will occur at the expense of wooded savannah areas. The paper recommends that the government should implement necessary steps to reclaim and protect vulnerable landscapes from further degradation. This could be achieved through collaboration amongst key stakeholders such as forestry commission, Environmental Protection Agency (EPA), Forest Research Institute, traditional authorities and the Ministry of Lands and Natural Resources. The landscape governance actions should focus on protecting forest areas and promoting sustainable land management practices in the savannah ecological zone of Ghana. The classification accuracy results were not perfect due to presence of cloud cover which affected the image pixel value. Also, it was cumbersome calibrating the model due to the high intensity of changes in the LULCC that occurred in the period under analysis owing to expansion in agriculture activities. This notwithstanding, the findings of the study are important and can be applied to other areas in the savannah zone of Ghana with similar socio-economic and ecological features.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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