

Research Article

Land Use Landcover Change Monitoring and Projection in the Dano Catchment, Southwest Burkina Faso

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Abstract Burkina Faso has long been experiencing intense land-use landcover changes (LULCC) which have resulted in widespread land degradation. Hence, the need to obtain LULC information for improved land-use planning and sustainable management of land-resources cannot be overemphasized. This study examined the historical LULCC in the Dano catchment and projected the situation in 2050 for business-as-usual (BAU) and afforestation scenarios. Multitemporal Landsat images of 1990, 2000, 2010 and 2016 were classified with an overall accuracy of more than 90%. The Cellular-Automata Markov approach was used to project the future LULC pattern after identifying major driving forces of LULCC. The results revealed a substantial expansion in settlement and cropland area of about 62% and 6% respectively, which triggered a 15% decrease in forest cover, thus paving the way for severe soil degradation. The increase in cropland, settlement area, water bodies, and the decrease of forest were at an annual rate of 3.8%, 10.5%, 6.97% and 2.53% respectively within the past 26 years. The projected LULC under the BAU scenario revealed further forest loss from 46.72% in 2016 to 38.54%, owing to an extension in agriculture from 38.51% to 46.69%. The afforestation scenario projected a potential increase in forest by 2.13% and a decrease in cropland by 2.09% in the future relative to 2016. This study illustrates the accelerated land degradation and the challenges on ecosystem sustainability of the Dano landscape, hence, appropriate interventions like reforestation, protection measures and policy option in strategic land-use planning are needed to resolve the further loss of forest cover.

Keywords *Land degradation; Dano catchment; Markov-cellular automata; Projection; Remote sensing*

1. Introduction

Land-use landcover change (LULCC) concerns have become the frontier in global change, as realized from global research agenda on environmental change. A significant unprecedented combination of demography growth, migration, accelerated socio-economic activities and other human exploitations in recent time have intensified these environmental changes with profound effect of land-use change. According to the World Atlas of Desertification (WAD3), over 75% land area of the Earth is already degraded and by 2050, about 90% could turnout degraded (Reynolds et al., 2018). Globally, Africa is

the most affected and that accounts for 65% of the total extensive cropland degradation of the world, with semi-arid and dry sub-humid zones about 70% degraded land (Thiombiano & Tourino-Soto, 2007).

Burkina Faso has experienced rapid socioeconomic development under considerable population growth. Increasing agricultural areas, urban expansion and forest depletion in the last 40 years have become a norm in a way to meet the increasing demand of the surging populace. This increased pressure on the available land resources and anthropogenic activities in various sectors, especially the economic sector, lead to land degradation thereby affecting food security, rural livelihoods and ecological sustainability (Moges & Bhat, 2018). The unplanned urban expansion and the mining activities that are going on in the area have led to the loss of croplands to commercial use, forest to farmlands; water and soil erosion due to deforestation and water pollution from the discharge of municipal garbage and industrial waste. In this context, there is much need to assess and understand land use changes over time and its driving forces as well as projections into the future.

Nowadays, several evolved methods and techniques of land use change assessment under successive distinct periods at finer scales using remote sensing and spatially explicit data for modeling purposes cannot be overemphasized. Satellite observations provide valuable surrogates and can reveal conversions and modifications of land changes that are connected to the condition of ecosystem services. Considerable number of researches have been conducted within WA to detect and address LULCC problems such as degradation (Braimoh & Vlek, 2004; Obahoundje et al., 2017), deforestation and desertification (Baatuuwie, 2015), environmental change due to urbanization (Tewolde & Cabral, 2011) agriculture and mining (Awotwi et al., 2018). However, they are mostly either about temporal change detection of land use or classification. Among those few are studies who showed changes in natural vegetation, and a large increase in croplands with annually increased population density (Ruelland et al., 2010; Ouédraogo, 2010). Moreover, few efforts have been made to predict future changes or accurately investigate LULCC in hydrological context over a long time in the Black Volta Basin (BVB) environment (Akpoti et al., 2016), and such investigations remain rare, especially in semi-arid zones. Recently, land surface models e.g. Land change modeler (LCM) have been employed by researchers to forecast LULCC (Gibson et al., 2018) to improve impact assessment in order to aid planning and sustainable land management. An example study observed a growing trend in settlement expansion which could lead to significantly increased surface runoff and change in drainage geography (Mahmoud Ibrahim, 2016). Other earlier works have also reported LULCC differences under different scenarios (Han et al., 2015; Deng et al., 2013). In addition, the choice of appropriate scale for these models to support land-use development necessitates a trade-off involving spatial extent and detail.

Explicitly, the long-term historical evaluations and projections into the future land cover changes at catchment scales are needed to avoid potentially catastrophic damage and the effect of surface processes on regional climate and ecosystem services. Moreover, this is essential to enable understanding of the degree to which LULCC is a threat to water resources at the Dano catchment. To address this critical need by providing a better quantitative understanding of LULC changes, this study aimed to analyze the historical (1990 to 2016 period) LULCC and project future (2050) LULC patterns for two scenarios: business-as-usual (BAU) and afforestation using the Land Change Modeler (LCM).

2. Materials and Methods

2.1. Study Area

The Dano catchment with an area of 582 km² located in the loba province, Southwest of Burkina Faso is situated at latitudes 7°00' - 14°30'N and longitudes 1°30' - 5°30'W (Figure 1). The climate of the area is a tropical transition zone with a pronounced dry and rainy season. The mean annual rainfall is 943 mm, with nearly 80% concentrated in the months of July to September considering 1970 to 2013

period of the Burkina Faso National Meteorological Service data. The recent climate-change study has identified trends of warmer and drier conditions and moderate to severe drought years (Kasei et al., 2010). Geologically, the catchment is composed of Paleoproterozoic basement, largely flat with an average slope of 2.9% and elevation ranging between 229 m and 509 m above sea level. The catchment is drained by several intermittent streams that dry up during the dry season and has easily erodible soils that render the area sensitive to pronounced land-degradation processes (Duadze, 2004). Landcover such as woody savannahs and shrubs are also exploited for wood and intensive use to produce the local beer “dolo”. In the catchment, rain-fed agriculture constitutes the major land-use with the production of some staple crops like cassava, yam, groundnut, maize and sorghum dominating. The rural population density in southwest Burkina Faso is between 41-60 persons per km² (Knauer et al., 2017), and largely depend on water supply from surface water.

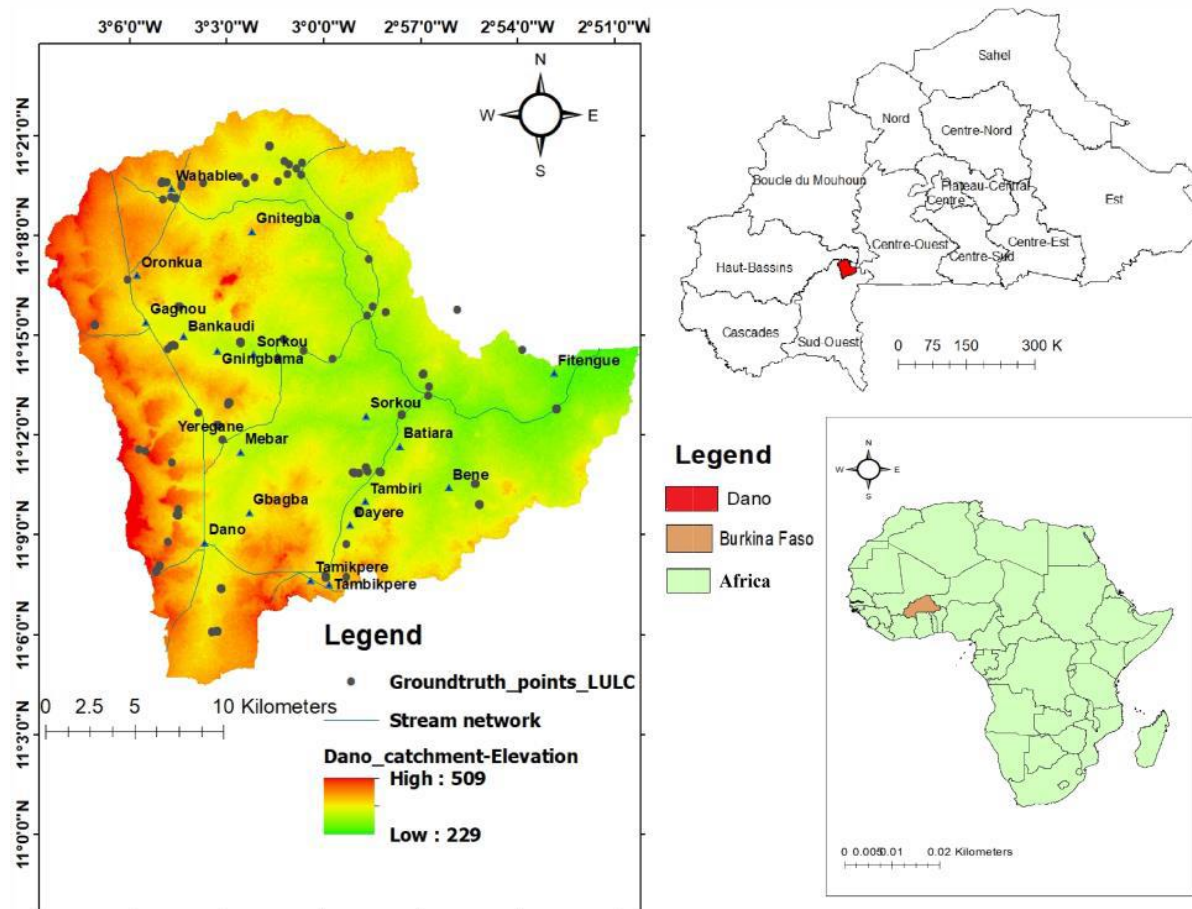


Figure 1: Map showing the location, Digital elevation and ground-truth LULC of Dano Catchment

2.2. Data

This research used four Landsat satellite images downloaded from the portal of EarthExplorer (<https://earthexplorer.usgs.gov/>) at no cost for the years 1990, 2000, 2010 and 2016 (Table 1). Scenes selections were based on the criteria of availability, acquisition dates and 10% cloud cover. In addition, ancillary data including slope and elevation derived from Digital Elevation Model (DEM) (<http://srtm.csi.cgiar.org/>) for modeling purposes were acquired. Field data were collected for training and as reference samples to validate the classified images. The field campaign was organized in the dry season of 2016 with a total of 150 GCPs (Ground Control Points) focused to ensure representative spatial locations for all readily mapped landcover types (e.g. grassland, etc.). Sixty per cent of these points were used for training and the remaining for validation of the 2016 LULC map. Other LULC reference samples for the year 1990, 2000 and 2010 were generated from Google Earth maps and

GLOBELAND30: a 30 m resolution global landcover dataset developed by the National Geomatics Centre of China (Chen et al., 2017) for training and validation.

Table 1: *Spatial data description*

Type	Dataset	Date	Source
Satellite images (30 m resolution, path/row 196/052)	Landsat 8 OLI-TIRS	Nov 27, 2016	EarthExplorer
	Landsat 5 TM	Nov 27, 2010	
	Landsat 7 ETM+ SLC-on	Nov 07, 2000	
	Landsat 5 TM	Dec 1990	
	DEM (30 m), road and river network		Shuttle Radar Topographic Mission
Reference data	Globeland30	2000, 2010	http://www.globallandcover.com/GLC30Download/index.aspx
	Ground control points (GCPs)	2016, 1990	Field campaign, GoogleEarth Image

(Sensor types: OLI: Operational Land Imager-Thermal Infrared Sensor; TM: Thematic Mapper, ETM+: Enhanced Thematic Mapper).

2.3. Classification and Accuracy Assessment

The methodology applied in this study is illustrated in a flowchart (Figure 2). First, standard image pre-processing through radiometric correction was performed on the images to remove atmospheric influences based on the metadata information and to uniquely decipher the direct relationship between the biophysical phenomena and acquired data (Coppin et al., 2004). This was followed by generating LULC maps via a step-by-step classification. The supervised classification method of Maximum Likelihood was used by incorporating ground surveys and information obtained from local knowledge (focus group discussion). The accuracy of the classification results obtained was checked using a confusion matrix created from comparing a classification result with a set of reference pixels or ground truth samples. In collecting reference points used for the accuracy assessment, the probability sampling method was followed to create the adjusted error matrix (Olofsson et al., 2013). The method involves three steps namely: sampling design, response design, and error-adjusted-area analysis. The technique allows computation of confidence interval estimates for statistical inferences and uncertainty measures. The sample design employed stratified random sampling in ArcGIS software for collecting sets of reference points to validate the LULC classification. Afterwards, the response design stage of determining the sampling unit of the reference data followed, in order to calculate the estimated area-adjusted matrix. Accordingly, bearing in mind at least a minimum sample of 60 per class in a total number of classes (Congalton, 1991), the stratified random points (Table 2) were created for 1990, 2000, 2010, and 2016 respectively.

Table 2. *Sample Points for LULC Validation*

LULC Category (Strata)	Sample sizes			
	1990	2000	2010	2016
Water Body	60	60	60	60
Settlement	60	60	60	60
Cropland	65	70	70	65
Forest	75	70	70	75
Grasslands	60	60	60	60
Total	320	320	320	320

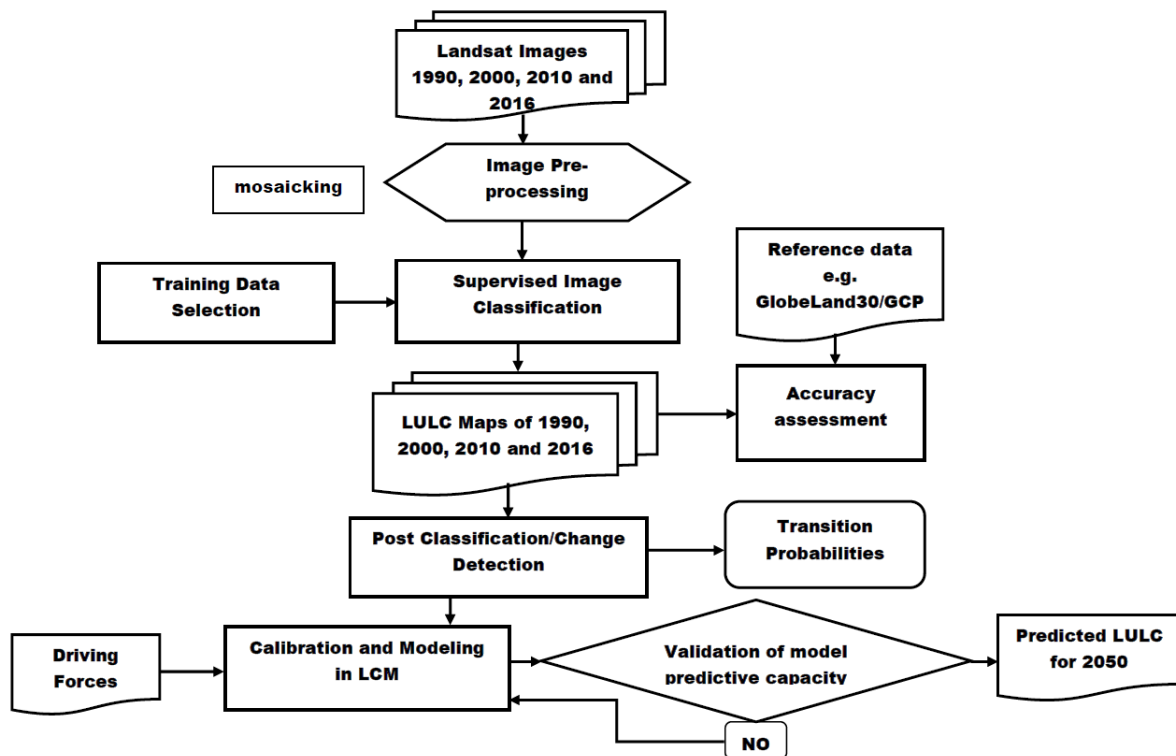


Figure 2. Methodology flowchart used in this study

2.4. LULCC Analysis and Indicators Identification

The LULC change analysis in this study was performed based on the widely used post-classification change analysis with the independently classified maps using Land Change Modeller (LCM). The change analysis aided the detection of LULC conversions by tracking the transition of each pixel between two-time steps of observation. The change detection module in LCM provides information on gains and losses by each LULC class, the net change of each class, contributors to the net change experienced by each class, and the transition of areas among LULC classes that has occurred between the two-time steps.

In addition, the quantification analysis of this spatiotemporal LULCC was realized through indicators like the spatial trend and Annual Land Use/Cover Change Rate (ALUCR) defined in equation 1:

$$ALUCR_{a,t} = \frac{LU_{a,t} - LU_{a,t-1}}{N_t - N_{t-1}} \times 100 \dots (1)$$

Where ALUCR (%) is the rate of LULCC per annum, $LU_{a,t}$ and $LU_{a,t-1}$ are the total land area of LULC category in hectares at current N_t and earlier time N_{t-1} . This also enabled change analysis on a class-wise basis.

2.5. LULC Model Implementation and Validation

The LCM was further used to predict LULC following the procedure: change detection, transition potential modeling and driving factors determination, change prediction, and model validation.

Change Detection - In this first step as earlier mentioned in section 3.3, mainly two-time categorical maps assessed between time-1 & time-2 enabled understanding of gains, losses and transition among the LULC classes as well as nature of change in the catchment from 1990 to 2016 (Figure 2). The changes from one class to another are imperative in identifying the dominant transitions and target

them for modeling. The change maps are created using the likelihood of transformation from one class to another - Evidence likelihood images. Landcover change between the years 1990 and 2000 were first analysed resulting in transition potential maps and probability matrix that illustrates the significant LULC transition at this phase. Emphasis was also given to the principal categories of change with areas more than 5000ha to limit the number of transitions to be modelled.

Transition Potential Modeling and Driving Factors Determination - Consequently, two major transitions were considered (forest to cropland and cropland to forest areas) in Transition Potential Tab. The Multi-layer Perceptron (MLP) neural network is a one direction network algorithm that flows from input to output with a hidden layer(s) in between (Nazzal et al., 2008) that allows for modeling multiple transitions at once. The transitions between the two timesteps are presented as a change matrix used for calibration and targeted for modeling into the future (Figure 2). In addition, major driving factors determined for modeling transition of historical change as predictor variables or constraints include slope, population (settlement), elevation, distance to roads and rivers. These were considered because they are noted to influence LULCC over time (Thorn et al., 2016). The LCM allows a quick look at the probable explanatory model power of the driving forces presented in the Cramer's V. The Cramer's V of 0.15 and above of any variable is useful, while values > 0.4 are good and preferred.

Change Prediction and Model Validation – The LCM uses the change rates from the change analysis and transition potential maps to predict the future LULC, in this case, 2010 (Figure 2). Ensuing Markov chain analysis, this step assists in determining the transition rates from one land-use type to another under certain intrinsic conditions. The hybrid cellular automata (CA)-Markov model is selected among several available and most commonly used land use modeling tools and techniques (such as Clue-S models, multi-agent models, or GEOMOD) because model is recognized as suitable to model the spatiotemporal dynamic changes in landscape patterns in the context of this paper and applied among many scientific communities (Mukhopadhaya, 2016).

Subsequently, the independently classified map of 2010 was compared to the predicted map from the initial two timesteps (1990 and 2000); a way of validating the land change model. The model validation is an important component in modeling aimed to ascertain the quality of the simulated 2010 map comparatively to a reference map (classified 2010 LULC map). The model when considered fit, after validation, was then used to predict LULC for the year 2050 using base maps of 1990 and 2016 LULC as illustrated in Figure 2. To show overall agreement between the observed and predicted maps, in three-dimensional space method (allocation disagreement and quantity disagreement based on Pontius & Millones (2011) techniques and Kappa Index of Agreement (KIA) are used. The following validation statistics of various Kappa indexes (Pontius, 2000) shows agreement between paired maps with variable LULC categories: Kappa for no information (Kno) giving the overall success of the simulation; Kappa for location (denoted as Klocation) showing agreement on location (Nadoushan et al, 2012). The KIA shown with Kstandard confounds disagreement of quantity with the disagreement of location (Hadi et al., 2014). In addition, comparisons of the simulated and the actual area extent of each LULC class were also performed.

2.6. Scenario Development

Scenario development is a recent prevalent practice in LULC research studies because it offers a possibility for assessing the present and future situations geared towards decision making. After the model predictive power assessment, this was then used to project for 2050 LULC with driving forces according to the underlying transition probabilities with years 1990 and 2016 as base maps. Two scenarios were developed and can be termed as (i) business-as-usual (BAU) based on the historical land-use changes between 1990 and 2016 and (ii) Afforestation-based scenario used to explore alternative environmental preservation pathways (Table 3). The afforestation scenario was created by altering the probability matrices for forest and cropland as predicted by the Markov model. This

scenario imbibed an increase in forest and grassland by 15% following the total annual LULC rate change.

3. Results

3.1. Spatial distribution and Accuracy of LULC

The independently classified images results of four different years are given in Figure 3. Five dominant LULC classes including Water body (rivers, lakes, ponds and reservoirs), settlement (mainly residential, roads, bare soils), Cropland (cultivated land - rain-fed or irrigated with partial tree cover < 10% and fallow lands), woody savannah (scattered trees – open savannah woodland and plantations with shrub undergrowth) and Grasslands (including temporarily flooded herbaceous vegetation (wetlands), murky water, dark soils and stones) were classified. Forest and cropland dominated the LULC classes while the lowest is water (Figure 4).

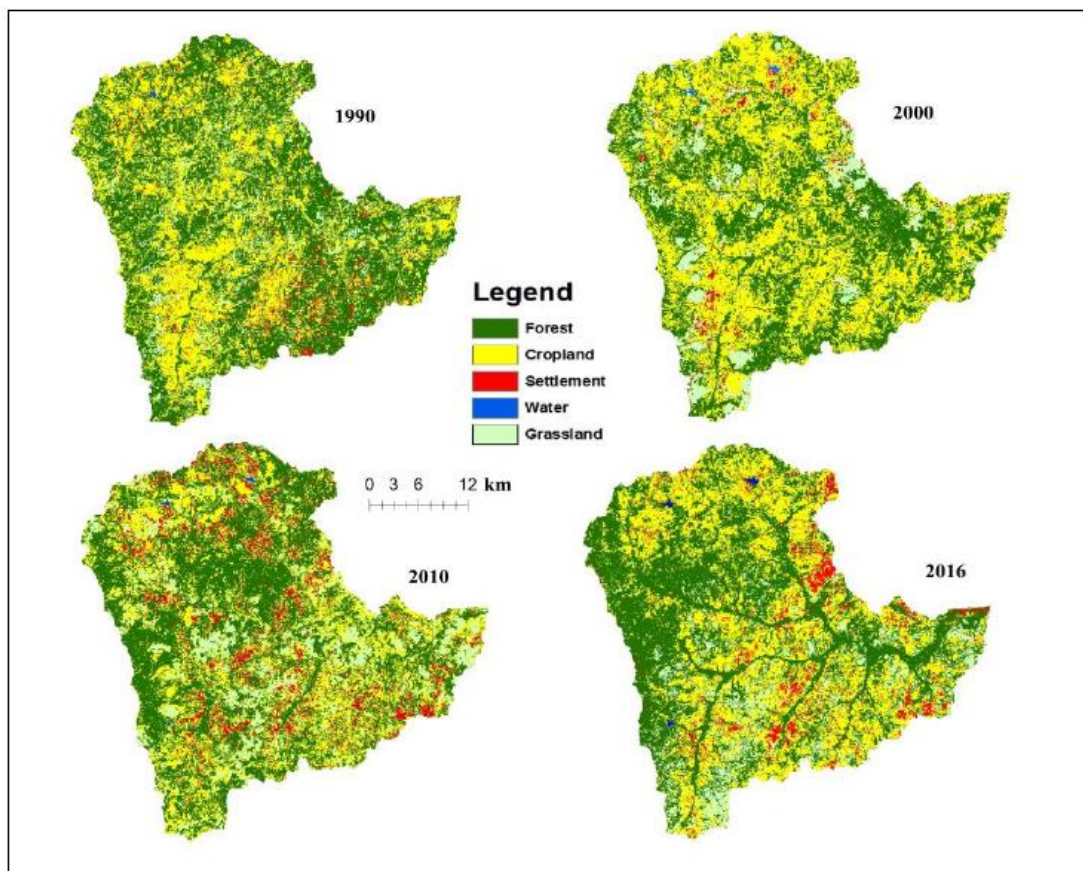


Figure 3: *Classified LULC maps of the Dano catchment*

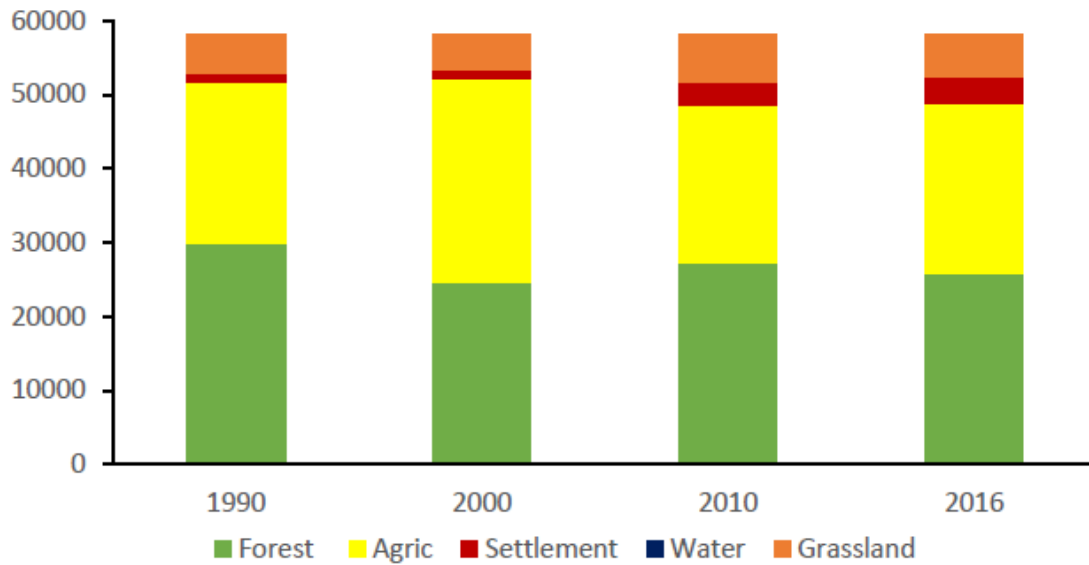


Figure 4: Proportions of LULC types in Dano Catchment

Accuracy assessment of the classified maps was carried out in order to validate these results. Table 3 shows the results achieved based on pixel count matrix (Appendix 1) which yielded overall accuracies (OA) of 90%, 93%, 88%, and 90% for maps of years 1990, 2000, 2010, and 2016 respectively. While the error adjusted area matrix achieved 87%, 90%, 84% and 84% correspondingly. The error adjusted area (Table 4) shows a general drop in overall accuracy because it considered the error of omission while estimating the area proportions.

Table 3: Percentage user’s (UA) and producer’s accuracies (PA) for each LULC class for the years 1990, 2000, 2010 and 2016 based on the pixel count matrix

Landcover class	1990		2000		2010		2016	
	PA	UA	PA	UA	PA	UA	PA	UA
Forest (Nij)	91	84	77	95	78	87	88	79
Agric	77	91	76	76	87	79	80	86
Settlement	94	83	58	92	90	87	94	97
Water	100	100	60	100	100	100	100	100
Grassland	92	93	58	93	87	88	90	92
Overall accuracy	90		93		88		90	

The least accuracy observed for 2010 LULC map is as a result of major spectral confusion observed between categories cropland, settlement and grassland. However, the area distribution (Table 4) reveals that for all categories of LULC, the maps fell within 95% confidence interval of the estimated area indicating good agreement between the classified images and ground-truths as well as the reliability of the classified maps (Olofsson et al., 2014).

Table 4: Spatial analysis result of error adjusted area of LULC maps for 1990, 2000, 2010 and 2016

Year	Landcover	Mapped area (%)	Estimated area (%)	Conf. interval
1990	Forest	51.53	45.77	4.84
	Agric	37.25	38.70	4.17
	Settlement	2.05	3.66	2.21
	Water	0.07	0.07	0.00
	Grassland	9.09	11.80	2.93
	Total	100.00	100.00	

2000	Water	0.09	0.09	0.00
	Grassland	8.24	8.94	1.80
	Forest	42.18	43.88	3.67
	Artificial surfaces	2.07	3.72	2.06
	Cropland	47.42	43.36	4.13
Total		100.00	100.00	
2010	Grassland	11.19	14.79	3.46
	Forest	46.74	46.20	4.68
	Agric	36.61	30.83	4.04
	Artificial surfaces	5.37	8.08	2.76
	Water	0.09	0.09	0.00
	Total		100.00	100.00
2016	Grassland	9.97	12.65	2.85
	Forest	44.48	38.87	4.74
	Artificial surfaces	6.11	7.41	1.71
	Water	0.12	0.12	0.00
	Agric	39.31	40.96	4.88
	Total		100.00	100.00

3.2. Change detection and Quantification

Land use change analysis results in Table 5 apparently showed that during the 1990 to 2016 period across Dano catchment, the significant land changes that occurred was forest conversion to all other classes and all other classes to settlement. Forest lost about 4006.32 ha (15%) of its total area with a persistent change of 70% while settlement and water increased by 2184.93 ha (62%) and 26.10 ha (39%) respectively.

Table 5: Main LULC conversions using the estimated area statistics from 1990 to 2016 in the Dano Catchment

Class	1990-2000		2000-2010		2010-2016		1990-2016
	Area change	ha	%	ha	%	ha	ha
Forest	-1095.45	-4.1	1349.19	5.3	-4260.06	-15.8	-4006.32
Agric	2711.91	12.0	-7292.28	-28.9	5905.94	32.9	1325.58
Settlement	38.07	1.8	2537.34	117.0	-390.47	-8.3	2184.93
Water	12.69	31.0	1.53	2.9	11.88	21.5	26.10
Grassland	-1667.22	-2.9	3404.18	5.8	-1243.69	-2.1	493.27

Forest degradation, grassland decrease, settlement and agricultural land expansion can be seen from the presented LULC changes in Tables 5. To further buttress this, analysis of the annual rate of land-use change (ARLUC) is computed in Figure 5 to highlight the importance of LULC focus of the study. The following results were obtained: forest decreased at the rate of 4.3% and 18.8% per year in the periods 1990 to 2000 and 2010 to 2016 respectively; while cropland increased at the rate of 10.7% and 24.8% with areas greater than 5,000 ha at a similar timeframe. Grassland decreased yearly by 32% and 16.9% in 1990 to 2000 and 2010 to 2016 decades respectively. The reverse of these changes (cropland reduction: 40.6%; forest and grassland increase: 5.5% and 39.5%) are seen in the 2000 to 2010 period. Settlement and water consistently increased in the entire timestamp.

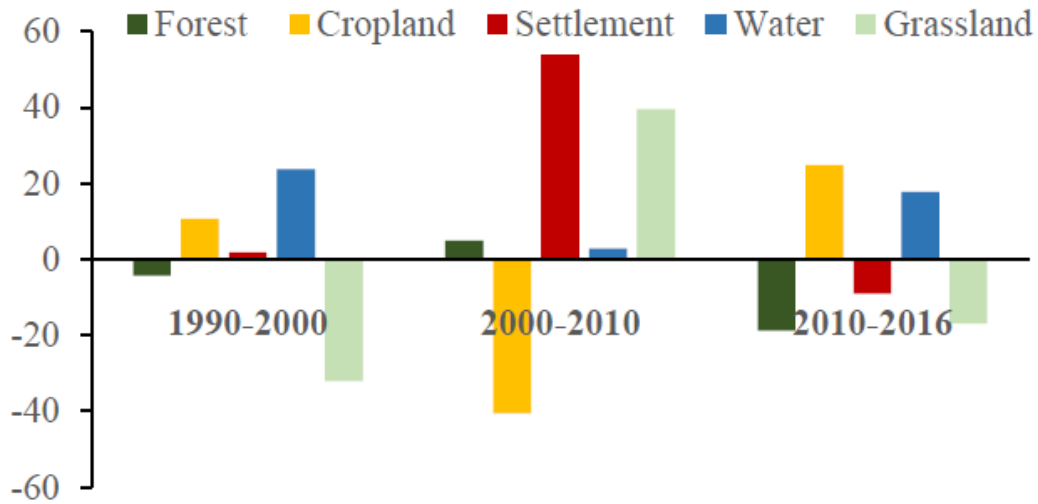


Figure 5: Annual Rate of Land-use Change (ARLUC in %/yr) from 1990 to 2016

3.3. Transition Probabilities and Driving Forces

The classified maps transition probabilities matrices are presented in Tables 6. The most important conversions were from forest to all other class: water, settlement, grassland and substantially to cropland – 5023 ha, hence, this is considered as the major transition in the land change model, since urban areas occupy less than 7% of the catchment. The diagonal values in the matrices represent the probability that each LULC class remains unchanged, while the off-diagonals represent the probability of transition to another class. In the period 1990 to 2000, forest and cropland had the highest probability of undergoing changes. The low unchanged transition in settlement class is from rapid development at that period and misclassification due to identical spectral signature with cropland in the catchment. The 1990 to 2016 period matrices show a general reduction in all classes except settlement (0.09) that increased. Cropland mostly reduced meaning that most conversions are within cropland. The high probability value for forest (0.47) can be attributed to forest recovery observed in the earlier change analysis (Figure 5).

Table 6: Markov chain matrix of LULC transition probabilities in different periods from 1990 to 2016 in the Dano Catchment

Period: from-to	LULC	Forest	Cropland	Settlement	Water	Grassland
1990-2000	Forest	0.5224	0.3833	0.0088	0.0003	0.0852
	Cropland	0.2986	0.6090	0.0003	0.0088	0.0586
	Settlement	0.1670	0.7132	0.0704	0.0088	0.0486
	Water	0.2396	0.1297	0.0022	0.5868	0.0418
	Grassland	0.4147	0.3852	0.0271	0.0040	0.1726
1990-2016	Forest	0.4787	0.3786	0.0514	0.0006	0.0906
	Cropland	0.4268	0.4185	0.0675	0.0015	0.0856
	Settlement	0.3573	0.4777	0.0908	0.0014	0.0727
	Water	0.3609	0.1438	0.0529	0.4214	0.0210
	Grassland	0.4895	0.3426	0.0385	0.0007	0.1287

The forest transition had a varying spatial trend over the catchment indicating a divergent predictor variable contributing to the change (Figure 6). The highest degree of forest area loss has occurred in the North and South sides of the catchment. Cramer's V values gave the correlation coefficient ranging from 0.0 to 1.0 signifying either a redundant variable or significant potential variable. Based on the values, settlement was a major player in the land use change followed by distance to water bodies, the

road and elevation factors. This implies that areas close by settlement have been cleared for food production so as to satisfy basic life needs. Taking these results into account to model land use change (agricultural land area increases and forest decrease); model calibration was performed for 2010 based on the transition probability grid from 1990 to 2000. These transitions were modelled in one sub-model using the produced transition map.

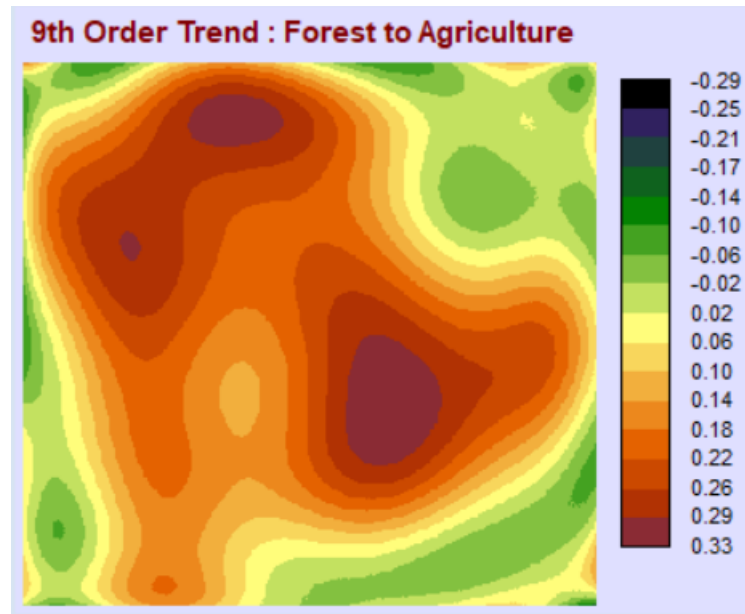


Figure 6: The Spatial trend of change from forest to cropland

3.4. Model Prediction and Performance Evaluation

Illustrated in Figure 7 is the comparison of the predicted 2010 agricultural expansion map and an independently classified map of the Dano catchment in 2010. Visual comparison of the simulated 2010 map with the classified map are reasonably similar and at a good confidence level (95%). However, over-prediction is seen for the forest at the far right (depicting the change of forest increase and cropland decrease that actually occurred between 2000 and 2010). This is due to models' less ability in capturing the random forest save interventions and newly developed areas. 41.67 and 47.92% in the extent of cropland and forest respectively were attained by the model (simulated) in 2010 while the actual map has an extent of 36.59% and 46.76%.

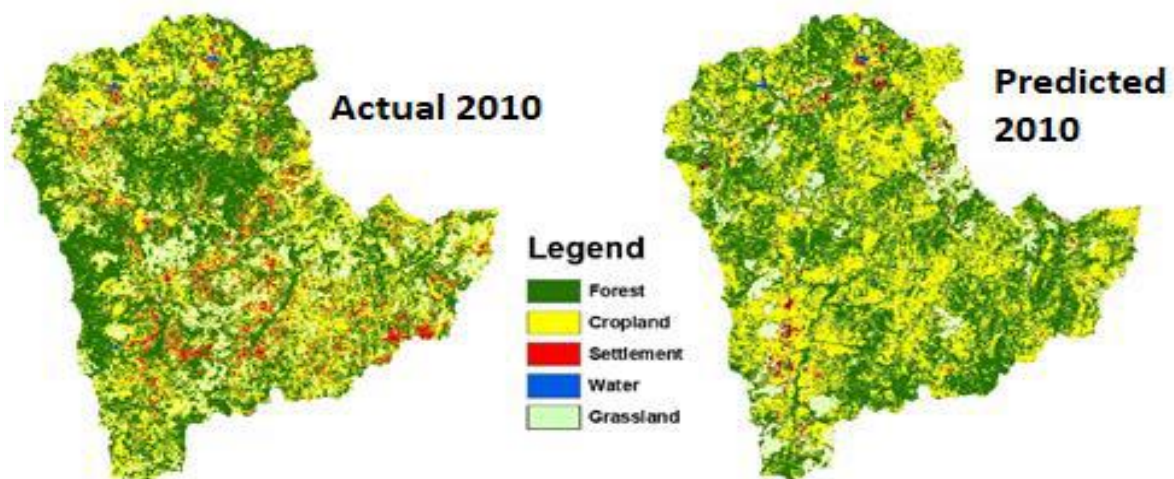


Figure 7: Comparison of the classified and predicted 2010 LULC maps

The model having attained an acceptable range of less of the observed, which can be emphasized on the inadequacy of forcing driver restrictions and poor model ability in capturing the randomly farming activities which occurred within settlement areas. Since statistical techniques are vital for model validation as visual validation remains subjective and misleading at times (Pontius and Chen, 2006), the Kappa for the projected and real map of 2010 is presented. Also, LULC mapping and analysis in this study was achieved using medium resolution images, therefore, detections using high-resolution satellite images could be more dependable.

Notwithstanding, the agreement and disagreement between the simulated and the classified maps of 2010 reveal Kno, Klocation and Kstandard values of 81%, 83% and 73% respectively. The model also showed quantity and location disagreement of 4.9% and 15.4%, respectively. The interpretation of these agreement values is that the most part of the study area experienced change, as the dominant classes of forest and cropland underwent changes during this period (Figure 8). The exchange is the largest component of error. Cropland and forest account for most of the exchange component while forest has the largest overall error in the quantity component. Likewise, LULCC is more pronounced (heterogeneous) at the local level and in areas of change, which indicates that CA_Markov model reasonably simulated the 2010 LULC patterns and thus, in a good position to predict future LULCC in the Dano catchment.

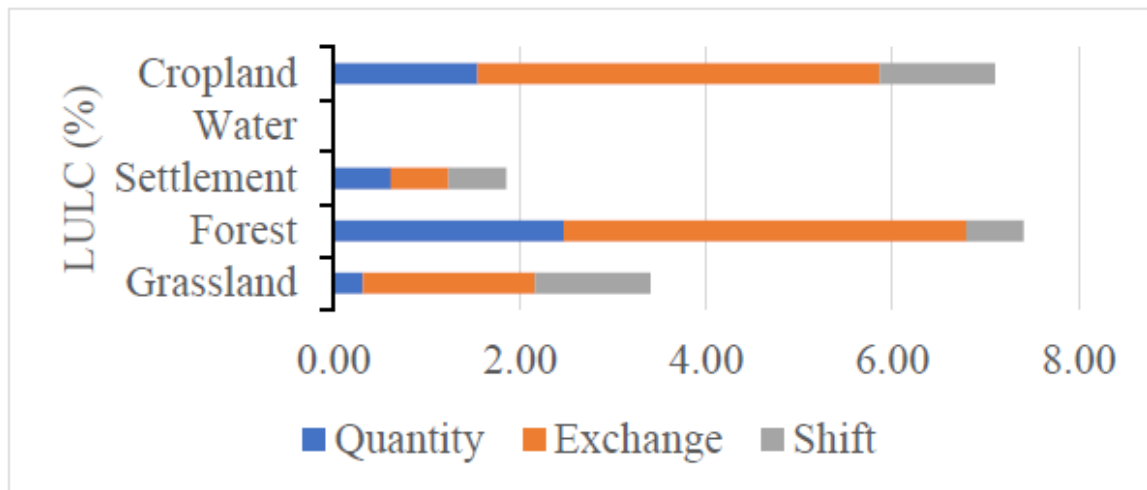


Figure 8: Quantity agreement (Quantity) and Allocation agreement (Exchange + Shift) of LULC map

After model validation, two scenarios LULC future projection into the year 2050 was simulated with 1990 and 2016 maps by applying the sub-model test implemented during the 2010 model calibration. The predicted 2050 maps in Figure 9 show that forest cover will decrease from 46.72% in 2016 to 38.54% and cropland area will expand from 38.51% to 46.69% under a business-as-usual scenario (Table 7). Contrarily to the BAU, the afforestation scenario projects forest increases by 2.13% compared to 2016.

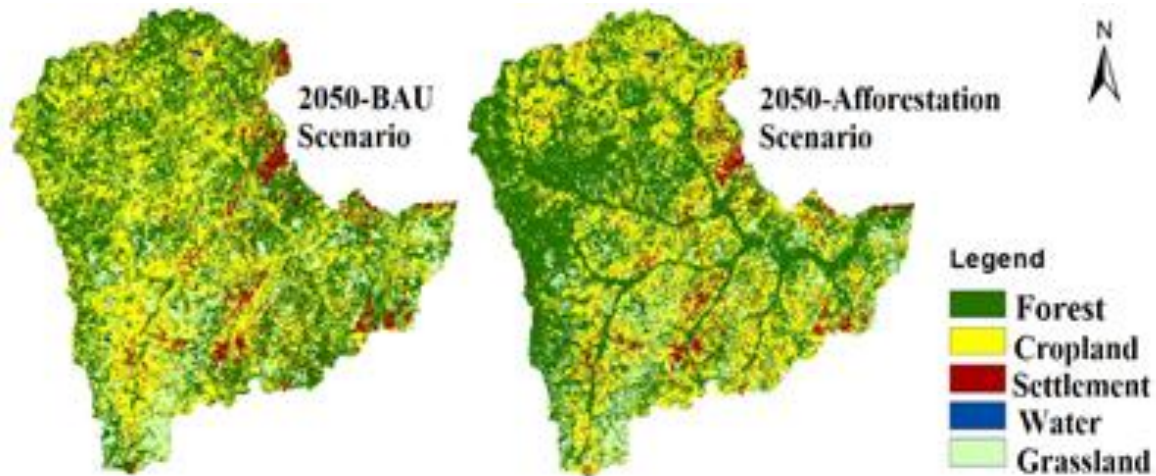


Figure 9: Trend and predicted (2050) LULC in Dano Catchment

Table 7: LULC change scenarios developed in this study

LULC	2016 Area in ha (%)	Scenario 1 (Current conditions or Business-as-usual) Area ha (%)	Scenario 2 (Afforestation) Area ha (%)
Forest	27211.05 (46.72)	22444.11 ha (38.54)	28437.66 (48.85)
Cropland	22427.82 (38.51)	27194.76 ha (46.69)	21201.21 (36.42)
Settlement	3149.46 (5.41)	3149.46 (5.41)	3149.46 (5.41)
Water	67.05 (0.12)	67.05 (0.12)	67.05 (0.12)
Grassland	5386.41 (9.25)	5386.42 (9.25)	5386.42 (9.25)

4. Discussion

4.1. LULCC Mapping in the Context of Hydrological Implications

Given the overall goal and framework of LULCC mapping, specific or targeted LULC can be monitored, which is mostly dynamic especially at a small scale. The quantified results provided clear evidence of substantial land-cover changes and forest cover degradation in the Dano catchment. Grassland has decreased between 1990 and 2000 by 2.43%, and between 2010 and 2016 by 17% while forest cover reduced by 4.3% and 18.8% of its area per year between 1990 to 2000 and 2010 to 2016 respectively (Table 7). There is an encroachment of settlement and farmland into water bodies, and forest occurred mainly along the river-lines as seen in Figure 4. A slight increase in Water body over the period analyzed was due to the creation of reservoirs for agriculture (irrigated) in the catchment.

Earlier studies in different parts of West Africa that investigated LULC changes and within similar timeframe have reported increases in cultivated land and shrubland areas in the periods investigated (Obahoundje et al., 2017). Results obtained from the historical Landsat classifications (Figure 4) confirmed the decrease in the extent of savannah woodland and grasses which is consistent with observation made by Yira et al. (2016) and revealed that the study catchment experienced interim losses in the cropland area between 2000 and 2010 (Forkuor et al., 2014). These local studies are illustrative of land-use change in small-scale farming communities.

The settlement class is seen to have tripled and hamlets of scattered houses are seen mostly surrounded by farmlands due to the rural nature of the catchment. But, in the recent decade (2010 and 2016), 9% decrease in the settlement class was observed which can be attributed to migration to cities

in search of better jobs and higher-quality education to improve their livelihoods as the area is close to the capital city and principal towns. If this settlement increase at a rapid rate, as observed continues, this would significantly decrease forest areas with the resultant effect on water yield (Akpoti et al., 2016) and further impact negatively via soil erosion. Forest has high capacities for regulating and supporting ecosystem services, such as carbon sequestration, the preservation of habitats and biodiversity. Increase deforestation rate also contributed to surface runoff increase and it is also responsible for downflow sedimentation (Yira, 2016). The rapid expansion of agricultural land use and urbanization are significant drivers of water quality degradation and inherently plays a leading role in water pollution.

4.2. Explaining the Driving Forces and Analyzing Connections at the Catchment Level

With increasing climate change impacts including variable rainfall and flood events, encroached water bodies used for farming make people and properties in those locations vulnerable. Uncontrolled lateral expansion of cultivated lands, deforestation, grassland degradation and loss of wetland in the area were the main forms of land change, which poses a direct and indirect threat to essential ecosystem especially water resources.

Numerous factors could account for the observed decrease in forest and cropland increase in the Dano catchment. The observed LULCC is governed by biogeographical and socio-economic factors and one obvious factor is rapid population growth. Several studies have noted that the growing population has often led to the expansion of the cultivated area in West Africa (Lambin et al, 2003, Ouédraogo, 2010). The population in the loba province (where Dano catchment is located) increased by 19% between 1996 and 2006 (INSD, 2007). Further insight into the agricultural expansion reveals significant strong correlations with population from 2001 and 2014 (Knauer et al., 2017), confirming a possible linkage between the observed cropland increase in the catchment from 2000 to 2016. The total rural population of Burkina Faso has also been reported to moderately increase up to 244,000 people at that time. Overall, cropland increased from 37 to 39 % during the study timeframe. Population growth increases the demand for more cultivated land, fuelwood, and infrastructural development; which invariably leads to vegetative cover losses. This can also be associated with certain agricultural and political policies in Burkina Faso (e.g. Community-Driven Development) which resulted in deforestation (Brimoh, 2009).

The distribution of rainfall is another determinant that was responsible for the observed changes in cropland area in the catchment during the period of investigation. For instance, the poor rainfall distribution in 2002/2008 (Figure 10) is a possible cause of the reduction in agricultural areas from 47% in the year 2000 to 37% in 2010. These inconsistent rainfall events which have been reported by other studies (Kabo-Bah et al., 2016; Tossou et al., 2017) cause drought events that contribute to land degradation. The increase in water bodies recorded for 2010 and 2016 can be linked to high precipitation events, reservoirs, and dam constructions.

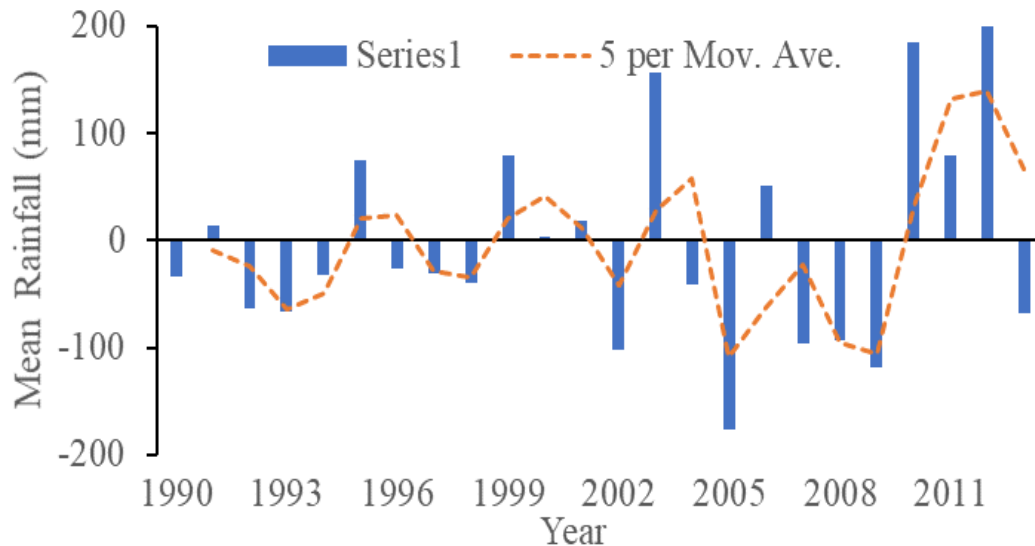


Figure 10: Long-term (1990 to 2013) annual rainfall (mm) anomaly in Dano

Further, this drastic decrease in the area of cropland is also likened to prevalent flooding in West Africa and other parts of Sub Saharan Africa (SSA) in 2007 which destroyed properties, eroded farmlands and led to the loss of lives (Levinson and Lawrimore, 2008). Although annual precipitation in Dano was low in the year 2007 as compared to 2006, careful examination of the mean monthly totals bared that anomalous rainfall amounts in July/August 2007 and little excess from the previous year (>50) mainly caused the flooding. Similarly, this analysis is supported by (Tazen et al., 2018) who investigated the relationship between flood trends and extreme precipitation events. The study concluded that especially in from the 2000s, the flood frequency increased from 2 to 3 per year since 1986. 40% loss of the cropland area consists of the total eroded areas. Soil erosion is widely experienced in the region. However, the percentage of cropland area increased at an annual rate of 24.8% in the last decade could be farmers' response to a possible farm loss in the previous years via agricultural intensification and extension.

In contrast to cropland decrease, forest increase observed at that period, in line with the recent study by Knauer et al. (2017) can be partly due to recovery, long-term fallow system, and reforestation via Reducing Emission from Deforestation and Forest Degradation (REDD) initiatives and policy on protected areas. In response to environmental concerns, a large number of restoration and protection measures have been implemented (enclosures of plantations, policy interventions, tree-planting campaigns). However, tree planting and assisted natural regeneration of indigenous trees are important drivers of regrowth/revegetation in this region (Bramoh, 2009).

Nevertheless, Dano experienced a decline in the forest resulting from deforestation for agriculture, bush burning, urban growth and possibly flood occurrence in the farming season of 2007. According to IUCN (2005), major accelerators of forest decline in the catchment's areas consist of human activities such as harvesting wood for cooking, the source of energy and poor forest management.

Also, low agricultural production has contributed to an increase in deforestation (Etongo, Djenontin, & Kanninen, 2016). Duaze (2004) observed that farmland soils were the lowest in fertility when compared to other land-use types. Generally, soils in this region are of low fertility and continuous farming will lead to degraded soils and low productivity. Upper soils are usually sandy and very susceptible to erosion and compaction. The declining soil fertility in farmlands in a combination of the growing population and other factors, put more pressure on land resources (Callo-Concha et al., 2013), therefore, leading to further land degradation. Moreover, the interrelation of this LULCC with climate change is expected to further lead to severe land degradation (Thiombiano and Tourino-Soto, 2007). As an important factor controlling a basin's hydrology, LULCC continuation in this area aid to

accelerate modification of the catchment's climate. Understanding these drivers at a small level is imperative to aid the formation of adequate policies.

4.3. Study Relevance to National and International Goals

This study results, even though on a small scale, are relevant in; 1) formulation and implementation of national development policies such as 'Politique Forestière Nationale' of Burkina Faso 2) achieving the United Nation's sustainable development goals (SDGs) and 3) decision making as input to biophysical and socioeconomic models. For instance, *Stratégie Nationale de Gestion des Feux en Milieu Rural* outlines policies and strategies aimed at sustainable forest and agricultural management so as to reduce the poverty of the rural areas and enhance the livelihoods of forest communities as outlined in Burkina Faso's national strategy for poverty reduction (MEF, 2004). These are to be adopted by the local government institutions (e.g. provinces, municipalities and departments) in Burkina Faso. As Dano catchment forms a substantial part of Ioba province, results obtained can contribute to achieving local scale targets in land use planning and climate change adaptation. Kalame et al, 2008 highlighted that the present forest policies in Burkina Faso, however, lacked clear objectives on climate change adaptation (and/or mitigation) but contain elements of risk management practice. In this regard, the objectives and result from this study, particularly the predicted LULC pattern, will assist relevant national authorities to develop specific strategies such as the development of pro-poor REDD policies that will ensure sustainable use of resources and attain economic opulence. On one hand, the predicted cropland expansion under the business as usual scenario (see section 3.4), will mean to encourage of agricultural management practices and policies that reduce GHG emissions and subsequent negative climate change effects. On the other hand, the pursuit of scenario 2 (afforestation), which predicted an increase in savannah woodland, will require promoting best practices and climate-smart agriculture (CSA) such that a reduction in cropland area will not necessarily lead to food insecurity.

In addition to national relevance, the study results can contribute to monitoring progress towards attaining SDG goals 6 (WASH) and 15 (Life on earth). For example, the historical and predicted LULC change pattern can provide indicators to address the different relevant targets as in the case of 15.1.1 & 15.2.1. Specifically, unsustainable LULC dynamics and land degradation observed in the catchment as cropland expansion and poor agricultural practices are indicators of ecosystem modifications such as the catchment water balance that will certainly lead to alteration of the hydrological regime. Similarly, LULC transition probabilities between the present state and predicted (2050) provide insight on the calculated indicator for forest area as a proportion of total land area (15.1.1). Trade-offs between agriculture and forest can be managed through spatial management and use of degraded lands. Land use intensification such as bush fallow should be encouraged as mitigation practices and incentives should be given to retaining tree cover. Equally, the outputs from this study can be used in ecohydrological models for decision making of ecological management. Combining the approach of hydrologic modeling and scenario analysis, (Bossa, Diekkrüger, & Agbossou, 2014) observed that savannah conversion to cropland intensified annual runoff with a high risk of flooding erosion rates. The predicted LULC pattern scenarios in this study can provide insight into how much the hydrological ecosystem (freshwater availability) will be impacted and an appreciation of whether or not SDG 6 can be achieved. Thus, climate change-related risks such as droughts and flood, recently found to have intensified as a result of LULC change (Sylla et al., 2016), can also be minimized when appropriate measures are taken based on results of such simulations.

5. Conclusion

This study examined the historical LULCC in the Dano catchment between 1990 and 2016 and projected the LULC patterns for two future (2050) scenarios using the CA-Markov chain model. Results revealed clear evidence of substantial land-cover changes and forest cover degradation in the catchment. The trend of decreasing in the forest and increasing cultivated land during the historical

period is expected to continue in 2050 under the BAU scenario, while under afforestation scenario a potential increase in vegetation was projected. Furthermore, the study findings provide solid evidence that deforestation reinforces land degradation across the catchment which poses a major threat to ecosystem sustainability of the landscape especially water resources for the future. To ensure food security and circumvent deforestation, a well-planned and sustainable land use practices would be desirable in the area. The outcome of this study is useful for the sustainable development of the future Dano watershed. The study recommends future research should pay more attention to the use of multiple socioeconomic predictors/drivers (e.g. Land policy data) of land degradation to improve the understanding of the environmental change effect caused by LUCC and the precision of the future projection.

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Conflicts of Interest

The authors declare no conflict of interest

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