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Analysing patterns of forest cover change and related land uses in the Tano-Offin forest reserve in Ghana: Implications for forest policy and land management

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ABSTRACT

Forest cover change is a major contributing factor to global environmental change. Whereas several studies have focused on the general land use and land cover dynamics, we focus on analysing forest cover change patterns in a protected landscape taking into consideration how other land categories are increasing at the expense of the forest. In this study, we analyse forest cover change patterns and associated proximate land use factors between 1987 and 2017 using Landsat images from the Tano-Offin Forest Reserve (TOFR) in Ghana. Using the Random Forest machine learning algorithm, we classified the images into forest, developed land, and agricultural land. The study finds that forest cover losses are 1.9 and 1.4 times the amount of forest cover gains in 1987–2002 and 2002–2017, respectively. We find that even though the forest cover is more likely to recover from the agricultural land, land developers mostly targeted the agricultural land. The focus of Ghana’s Forest and Wildlife Policy and the underlying process of forest cover change in the TOFR suggest that a country’s forest policy should focus on a combination of diverse and spatially explicit proximate factors that are likely to threaten the integrity of forests.

1. Introduction

Different agents, depending on location, contribute to land cover change in forest reserves (John et al., 2014). Land use patterns reflect the differences in decisions made by land managers, and hence, intricate land cover change patterns are produced by different levels of organisation in a highly dynamic manner (Bramoh, 2006). Land cover change, a process of altering or transforming the biophysical state of the surface and the immediate subsurface of the earth (Turner et al., 1995) is related to land use, a process which ‘involves both the manner in which the biophysical attributes of the land are manipulated and the intent underlying that manipulation - the purpose for which the land is used’ (Turner et al., 1995 p. 20). Even though different agents are contributing to the modification or transformation in the biophysical characteristics of the earth’s surface, in recent times, most of the modifications or transformations are a result of anthropogenic land uses (Turner et al., 1995; Meyfroidt and Lambin, 2011; Meyfroidt, 2015; Briassoulis, 2019). Identifying the link between land uses and land cover change patterns and understanding how land uses contribute to land change would enable policymakers to design appropriate responses that would reduce anthropogenic impacts on the environment (Bramoh, 2006; Alo and Pontius, 2008; Estoque and Murayama, 2015; Agyemang-Duah et al., 2021).

Forest ecosystems, national parks, and forest reserves do not meet the expectation regarding the ecological function they are to perform despite several efforts made to protect these resources, especially in tropical regions (Rodríguez and Young, 2000; DeFries et al., 2005; Barlow et al., 2007; Kusimi, 2015; Aditya and Ganesh, 2019). This
ecological malfunctioning is because of pressures such as forest fires, floods, climate change, and increasing anthropogenic activities (Hansen and DeFries, 2007; Kusimi, 2015; Snapir et al., 2017). The anthropogenic pressure on forest resources in Ghana is similar to that of other tropical forest areas in the world. Previous studies in Ghana have noted that the peripheries of most forest reserves, including the Tano-Offin forest reserve (TOFR), are being converted to agricultural land, developed land, and lumbering sites, and such conversions are likely to intensify in the future as the use of land for livelihood activities increases (Alo and Pontius, 2008; Kusimi, 2008; Damnyag et al., 2013; Kusimi, 2015). In most of these forest fringes, communities depend on non-timer forest products (NTFPs) for their livelihoods and engage in subsistence farming as well (Appiah et al., 2009; Boafo, 2013; Lambini and Nguyen, 2014; Kusimi, 2015; Sobeng et al., 2018). These activities are likely to contribute to the degradation of the forest. However, the Forest and Wildlife Policy of Ghana, 2012, emphasises non-consumptive values of the forest and aims at creating a balance between timber production and marketing to satisfy, particularly, domestic wood demands (Ministry of Lands and Natural Resources, 2012). With land uses such as illegal mining and chainsaw milling being issues of concern, the 2012 policy (a revised version of the 1994 policy) was devised to ensure the Forestry Commission, together with security agencies combat the illegal activities and reverse the increasing pace of deforestation and forest degradation in Ghana (Ministry of Lands and Natural Resources, 2012). Nonetheless, the policy does not focus much on how subsistence livelihood activities (e.g., farming) and land uses such as human settlement development would likely promote forest loss and degradation.

The main challenge faced by forest managers is how to reconcile the needs of society with forest conservation objectives, especially in communities that subsist on the forest reserves, amid the increasing push for the implementation of REDD+ (Reducing Emissions from Deforestation and Forest Degradation) programmes in developing countries. Wiggins et al. (2004) have found that in many localities in Ghana, forest policies are not implemented in communities where land use pressures are leading to the degradation of protected forests. Forest users ignore regulations on the use of forest reserves because such regulations are seen as inconveniences to them (Wiggins et al., 2004). This tendency would likely encourage the illegal use of forest resources and in turn contribute to the degradation of the forest reserves. However, the degradation of forest ecosystems is likely to adversely impact the forest resource-dependent communities (Boafo, 2013). Therefore, the search for livelihoods should be done more sustainably to prevent the future cost of reclaiming degraded forests, a situation that could further impoverish subsistence farmers in forest fringe communities (United Nations, 2015).

Many of the previous land change studies (e.g., Schueler et al., 2011; Appiah et al., 2015; Coulter et al., 2016; Tadesse et al., 2017; Gashaw et al., 2017; Ramachandran et al., 2018) have focused on general land cover change patterns with little or no reference to the land use dynamics in the forest reserves and how these dynamics potentially influence forest policy development. Moreover, from these studies, little is known regarding how other land categories increase at the expense of forest as well as how forest cover increases at the expense of other land categories in protected areas where livelihood and other anthropogenic activities are likely to degrade the forest cover. Coulter et al. (2016), for instance, found a reduction in the forest cover due to agricultural activities in southern Ghana. However, the scope of the study did not specifically focus on measuring and analysing forest change in the forest reserves. A prominent study by Kusimi (2015) characterised land disturbances in the Ateawa forest reserve in the eastern region of Ghana. Nonetheless, to evaluate different forms of disturbances at different scales and locations, and to gather information regarding the characteristics of multiple disturbances for modelling future land change and future policy amendment, further studies in other forest reserves (e.g., the TOFR) are necessary.

With the aid of remote sensing (RS) and Geographic Information Systems (GIS) approaches, our objective is to analyse the quantity and patterns of forest change and associated land use patterns between 1987 and 2017 using Landsat images from the TOFR. With this objective, we answer the following research questions. By how much is the quantity of forest cover increased or decrease over time? Which categories of land use and land cover are increasing at the expense of the forest cover in the protected area? Which of the land use and land cover categories transitioned to forest cover over time in the forest reserve? By answering these research questions, we show patterns of forest losses and forest regrowth, and as well inform future management strategies and policies geared toward effective reconciliation between the dynamics of natural regeneration, forest conservation efforts, and land use allocations. This study serves as a critical step towards exploring the broader dynamics of the coupled human-environment relationship in many other forest reserves, especially in tropical forest regions where land uses are similar to that of the TOFR. Besides, as Ghana prepares to roll out the REDD+ project across the country, understanding the dynamics of forest change and their proximate driving processes in the TOFR would provide useful information for the effective implementation of the project. Through this study, the rate of forest cover reduction, forest regrowth, and the sustainability of the terrestrial land uses could be explicated.

The current RS and GIS technologies are useful for providing land change information in forest reserves to inform policymakers about the pattern of forest change, especially in the forest reserves where there are different scales of anthropogenic land uses (Kusimi, 2015; Oduro Appiah and Agyemang-Duah, 2021). RS and GIS have been successfully used in many locations in Ghana to measure land change (see examples in Alo and Pontius, 2008; Kusimi, 2015; Kpianbaahre and Oduro Appiah, 2019; Oduro Appiah et al., 2021). By using RS and GIS, we measure forest change with a focus on the analyses of change and transition patterns between the forest cover, agricultural land use and land cover, and the developed land category. Understanding the land use-forest change interplay is critical, as it could contribute partly to the attainment of United Nations’ Sustainable Development Goal 15 which seeks to protect, restore, and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt biodiversity loss by 2030.

2. Theoretical background and concepts

The theory of Agricultural Adjustment to Land Quality (AALQ) (Mather and Needle 1998) and other concepts explained under this section form the theoretical basis of this study. According to Mather and Needle (1998), the continuous search for quality land and soil for food crop production leads to the clearing of forest lands to use for agricultural activities. Mather and Needle (1998) have theorised that the move from one parcel of land to another due to the need for quality land is a potential for the abandoned land to regrow into forest cover. This can be likened to the transition from agricultural land to forest cover as agricultural activities come to an end and the land is abandoned or not put to use. AALQ explains the expansion in agricultural land at the expense of the forest cover in forest reserves. Conversely, it also explains the possibility of forest recovery from agricultural activities in forest reserves. In this study, we use the AALQ to explain the possibility of forest regeneration, that is, the conversion of agricultural land to forest cover.

The analysis of the causes of land change has shifted from focusing on just a single factor to multiple and more complex factors. These factors range from proximate (direct) causes to indirect and underlying factors that contribute to changes in land cover (Geist and Lambin, 2002). The change analysis in this paper, however, measures the proximate (direct) changes and also discusses some of the indirect factors contributing to forest change in the TOFR. For instance, this change analysis is likely to broadly establish the changes in the forest cover contributed by agricultural activities, expansion in rural settlements, road network expansion, and mining activities. However, the indirect (underlying) processes of forest change including an increase in
population, government policy and the need to increase accessibility to remote areas, and government policy to lease public lands for agricultural activities could not be measured with our GIS and remote sensing analysis.

Improved understanding of the complex dynamic processes underlying land use change will allow for more reliable projections and more realistic scenarios of future changes. Lambin et al. (2003) have posited that understanding the positive and negative feedback in the landscape is a necessary precondition for predicting future land use and land cover dynamics and also improve land use and resource governance. Positive feedback loops intensify change and lead to the degradation of the ecosystems and hence impoverishing communities that depend on services from the ecosystem. Negative feedback loops include institutional and technological innovations that lead to a decrease in the rate of change or reversal of the land change trends (Lambin et al., 2003). In the TOFR, agricultural expansion, residential, and transportation development are likened to the positive feedback loops. These are underlying processes that could threaten the forest ecosystem in the TOFR. Conversely, the decision to declare the reserve as a Globally Significant Biodiversity Areas (GSBA) and engage in forest plantation could be the negative feedback loop for improving the integrity of the forest ecosystem.

3. Materials and methods

3.1. Description of the study area

The TOFR is the largest forest reserve in the Atwima Mponua District (AMD) of Ghana. It lies within longitude 2° 17’0”W and 1° 59’0”W and latitude 6° 20’0”N and 6° 60’0”N (Fig. 1). The TOFR covers an area of about 516 sq. km and is found in the wet semi-equatorial forest zone in Ghana. There are deciduous, semi-deciduous, and evergreen forests in the study area, but the vegetation is primarily the semi-deciduous forest made up of valuable trees such as Wawa, Sapele, Esa, and Asafena (Derkyi et al., 2013; Ghana Statistical Service, 2014).

There are two main rainfall seasons in the study area. The first and major rainfall seasons occur between March and July and peaks in May of every year. The second season starts in September and ends in November. Generally, the average annual rainfall ranges between 1700 and 1850 mm per year. Despite the heavy rainfall during the year, the period between December and February is dry and hot. The average annual temperature is about 27 °C. However, the mean monthly temperatures range between 22 °C to 30 °C throughout the year (Ghana Statistical Service, 2014). Thus, these favourable climatic conditions coupled with well-drained soil in this forest zone are necessary for the growth of trees, cash and food crops such as cocoa, rice, plantains, and vegetables (Ghana Statistical Service, 2014). The favourable climatic and soil conditions are likely to explain why about 85% of the population in the AMD are involved in crop cultivation. In the rural areas of the AMD such as the communities around the forest reserve, about nine out
of ten households (88.3%) are agrarian households whereas in the urban settings, 64.4% of households engage in agriculture. Most households in the district (98.6%) are involved in crop farming, and the rest are involved in animal rearing (Ghana Statistical Service, 2014).

The TOFR is one of the GSBAs in Ghana (Derkyi et al., 2013). Despite its status as a protected area and a GBSA, the TOFR faces threats such as legal and illegal farming and chainsaw milling (Derkyi et al., 2013). These human activities have undermined the integrity of the TOFR (Addo, 2013). Due to limited opportunities for non-farm employment, most of the villages in and around the forest reserve engage in farming activities, which means that the local economy of the area is supported by agriculture (Derkyi et al., 2013; Akamani and Hall, 2015; Sobeng et al., 2018). There are villages in and around the forest reserve including Akuta, Adadekrom, Kyirayaso, Bofaaso, and Kyekyewere. Whereas village-level population size is not available, a study by Sobeng et al. (2018) revealed that each of these notable villages has a population of about 1000 people which is likely to increase in the future. Even though human activities are likely to contribute to forest degradation, over the past few decades, land management initiatives such as tree planting, including agroforestry, would likely ensure a balance between socio-economic and ecological objectives in the future (Derkyi et al., 2013).

3.2. Data

We made use of Landsat images acquired by the United States Geological Survey in December 1987, 2002, and 2017. The study area is an area with a significant cloud cover because of the long raining season, and as noted by Murakami et al. (2001), the main limitation of doing a time series analysis is the difficulty in getting cloud-free land cover data. Thus, we selected the Landsat images from the month of December because of the following reasons. First, the month of December does not fall within the rainy season and thus, has very low or no clouds cover. In other words, we targeted images captured in December because we wanted to have cloud-free images for our analysis. We note that all the images selected from December 1987, 2002, and 2017 were cloud-free. Second, we selected all our images from December to reduce differences that may result from phenological changes in the forest plants; we aimed to maximise spectral stability to measure the actual changes in the land cover of the forest reserve. We considered two periods (1987–2002 and 2002–2017) in the time series analysis of land change. We used 1987 and 2002 images from the Landsat Thematic Mapper (TM) 5, which provides 30 by 30 m spatial resolution images. We also used a 30 by 30 m spatial resolution Landsat Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) 8 2017 image (see details of images in Table 1).

Whereas disturbances finer than 30 by 30 m such as road construction may not be apparent in the images, broader anthropogenic footprints such as human settlement development, and agricultural development are apparent and visual in the Landsat images. Even though images higher in spatial resolution than 30 by 30 m could have been used in this study, the Landsat images freely available are still suitable for a study to assess land use processes in the forest ecosystem and have been used in several studies in more complicated landscapes than the TOFR (e.g. Basommi et al., 2015; Acheampong et al., 2018). We took a sample of 288 geographically referenced points (ground truths) from the TOFR using a hand-held Global Navigation Satellite System (GNSS) device for use in the accuracy assessment of the classified 2017 Landsat image. Another set of 288 ground truths were sampled from the original 1987 and 2002 Landsat images for assessing the accuracy of the classified 1987 and 2002 images, respectively.

3.3. Landsat image classification process

We classified the Landsat images into agricultural land, developed land, and forest land categories based on field observation in the TOFR landscape and visual inspection of the Landsat and Google Earth Pro images. The forest land cover includes vegetated trees of both deciduous, semi-deciduous, and evergreen plants. The agricultural land use/land cover is made up of row crops, footprints of harvested crops, and herbaceous plants. The developed land class is made up of human settlement land use, industrial (mining) land use, and transportation land use/land cover.

To attain these final land classes, we composited image bands 1, 2, 3, 4, 5, and 7 of the TM 5 images and bands 2–7 of the OLI/TIRS 8 images. We made use of only tier 1 surface reflectance images. According to the United States Geological Survey (USGS), the tier 1 images are of quality (geometrically and radiometrically corrected) which facilitates time-series analyses without any further corrections or preprocessing. However, even though the tier 1 images are of higher quality, the ones collected for the TOFR still had haze cover. In ERDAS IMAGINE, we applied the Atmospheric and Topographic Correction (ATCOR) tool, and this made sure that all haze covers are removed from the images. This operation improved image visualisation and discrimination between the land classes.

Land change researchers use different classification algorithms to classify satellite images. These algorithms range from the parametric supervised and unsupervised classification to non-parametric supervised machine learning algorithms. The non-parametric classifiers have gained prominence in recent years due to their higher accuracy in classifying satellite images (Lu and Weng, 2007; Qian et al., 2015; Löw et al., 2015). Even though classifiers are selected at the discretion of researchers, the classification accuracy power of the algorithms is likely to influence the choice of classification algorithm used. We used Random Forest, a machine learning classifier for the Landsat image classification. Random Forest algorithm searches only within a randomly selected sample of the input variables to determine a split (Breiman, 2001; Gislason et al., 2006; Griffiths et al., 2014). Each of the trees in the Random Forest votes for the most popular class as the input and the final decision is made based on a majority vote across all the trees (Breiman, 2001).

In this study, we trained Random Forest models using 500 decision trees. The square root of the number of input bands was used as the number of random features at each of the decision trees (see example in Gislason et al., 2006). We trained the RF classifier using 215, 120, and 117 training samples of forest cover, agricultural land, and developed land, respectively, and these samples were selected from the original Landsat images. With the Random Forest algorithm, we created multiple CART-like ensembles of individual trees with each of the trees trained on a Bootstrap sample of the original training data. Random Forest classifier does a more accurate classification and performs better than some machine learning algorithms because it uses a group of classifiers instead of a single classifier (Gislamire et al., 2010). Apart from the accuracy, Random Forest can handle noise in data, does complex measurements, and works well with a small number of training samples relative to the size of the study area (Rodriguez-Galiano et al., 2012). In this study, the classified Landsat images were assessed for accuracy using the 288 geographically referenced points collected from the TOFR.

| Table 1 | Landsat images used and their properties. |
|-----------------|-----------------|-----------------|-----------------|-----------------|
| **Image acquisition date** | **Landsat Sensor** | **Cell size** | **Target WRS Path and Row** | **Projection** |
| 2017-12-25 | OLI/TIRS 8 | 30 | path = 195, row = 055 | WGS84 |
| 2002-12-23 | TM 5 | 30 | path = 195, row = 055 | UTM,ZONE 30N |
| 1987-12-31 | TM 5 | 30 | path = 195, row = 055 | WGS84 |

Note: TM is Landsat Thematic Mapper, and OLI/TIRS is Operational Land Imager/Thermal Infrared.
and the original 1987 and 2002 Landsat images. The agreements and disagreements between the reference data and the classified Landsat images have been reported in the results section of the paper.

3.4. Calculating land change using intensity analysis

3.4.1. Description of intensity analysis

We used a post-classification change detection technique to calculate the number of pixels of land cover that converted from one land category to another. The number of pixels showing land cover conversions was used in calculating the annual percentage change (losses and gains) and transitions in the land cover categories with the aid of intensity analysis. With the intensity analysis, changes in the land categories were calculated at three levels: time interval, categorical, and transition levels (Aldwaik and Pontius 2012). At each level of the analysis, a hypothetical uniform change or intensity is compared with an observed change or transition. The notations describing the elements of the equations used in calculating either the change or transition at every level of the analysis are in this subsection (3.4.1). The remaining subsections under Section 3.4 show how the equations were used in calculating land changes in the TOFR.

J number of categories; i index for a category at the initial time point for a particular time interval; j index for a category at the final time point for a particular time interval; m index for the losing category in the transition of interest; n index for the gaining category in the transition of interest;

T number of time points; t index for the initial time point of interval [Yt, Yt + 1], where t ranges from 1 to T − 1;

Yt year at time point t;

Cti number of pixels that transition from category i at time Yt to category j at time [Yt, Yt + 1];

Si annual intensity of change for time interval [Yt, Yt + 1];

U value of uniform annual change/intensity for time interval

3.4.2. Interval level of the intensity analysis

Eq. (1) calculates the gains Gij in each of the categories, and Eq. (4) calculates the losses Lij in each of the land categories. Eq. (1) calculates a value for uniform intensity for time interval t for the category level of the analysis. Therefore, Eq. (1) connects the analysis at the interval level to that of the category level. If values of Gij are equal for all j, then they would be equal to Si. Likewise, if values of Lij were equal for all i, then they would be equal to S. At the category level, if the observed gains and losses are higher than the uniform change U (see Eq. (2)), then the categorical change is active. If the observed change is less than the uniform change, then the categorical change is dormant.

\[
G_{ij} = \frac{\sum_{i=1}^{J} \left( \sum_{j=1}^{J} C_{ij} - C_{ij} \right)}{Y_{t+1} - Y_t} \times 100%
\]

(3)

\[
L_{ij} = \frac{\sum_{j=1}^{J} \left( \sum_{i=1}^{I} C_{ij} - C_{ij} \right)}{Y_{t+1} - Y_t} \times 100%
\]

(4)

3.4.3. Category level of the intensity analysis

Eq. (5) shows how a transition Rmn ‘TO’ a category from other categories is calculated. Eq. (6) shows how the uniform intensity Wmn of transition to a category n from all the other categories is calculated. Uniform transition at the transition level is the rate calculated as the quantity of land change distributed uniformly across the entire time extent. If the quantity of land transitions from any of the other categories to n is below a uniform transition intensity Wmn, then n category avoids that particular category. If the quantity of land transition from a particular category to n is above the uniform transition intensity, then that category is targeted by n.

\[
R_{mn} = \frac{C_{mn} / (Y_{t+1} - Y_t)}{\sum_{i=1}^{J} C_{ij}} \times 100%
\]

(5)

\[
W_{mn} = \frac{\left( \sum_{i=1}^{J} C_{mi} \right) / (Y_{t+1} - Y_t)}{\sum_{j=1}^{J} \left( \sum_{i=1}^{I} C_{ij} \right) - C_{mn}} \times 100%
\]

(6)

Eq. (7) shows how the transition intensity ‘FROM’ category m to other categories is calculated. Eq. (8) calculates the value for the uniform transition intensity. If the quantity of land transition (Qmn) from m to another category below a uniform transition intensity Vmn, then category m is avoided. If the quantity of land transition in m is above the uniform transition intensity, then the category m is targeted by the other land category.

\[
Q_{mn} = \frac{C_{mj} / (Y_{t+1} - Y_t)}{\sum_{i=1}^{J} C_{ij}} \times 100%
\]

(7)

\[
V_{mn} = \frac{\left( \sum_{i=1}^{J} C_{mi} \right) / (Y_{t+1} - Y_t)}{\sum_{j=1}^{J} \left( \sum_{i=1}^{I} C_{ij} \right) - C_{mn}} \times 100%
\]

(8)
4. Results

4.1. Accuracy assessment of classified Landsat images

We achieved high levels of accuracy from the Random Forest classification algorithm (see Tables 2-4). As high as 94.79%, 96.53%, and 97.22% overall accuracies were attained for 1987, 2002, and 2017 classified images, respectively. However, some variabilities exist in the levels of accuracy among the specific classes of land. The most accurately classified is 1987, 2002, and 2017 forest land classes whereas the least accurately classified is the developed land category (see Appendix 1).

4.2. Quantity of land categories—forest, agricultural land, and developed land

The forest land class is the largest land category (see Table 2 and Fig. 2). The dominant anthropogenic land use, which is the agricultural land, follows as the second-largest land category. Fig. 2 further depicts the three land categories, namely: forest, agricultural land, and developed land.

4.3. Interval and category levels of intensity analysis

The interval level of the intensity analysis shows an observed annual change of 3.02% (uniform change = 0.67%) between 1987 and 2002. Between 2002 and 2017, a change of 1.27% (uniform change = 0.67%) was measured in the TOFR. The interval level of the analysis does not provide details of the observed changes because the changes measured do not show whether there is a decrease or increase in the forest, developed land, and agricultural land. However, changes at the category level were derived from the interval level of the analysis (refer to Eqs. (3) and (4)) and their connections with Eq. (1). At the category level of the analysis, forest losses are more than forest gains (see Table 3). It was more likely for agricultural land and the developed land categories to increase more than to decrease in both periods. The net gain in the agricultural land category was higher than that of the developed land category in the first period, but in the second period, the net gain in the developed land was higher than that of the agricultural land (see Table 3).

4.4. Transition level of the analysis: land conversions in the forest reserve

The transition level of the intensity analysis provides details of the land conversions between forest cover and other land categories. For instance, 2.8% of agricultural land converted to forest between 1987 and 2002 (see Table 4; also, see Fig. 3). A similar pattern of agricultural land conversion to forest occurred between 2002 and 2017 (see Fig. 3). In the two periods, land conversion from forest to agriculture was higher than conversion from forest to developed land category (see Tables 6 and 7). The high amount of net gain in the developed land category measured between 2002 and 2017 (see Table 3 above) is mostly from agricultural land (see Table 5).

5. Discussion

5.1. Land change (gains and losses)

From the analysis, for the past three decades, the landscape of the TOFR has changed due to the two broad geospatially-measurable anthropogenic activities. The results indicate that forest cover was the largest land cover type in 1987, 2002, and 2017, and it was less likely that the forest cover would increase as compared to the anthropogenic land uses given the rate at which the agricultural land and developed land have expanded. However, the outcome of our analysis suggests that agricultural land increased more than the developed land. Moreover, the result of the forest change analysis implies that forest loss is about twice the gains (net loss), and this suggests that the rate at which the TOFR is losing its forest cover is higher than that at which it is gaining forest cover. This outcome of our study is consistent with that of a study from the Kogya forest reserve in Ashanti Ghana, where there is a significant net loss in the forest cover (Janssen et al., 2018). Also, our findings are consistent with the findings by Hansen et al. (2013) who measured more forest losses than gains in the global forest cover, with the tropical areas experiencing the most substantial quantity of forest losses. In comparison with Hansen et al. (2013), our results suggest that the TOFR is part of the local areas contributing to the global net losses in the forest cover.

Furthermore, the results suggest that the quantity of gain in agricultural land is almost equal to the quantity of loss, especially between 2002 and 2017. This land change pattern is likely to be as a result of the Taungya reforestation, a system aimed at allowing farmers to do a mix of food crop farming and planting of trees (Menzies, 1988; Acheampong et al., 2016; Akamani and Hall, 2019). Hence, any piece of forest land cleared for farming is likely to be replaced in the future by forest cover after the agricultural activities. This form of forest recovery is more likely to be the case because, from the analysis, the agricultural land decreased due to an increase in the quantity of forest. Thus, the transition analysis reveals that in the two periods, agricultural land was more likely to transition into forest cover. Even though the reforestation system has not been fully successful in Ghana, Akamani and Hall, (2019) have noted that it has ensured responsible use of resources and prevented community members from engaging in environmentally destructive practices, including illegal logging, as a source of livelihood in the forest areas. In a similar study, Kalame et al. (2011) concluded that the Taungya reforestation system has been a profitable venture for the government, farmers, landowners, and communities, as well as the environment and thus, provided a ‘win-win’ situation regarding achieving both socio-economic and ecological objectives. In Ghana, the Taungya system has been in practice since the early 1950s to replace lost forest cover in forest reserves where demand for land for anthropogenic activities (e.g., agriculture) is on the rise (Ministry of Lands and Natural Resources, 2012). In such a situation, the Taungya system acts as a negative feedback loop (see Lambin et al., 2003) and a proximate factor for land change (see Geist and Lambin, 2002), and it could be an important land management strategy for facilitating forest recovery in tropical regions where there are pressures on forest cover because of agricultural activities. The importance of these land use and land cover dynamics which involve the mix of food/cash crop cultivation and tree plantation is the mitigation of resource use conflict from ‘tragedy of enclosures,’ a condition caused by the creation of forest reserves which deprives inhabitants of their sources of livelihoods (Monbiot, 1994;
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Andresen and Højrup, 2008).

5.2. Land cover transitions

The results from the TOFR suggest that agricultural land is the primary source of land for activities of developers, and that the developers are less likely to use forest land for their activities. Developers systematically avoid the forestland in the TOFR to some extent. However, the increase in the quantity of the developed land between 2002 and 2017 is likely due to the increasing population and its associated demand for land for human settlement development (Boserup, 2017). For instance, within the district (Atwima Mponua) where the TOFR is located, the population has been increasing by 0.9% per year since 2000 (Ghana Statistical Service, 2014). Political ecologists theorise that, over time, the pressure of population and political forces can create tension between national conservation goals and community livelihoods (see Bryant, 1997; Bryant and Bailey, 1997; Forsyth, 2004). With time, such pressure could dissipate gains made in forest recovery or worsen current trends of deforestation.

The transition from forest to agriculture in the TOFR corroborates findings from other tropical forest studies (see Arima et al., 2011; Reddy et al., 2016; Vijay et al., 2018). Bourgoin et al. (2020) for instance, have noted that in the Central Highlands of Vietnam, an expansion in agricultural frontiers contributes to forest cover vulnerability and degradation. In West Africa, Norris et al. (2010) have identified human activities including expansion in agricultural activities, wood extraction, and infrastructure extension as the cause of forest landscape modification. However, in most of the tropical rainforests of West Africa, remote sensing studies have shown that agriculture significantly contributes to forest landscape change (Norris et al., 2010). With specific reference to forest reserves, the transition of forest cover into agricultural land in the

### Table 3

<table>
<thead>
<tr>
<th>Land category</th>
<th>Gains percentage of 2002 category</th>
<th>Losses percentage of 1987 category</th>
<th>1987–2002 net loss/gain</th>
<th>Uniform Intensity percentage of the interval’s domain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forest</td>
<td>4.33</td>
<td>-8.06</td>
<td>-3.73</td>
<td>3.02</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>5.07</td>
<td>-2.72</td>
<td>2.35</td>
<td>3.02</td>
</tr>
<tr>
<td>Developed land</td>
<td>2.51</td>
<td>-1.13</td>
<td>1.38</td>
<td>3.02</td>
</tr>
</tbody>
</table>

### Table 4

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>FromCategory</td>
<td>Transition Intensity% of 1987 category</td>
</tr>
<tr>
<td>Forest</td>
<td>Uniform Intensity% of 1987 non-forest</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>2.80</td>
</tr>
<tr>
<td>Developed land</td>
<td>0.002</td>
</tr>
<tr>
<td>Forest</td>
<td>Uniform Intensity% of 1987 non-agricultural land</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>0.75</td>
</tr>
<tr>
<td>Developed land</td>
<td>0.16</td>
</tr>
<tr>
<td>Forest</td>
<td>Uniform Intensity% of 1987 non-developed land</td>
</tr>
<tr>
<td>Agricultural land</td>
<td>0.14</td>
</tr>
<tr>
<td>Developed land</td>
<td>0.45</td>
</tr>
</tbody>
</table>

Fig. 2. Land use/land cover classes in the Tano-Offin forest reserve.
TOFR echoes the findings from the Atewa Forest Reserve (AFR). Kusimi (2015) reported that pressure from farmers at the fringes of the AFR has converted forest cover into agricultural land and bushes. Alo and Pon- tius (2008) found that logging is the leading contributor to forest cover loss inside protected areas whereas agricultural activities are the primary significant factor for forest cover loss outside of the protected areas in most of southern Ghana. Nonetheless, the forest change pattern in the TOFR is different because agricultural activities and the expansion in the developed land inside the reserve are the major proximate factors contributing to forest change. Similar to our findings, Janssen et al. (2018) have found that arable farming is the main contributing factor for forest loss in the Kogya forest reserve area. In the Brong Ahafo and Western Regions of Ghana, forest loss is mostly attributed to human settlement development (Benefoh et al., 2018). Whereas human settlement development is part of the developed land in the TOFR, in general, the developed land does not primarily target forest cover. This reveals the differences in land use dynamics in different parts of Ghana.

Furthermore, the results suggest that forest growth systematically targeted agricultural land, and hence, it was more likely for the forest land to recover from agricultural activities. This mode of forest recovery could be due to the establishment of forest plantations or the reversal of agricultural land to forest through natural regeneration. This assertion is supported by Kusimi’s (2015) scholarly work, which found that the abandonment of land cover types such as agricultural land and bare land is likely to change the biophysical characteristics of the land cover and convert them to other land cover classes. Even though forest recovery is likely to improve the ecological integrity in the forest area, it is known to have food security implications as farmers would not get the opportunity to do continuous food cultivation (Feng et al., 2002).

Moreover, the results suggest that whereas developers avoid forests to a greater extent, they tend to target agricultural land, a land category likely to be converted into forest cover. The developers, therefore, indirectly target forests. The relationship between land use processes and land cover change characteristics could be indirect. Hence, this insight from the TOFR shows there is a complicated relationship between land cover change and the factors or processes contributing to the

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**Table 5**

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Transitions TO Forest</th>
<th>Uniform Intensity% of 2002 non-forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural land</td>
<td>0.0005</td>
<td>2.26</td>
</tr>
<tr>
<td>Developed land</td>
<td>2.10</td>
<td>2.60</td>
</tr>
</tbody>
</table>

**Table 6**

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Transitions FROM Forest</th>
<th>Uniform Intensity% of 2002 non-forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural land</td>
<td>4.22</td>
<td>2.71</td>
</tr>
<tr>
<td>Developed land</td>
<td>1.19</td>
<td>2.71</td>
</tr>
</tbody>
</table>

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Fig. 3. Land change/transition areas in the Tano-Offin Forest Reserve. The plain (white) areas in the study area boundary indicate locations that have not changed in the periods between 1987 and 2002 and 2002 and 2017.
Table 7

<table>
<thead>
<tr>
<th>Time Interval</th>
<th>Transitions FROM</th>
<th>ToCategory</th>
<th>Transition</th>
<th>Intensity%</th>
<th>2002 non-forest</th>
<th>2002 category</th>
<th>% of 2002 non-forest</th>
<th>% of 2002 category</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002–2017</td>
<td>Forest</td>
<td>Uniform</td>
<td>0.02</td>
<td>1.96</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Agricultural land</td>
<td>Transition</td>
<td>3.92</td>
<td>1.96</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Developed land</td>
<td>Transition</td>
<td>0.02</td>
<td>1.96</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The theory of Agricultural Adjustment to Land Quality (AALQ) explains the transition of land from agriculture to forest (Mather and Needle, 1998). The AALQ theorists argue that a piece of land released from agricultural activities would possibly convert into forest. From our analysis, we show that part of the agricultural land regenerated into forest land in locations where there are limited agricultural land by developers as evident from our analysis. It is not likely for forestland to regenerate after developers have used it for expanding the developed land.

change. This form of human-environment interaction in the TOFR can be said of other reserves in Ghana and beyond through the concept of ‘progressive contextualization’ (Vayda, 1983) which explains human-environment relationships by placing them within progressively wider or denser contexts. That is, comparing the translocal to broader contexts with similar environmental challenges. The land use processes (e.g. cutting down the forest trees for agricultural and developed land expansion) have been the proximate factors for the forest change pattern in the TOFR. However, forest land cleared for agricultural activities would likely regenerate when activities come to an end, and the agricultural land is abandoned (Neptad et al., 1991). In the TOFR, re-growth of forest could be made less likely due to the use of agricultural land by developers as evident from our analysis. It is not likely for forestland to regenerate after developers have used it for expanding the developed land.

The proximate factors contributing to change in forest land are likely to be different in different locations depending on the types of anthropogenic activities taking place. For instance, in the AMD where more than 85% of the population engages in agricultural food crop farming (Ghana Statistical Service, 2014), it is evident that the significant threat to the forest reserve would be encroachments due to agricultural activities. Conversely, in communities where the primary economic activity is wood processing, the significant proximate factor for forest degradation would likely be logging. Whereas focusing on proximate factors may be necessary, paying attention to the underlying social, economic, cultural, and political factors are equally relevant because such factors drive the human-environment interactions which result in land use and land cover change over time. For example, in the TOFR, combating the increasing agricultural land may be unlikely without the provision of alternative livelihoods to the people (in the admitted village) whose lives revolve around subsistence farming, both socio-economically and culturally.

Policymakers and resource governance plans would have to reconcile the ecological, socio-economic, and cultural values of the TOFR and use optimal measures that satisfy all stakeholders who are affected by the TOFR or whose activities affect the TOFR. In the Eastern Mau forest reserve (in Kenya) where food crop farming and developed land expansion contribute significantly to forest loss, Were et al. (2013) have recommended an integrated policy that includes agricultural productivity enhancement while restoring and conserving the forest ecosystem. This recommendation has been reiterated by Ward et al. (2018), whose scholarly work highlights the adverse livelihood outcomes resulting from protected area-related regulations in Madagascar. An integrated land management and policy consideration could reduce the rate of agricultural expansion, preserve rural livelihoods, and achieve conservation goals.

The rate at which the developed land increased (with a net gain of 1.38% and 1.1.73% in 1987–2002 and 2002–2017, respectively) as indicated in our study results shows the need to incorporate the task of regulating the rate at which communities admitted into the TOFR expand. For instance, the forest policy of Ghana does not address the unforeseen but inevitable increase in population and its associated increase in the developed land. The results from TOFR show that developed land systematically targets agricultural land. Therefore, within the reserve, there could be a competition for land for food crop cultivation and development (e.g., human settlement, mining, and access roads). The results from the TOFR corroborate with other studies in Ghana which have found that the developed land expansion is a threat to food security because of the higher rate of transition from agricultural land to developed land (Appiah et al., 2019; Korah et al., 2018). Land managers and land use planners are, therefore, to ensure sustainable use of the various land categories by the communities admitted into the forest reserve. For the agricultural land actively increasing more than any other land category, it is the responsibility of forest managers to ensure that the adverse or unintended effects are managed to maintain the ecological integrity of the forest.

6. Conclusion

In this study, we measured forest cover change in the Tano-Offin Forest Reserve and showed how land use categories resulting from human-environment interactions are contributing to changes in the forest cover. With the Random Forest classification algorithm, high levels of accuracy were achieved in classifying 1987, 2002, and 2017 Landsat images. Thus, we measured minimal commission and omission errors in the mapped land classes, and some of these minimal errors could account for some of the observed land changes we measured. The
intensity analysis of the land use and forest change dynamics has revealed land changes beyond measuring only the net changes in the land cover. It could be beneficial in determining land conversions in locations with increasing anthropogenic-induced vegetation cover changes and thus, likely to inform the need for land use policy amendment.

The study finds that the expanding developed land avoided the forest cover yet targeted the agricultural land, the land category that was likely to convert into forest cover.

Based on this result we conclude that the conversion from agricultural land to forest cover would be fully possible if there are plans to ensure that abandoned agricultural land is reserved specifically for forest recovery and not taken over by other land uses. In locations where vegetation cover (e.g., forest) is under very strict protection, and the developers are restricted from developing at the expense of the vegetation, abandoned agricultural land is likely to be put to other uses since that might be the only way developers could undertake their activities without tampering directly with the integrity of the vegetation.

With the results from the TOFR, we conclude that forest policy formulation should incorporate multiple and a variety of proximate and underlying factors contributing to forest cover change depending on the location, culture of forest communities, and the socio-economic characteristics of the communities whose activities are a threat to the forest reserves. A forest policy that targets the proximate factors such as the ones we have found in this study may be futile if the indirect factors driving the proximate factors are not attended to. The onus is on forest managers to further investigate the factors that drive the land use processes found in this study, especially factors that could not be captured in this land change analysis due to the spatial resolution of the Landsat image. Moreover, since we did not capture a lot of land classes (e.g., dense forest, open forest, grassland) because of the spatial resolution of the Landsat images, we recommend that future studies could use high-resolution images to present further understanding of the loss of ecologically significant forest types. Furthermore, future studies that explore the explanatory variables accounting for the quantity and pattern of forest patches are recommended for the understanding of how anthropogenic and biophysical factors influence the forest cover patches.

Declaration of Competing Interest

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Compliance with ethical standards

The authors wish to declare that they have no conflict of interest. This study did not involve any human subjects.

Supplementary materials


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