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Analyzing Variations in Size and Intensities in Land Use Dynamics for Sustainable Land Use Management: A Case of the Coastal Landscapes of South-Western Ghana

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Abstract: Land use/land cover change (LULCC) studies are gaining prominence among environmentalist and land use planners. This is due to the effects of LULCCs on natural ecosystems and livelihoods. In the coastal landscape of south-western Ghana, there exist knowledge gaps in the variations in size and intensities in LULCCs and the degree of change among land cover types in LULCC studies. Such studies are important for identifying periods of rapid land cover transitions and their implications on the landscape. Using change detection, intensity analysis and informal stakeholder conversations, the land use system dynamics of the study landscape was analyzed over a 34-year period to assess the variations in size and intensities in LULC transitions and its implications. The results showed a dynamic landscape driven primarily by rubber and settlement expansions. Rubber and settlement increased threefold (172.65%) and fourfold (449.93%) in the 34-year period mainly due to rubber outgrower scheme and onshore infrastructural developments, respectively. Gains in rubber and settlement targeted arable lands. The LULCC implies local food insecurity issues, declines in ecosystem services and compromised livelihoods, hence, the enforcement of the Land Use and Spatial Planning Act (2016) is recommended in land use planning in the coastal landscapes of south-western Ghana.

Keywords: land use dynamics; intensity analysis; socio-economic factors; sustainable landscape development; Ghana

1. Introduction

The sustainability of landscapes remains a challenge in many parts of the world. There are greater concerns about the potential loss in the delivering of ecosystem goods and services from landscapes to humankind [1]. Several factors such as land use changes, climate change, biodiversity decline and ecosystem degradation are noted threats that reduce the capacity of landscapes to provide benefits to humans [2–5]. Unfortunately, the region that tends to be more vulnerable to and suffers from the impacts of landscape degradation are the local communities in the Global South, especially in Sub-Saharan Africa (SSA). In SSA, the landscapes within local communities are created by socio-ecological systems, which often consist of local people and their local ecosystems in a strongly interdependent and interrelated manner [6,7]. The interaction within socio-ecological systems are the result of spatially heterogeneous and mosaic landscapes exhibited in many parts of SSA [8]. Several studies indicate the pressures within the interaction of socio-ecological systems in SSA. A recent study found a greater portion of the world's nature-dependent people in the locations of SSA [9–11]. SSA is also known as the fastest urbanizing region in the world, where rapid population, uncontrolled infrastructure and settlement expansions are accounting for the 4.1% population growth rate in SSA, compared to the 2.0% global rate [12]. Other studies also indicate how factors, such as extreme poverty, result in the overuse of natural resources and environmental degradation in SSA [13,14]. These added pressures contribute to landscape changes, which is more intense now than before. Increasing understanding on the changing landscape and the trade-offs in land use/land cover (LULC) dynamics is of greater concern towards the sustainable development of the landscapes [15–18].

The south-western part of Ghana consists of a coastal landscape characterized by smallholder agricultural farming. Like many others, this landscape faces increasing competition between meeting the growing livelihood, material and food needs of inhabitants, biodiversity and ecosystem sustenance. In recent years, the landscape has witnessed socio-economic activities, which is driving in-migration, population increase and associated LULCCs [19–24]. The modification in land uses to meet the increasing population needs on the landscape is occurring at the expense of arable and fallow lands, which had a primary function for producing food and supporting local livelihoods [19,25]. According to [26], LULCC is regarded as the most important variable of global change affecting ecological systems, with an impact on the environment as great as that associated with climate change. Hence, considering the nature of the study landscape, which has the challenge of producing food and supporting rural livelihoods, makes this study important for understand the changing land use systems and their implications over time.

Research with an interest in LULC dynamics of the coastal landscapes of south-western Ghana has grown in recent years. Previous studies have examined the driving forces, pressures and implications of LULC dynamics [22,27], land acquisition and conflicts [28,29], and livelihoods [30]. However, these studies provided no spatial dimension. In contrast, studies that focused on the spatial composition of LULC dynamics focused mainly on the transitions among land cover types. These studies failed to address the variations in size and intensities among land cover transfers [19,21,27,31]. In general, the degree to which LULC is changing, in terms of gains and losses, spatial patterns of change and underlying processes contributing to LULC changes, are largely unknown in LULCC studies in the coastal landscapes of south-western Ghana. Understanding these knowledge gaps helps in identifying periods of rapid land cover changes and the underlying causes to support effective sustainable land use management. The lack of such information makes integrating information on LULCC into land use planning and management challenging and anecdotal in the study landscape. The sustainable development goals (SDG 2) emphasize the sustainability of smallholder mosaic landscapes for food security and livelihoods, hence land use activities that demonstrate sustainability functions should be promoted. In light of this, understanding the above-mentioned knowledge gaps in the coastal mosaic landscapes of south-western Ghana is therefore important. It provides the basis for sustainable landscape management in the area.

In spatial mapping of complex mosaic landscapes, such as the coastal landscapes of south-western Ghana, misclassification issues arise when an attempt is made to map and quantify land cover types. This is due to the inherent heterogeneity of such landscapes [31–33]. However, as demonstrated in several studies, e.g., [19,34–39], the combination of GIS techniques helps to improve the classification of such complex landscapes using medium resolution satellite images such as Landsat. In order to understand the dynamics of LULCC and the variations in the sizes and intensities of land cover transfers between land cover types, accurate mapping of complex and heterogeneous mosaic landscapes is a prerequisite. By generating information on the variation in size and intensity among land cover transfers, it is possible to identify periods of rapid land cover transitions and identify the changes to smallholder livelihoods, which is essential for policy consideration and sustainable development of the landscape.

This study, therefore, seeks to apply combined GIS techniques of manually digitized polygons with supervised classification and intensity analysis to address the above knowledge gaps, specifically by:

1. Mapping the land use/land cover types, from 1986 to 2020, of the study landscape.
2. Determining the changes that have occurred from 1986 to 2020 in the study landscape.
3. Determining the variations in size and intensities in the spatial and temporal patterns of land cover transition.

2. Materials and Methods

2.1. Study Site

The study was conducted in the Ahanta West Municipal Assembly (AWMA) of Ghana, located in the coastal landscapes of south-western Ghana (Figure 1). The municipality lies between longitude 1°45′00″ W and 2°13′00″ W, and latitude 4°45′00″ N and 4°57′00″ N. The areal extent of AWMA is 591 km^2 and has a population of 138,192 [40]. Ahanta West Municipal Assembly is generally characterized by flat lands and falls largely within the high rainforest vegetation zone. Ahanta West Municipal Assembly is bounded to the west by the Nzema East Municipal Assembly, to the east by the Sekondi–Takoradi Metropolitan Assembly (STMA), to the north by Mpohor Wassa East District and Tarkwa-Nsuaem Municipal Assemblies, and to the south by the Gulf of Guinea.

The municipality is among the wettest places in Ghana, experiencing a double-maxima rainfall with a mean annual rainfall exceeding 1700 mm. The relative humidity is very high, and it averages between 75% and 80% during the rainy season and 70% to 80% during the dry season [41]. The highest monthly mean temperature is 34 °C between March and April, while the lowest mean temperature of 20 °C is recorded in August. The region has a dendritic drainage pattern and positively impacts soil fertility for agricultural purposes and other local livelihood support [42,43].

The landscape of AWMA is largely rural, with about 66.8% of the population dependent on the natural environment and ecosystems for food and livelihood [42]. Though largely rural, AWMA is also unique in its fast-growing peri-urban areas. In recent years, AWMA has become the 'epicenter' of ongoing socio-economic activities within the coastal landscapes of south-western Ghana, resulting in land use/land cover transformations in varying degrees.

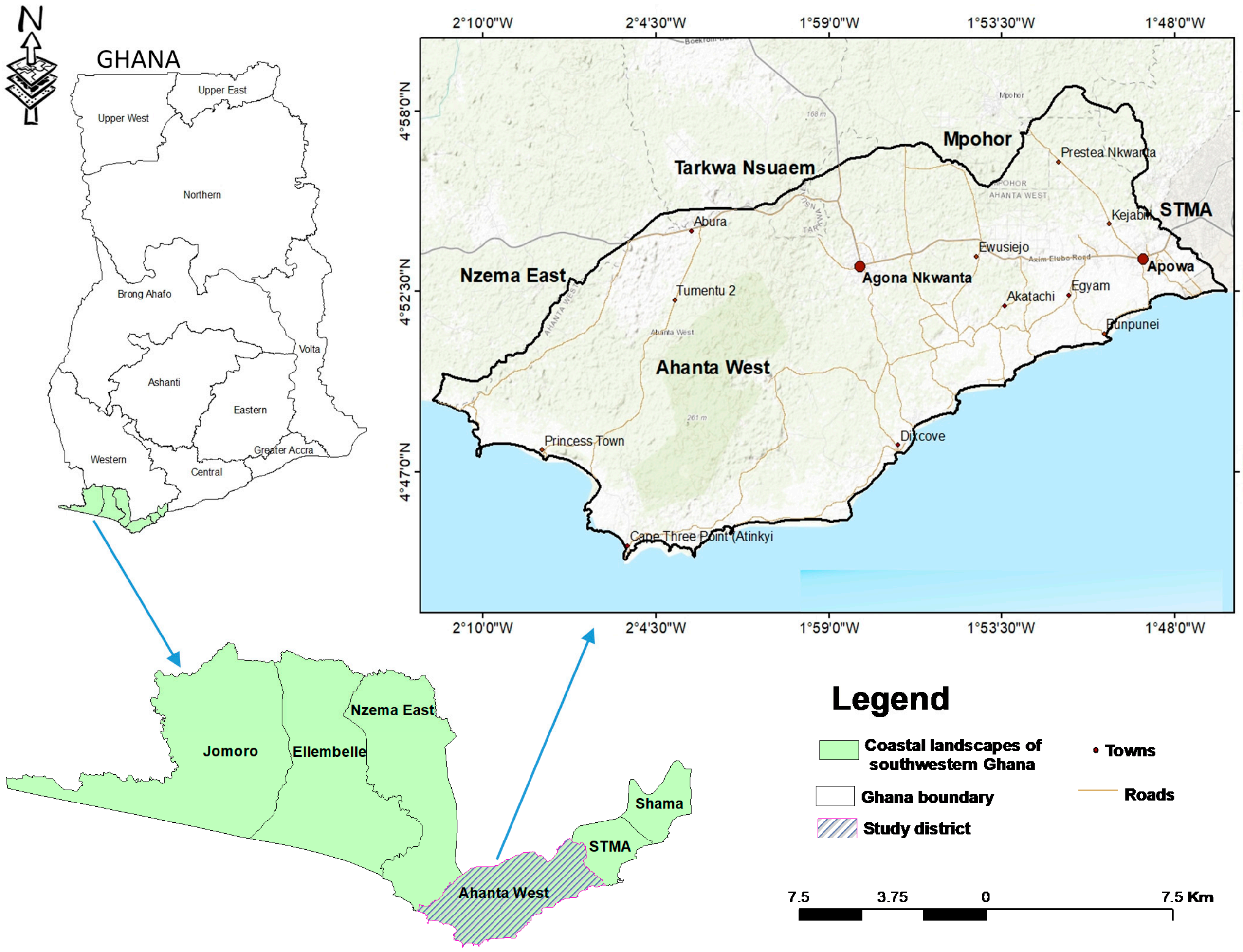

Figure 1. Location of AWMA on the coastal landscape of south-western Ghana.

2.2. Satellite Imagery Acquisition and Processing

Following the methodological flowchart in Figure 2, first, the study used cloud-free multi-temporal Landsat images from 1986, 2002, 2015 and 2020 of AWMA (Table 1). Ortho-rectified Level 1 Landsat data of path/row 194/57 were downloaded from the USGS Earth explorer web platform (https://earthexplorer.usgs.gov/, accessed on 25 August 2021). The images were selected based on availability, absence of cloud cover (10% cloud cover threshold), and low haze levels. Although the four images are not anniversary images, they were all dry season data and had similar atmospheric and phonological conditions [7]. Hence the study performed radiometric corrections involving top of atmosphere reflectance (TOA) and dark object subtraction (DOS) before further analysis began. Finally, the image bands were combined into a single multispectral image composite, and the study area was extracted using the district boundary shape file.

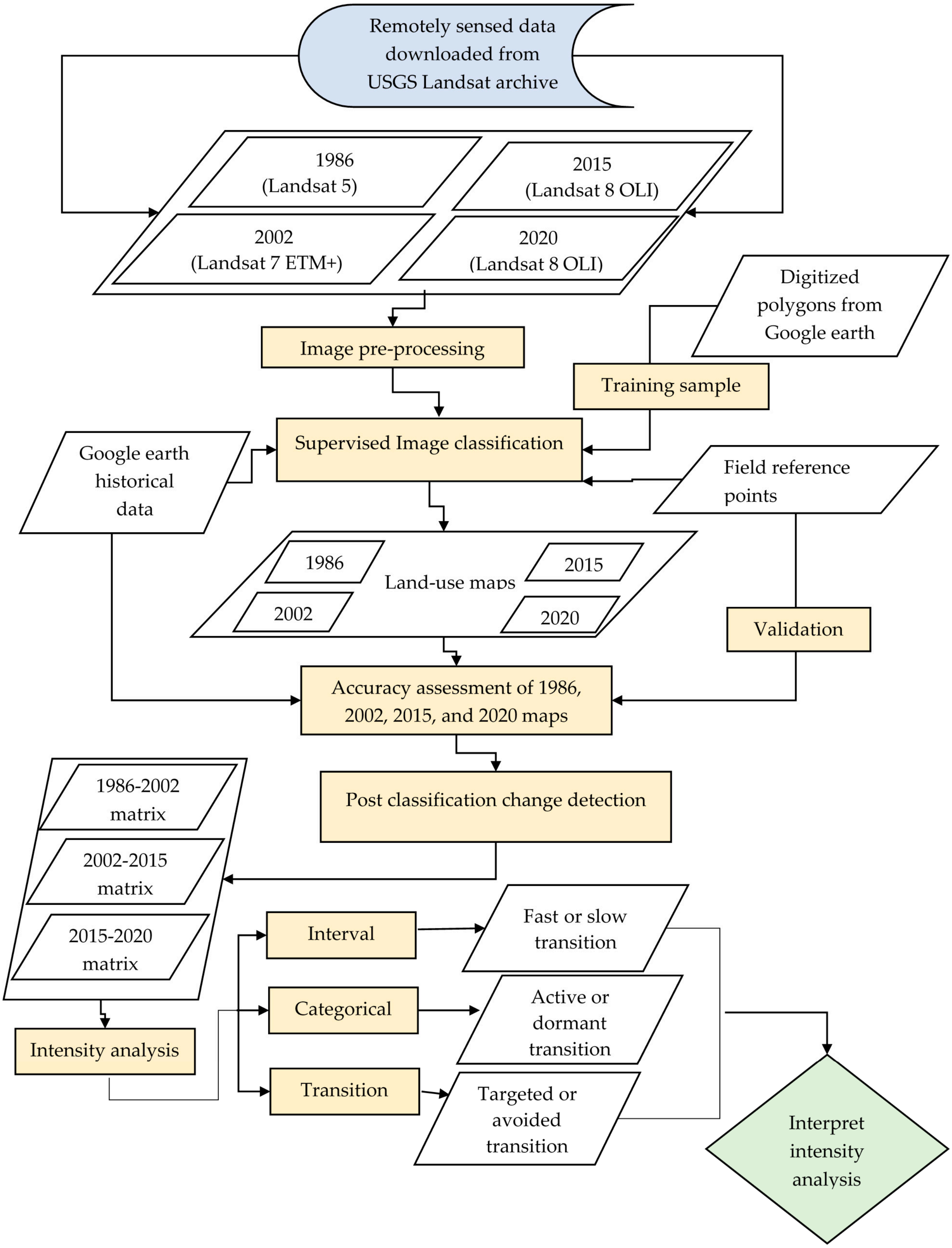

Figure 2. Methodological flowchart for the LULCC and intensity analysis study.

Table 1. Information on Landsat images acquired for the study.

Data	Acquisition Date	No. of Bands	Spatial Resolution (m)
Landsat 5 (Thematic Mapper (TM)	29 December 1986	7	30
Landsat 7 (Enhanced Thematic Mapper (ETM +)	15 January 2002	8	30
Landsat 8 (Operational Land Imager (OLI)	11 January 2015	11	30
Landsat 8 (Operational Land Imager (OLI)	9 January 2020	11	30

2.3. Identification of Classification Scheme

The study used a classification scheme that was generated through researchers' existing knowledge of the study site [44,45]. This was further agreed upon with stakeholders on the study landscape to reflect context-specific land cover types. There were eight land cover types identified and used in this study (Table 2).

Table 2. Classification scheme of land cover types used in the study.

LULC Types	Description
Settlement	Rural communities, residential areas, industrial areas, land covered with buildings, bare concrete grounds, roads and other man-made structures
Rubber	Rubber (established plantations and outgrower smallholder plantations)
Palm	Oil palm farms (smallholder* and large-scale plantations). Also included in this category are coconut farms *
Cropland	Annual and biannual food-crop farms. Examples: plantain, cassava, cocoyam and vegetables
Forest	Cape Three Points forest reserve
Shrubland	Land areas with woody vegetation, including open areas, bushes and fallow lands.
Waterbody	Rivers
Wetlands	Wetlands and mangroves

* Smallholder oil palm and coconut farms are integrated with food-crops.

2.4. Field Data Collection and Processing

Field data collection was carried out from March to May 2020, to gather representative datasets as ground truth data. The ground truth data were collected by mapping representative land cover types as points and polygons using a handheld global positioning system (GPS) unit. Since the landscape is highly heterogeneous, the polygons helped to increase the accuracy of matching the sampled area with the corresponding land cover type on the image. Two hundred and seventy-eight (278) ground truth data were collected to classify the 2020 image. Additionally, 356 polygons indicating representative land cover types (Figure 3) were extracted from Google Earth high spatial resolution imagery for inaccessible areas, via on-screen manual digitizing [36]. Six hundred and thirty-four (634) points and polygons were gathered as reference data (376 for classification, 258 for validation) for the 2020 Landsat 8 operational land imager (OLI). Aerial photos from the AWMA physical planning unit were also utilized as well as historical google earth digitized polygons.

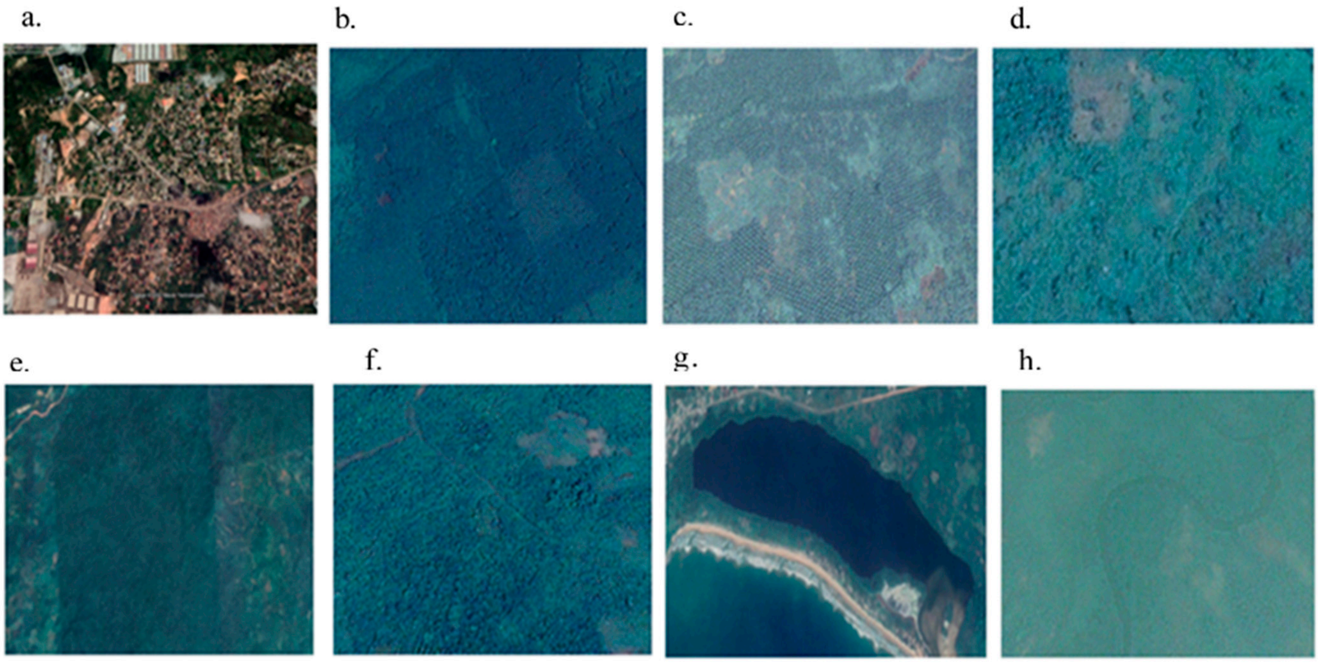

Figure 3. Screenshots of land cover types used in the classification (clipped from google earth image, date: January 2020), (**a**) settlement, (**b**) rubber, (**c**) palm, (**d**) cropland, (**e**) forest, (**f**) shrubland, (**g**) waterbody, (**h**) wetland.

To classify and validate the images of 1986, 2002 and 2015, informal discussions with local stakeholders provided historical information about LULC in the study area. The stakeholders were selected from the following communities: Princess town, Cape Three Points, Akatakyi, Tumentu, Akwidiaa, Abra, Miemia, Apowa, Ponpone, Dixcove and Egyam. The local stakeholders consisted of farmers, chiefs, local inhabitants and the local authorities (e.g., extension officers). A stakeholder engaged in conversation must either has resided on any of the selected towns for over 35 years and/or engaged in various forms of land use activities. Further engagement with the local authorities at the district level generated information on land cover and land use trends. The stakeholders were engaged informally through oral conversations and validation of hearsay. Information gathered from the stakeholder conversations was used to validate the land cover maps and to support the underlying causes of the drivers of land cover transfers on the study landscape.

For identifying and classifying the established plantation areas, shapefiles for the two commercial plantation sites (rubber and oil palm) were acquired from the respective institutions (Ghana Rubber Estate Limited and Norpalm). The shape of the two plantation sites was maintained throughout the four-year land cover maps because the plantations were already established before the start of the study period. The reason for this is that, this study places emphasis on changes in smallholder land cover and use rather than changes in plantation land cover. This is because changes in a plantation site are the primary management goal of the respective plantation firm and do not free up land for smallholder use.

2.5. Land Use/Land Cover Classification

Spectral signatures were extracted from the Landsat images and applied in the maximum likelihood classification (MLC) decision rule to perform a supervised classification in ArcGIS 10.7.1. The training dataset (376 reference data) was used to classify the 2020 image. Similarly, training datasets from Google Earth historical data were used to classify the 2002 and 2015 images. Classification of the 1986 image was based on trends and patterns of unchanged land cover types in the latter images. Misclassified land cover types in all images were correctly classified using on-screen digitized polygons from Google Earth data in ArcGIS Pro.

Validation datasets obtained for each of the four images were used as reference data for the accuracy assessment. The accuracy assessment process resulted in the error/confusion matrixes from which the overall accuracy, kappa statistics, producer and user accuracies were computed

2.6. Change Detection

The study employed post-classification change detection to assess the land transitions between 1986, 2002, 2015 and 2020 and identify land cover types that significantly contributed to the change processes in the landscape. The spatial distribution of change, proportions and rates of change and the transition over time were the focus during the change detection assessment [46]. Change detection approaches continue to be the most often employed methodology in land cover monitoring and assessment studies. The procedure is thought to be time consuming and very sensitive to the combined errors in the two time-period images used [47,48]. However, because of the capacity of the analysis to minimize atmospheric, sensor, and environmental impacts on the output transition matrix, its' use was appropriate for this study [49,50]. Change detection quantifies the differences between independently created land cover maps for two time-periods by analyzing the spatial distribution and areal extent of land features [51].

The union of two time-period LULC maps were used in this analysis, resulting in a LULC change map and a transition matrix. The transition matrix showed the areas changed in converting one land cover type from the initial year to the end of the final year for the two time-periods used. The values indicate the persistence in the diagonal of the transition matrix. On the other hand, the off-diagonal numbers represent the transitions that happened in the land cover categories across the two time-periods. Furthermore, the transition matrix displays the gross gains, gross losses and net change, which is useful information for understanding the types of transitions in the landscape [52]. The aggregate of all individual land cover types in the previous year that have shifted from other land cover types in the subsequent year is called gross gains in land cover mapping. Gross losses are the sum of all land cover types that have changed from the previous year to other land cover types in the subsequent year, whereas net change is the absolute difference between gross losses and gross gains.

2.7. Intensity Analysis in Land Cover Transitions

In the change detection analysis, the transition matrix produced offered a basic overview of the land cover stocks (composition and quantity), and the transfers among land cover types for the study periods 1986–2002, 2002–2015 and 2015–2020. However, the analysis does not identify the underlying processes that drove the changes on the landscape [52]. To address this, intensity analysis, a qualitative framework developed by [53], was used to better understand the underlying processes behind the land cover transitions in the study region [54]. Intensity analysis can be performed at three levels: time interval, categorical, and transition levels [53]. The interval level analysis computes the rate of change and variations in size across a time interval. Categorical level analysis analyzes the variations in intensity of change among land cover types/categories. Finally, transition level analysis focuses on the variations in size and intensity in the gaining land cover type/category compared with other land cover types in each time interval [48,55].

All the three levels of analysis generate a uniform intensity lines, representing a hypothetical condition in which uniform change distribution occurs across all categories. When compared with the uniform intensity, the estimated area in the interval level analysis determines the time interval with the slow or fast annual rate of change. Category level intensity exceeding the uniform line is referred to as an active category, and if the intensity is below the uniform line, it is termed a dormant category. In the same way, in transition intensity, if a gaining or losing category exceeds the uniform intensity line, it is termed as targeted. If it does not reach the uniform intensity line, it is termed as an avoided category [53]. Using equation-infused spreadsheets developed by Aldwaik and Pontius Jr, [56], the transition matrices of 1986–2002, 2002–2015 and 2015–2020 were used as inputs for calculating variations in the size and intensities of land cover types at all three levels of intensity analysis.

3. Results

3.1. Land Use/Land Cover Maps of AWMA for the Years 1986, 2002, 2015 and 2020

The accuracy assessment produced from the error/confusion matrix is shown in Table 3. The overall accuracy of 84.81%, 88.58%, 90.84% and 92.56% was obtained for the 1986, 2002, 2015 and 2020 LULC maps, respectively. Producer accuracy (PA) and user accuracy (UA) were produced using the confusion matrix. Producer accuracy refers to how accurate the prediction is for the specific land cover category. User accuracy measures the probability that the location of a pixel on the map corresponds to the location of the land cover type in the real world. The lowest PA was recorded in the 2002 image for shrubland (72.73%) while the highest of 100% recorded for both UA and PA was seen in several land cover types, for the four respective years.

Table 3. Accuracy assessment results of the LULC classification.

LULC Types	1986		2002		2015		2020	
	PA%	UA%	PA%	UA%	PA%	UA%	PA%	UA%
Settlement	100.00	90.91	100.00	96.97	93.33	100.00	96.67	98.31
Forest	82.09	90.16	92.00	100.00	92.31	92.31	100.00	100.00
Rubber	83.33	82.19	87.18	94.44	92.39	90.43	88.64	91.76
Palm	81.08	83.33	91.11	87.23	92.00	88.46	88.31	88.31
Wetland	88.33	88.33	86.21	92.59	90.91	90.91	96.77	100.00
Shrub land	80.46	81.40	80.00	72.73	86.27	83.02	92.59	90.36
Cropland	85.11	81.63	85.07	86.36	90.52	95.45	89.69	87.00
Waterbody	92.31	92.31	100.00	92.31	88.89	88.89	100.00	100.00
Overall Accuracy	84.81		88.58		90.84		92.56	
Kappa Coefficient	0.82		0.87		0.88		0.91	

The classified LULC maps and their statistics for 1986, 2002, 2015 and 2020 are represented in Figure 4 and Table 4, respectively. Palm (32.4%) and shrubland (28.9%) were the most dominating land cover types in 1986. Cropland covered 13.2%, rubber and forest covered 10.0% and 10.9%, respectively, while settlement, wetland and waterbody occupied less than 5% of the study landscape (Figure 4). The distribution of palm covered almost the entire landscape. Information from key local informants showed that palm distribution in the western landscape was mainly coconut farms. In contrast, palm distribution in the eastern part of the study landscape was mainly oil palm farms. Small patches of palm, together with cropland and shrubland, were distributed across the landscape, primarily around human settlement (communities), whereas rubber and vast tracts of palm were limited to specified plantation blocks.

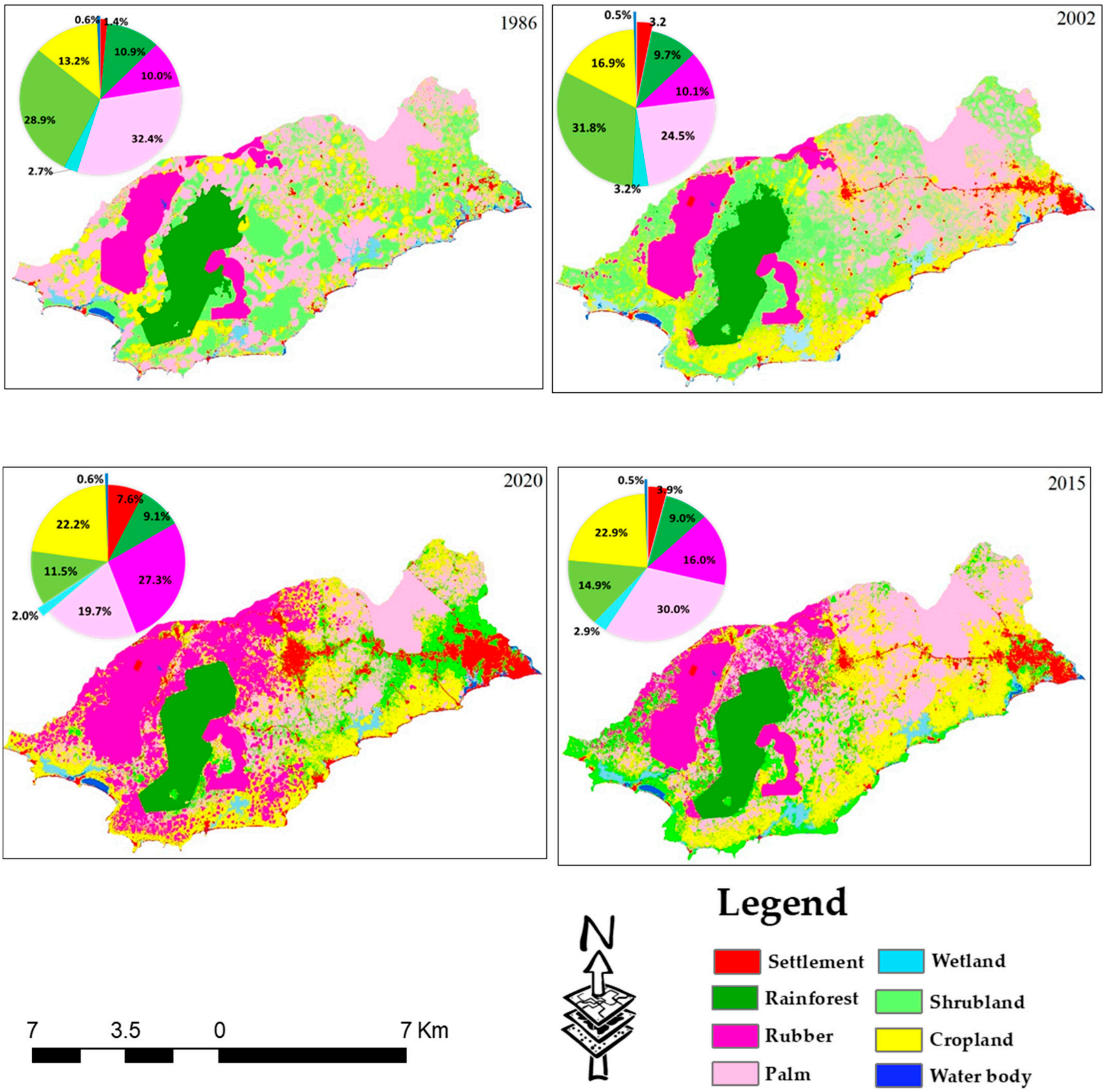

Figure 4. Land cover maps and percentage land share of each land cover types for the years 1986, 2002, 2015 and 2020.

In 2002, the land cover types had not changed; however, the spatial distributions and proportions of these eight land cover types had changed. Palm had reduced in area coverage to 24.5%, shrubland had slightly reduced to 31.8%, while cropland had also increased to 16.9%. Forest now covered an area of 9.7%, with a slight increment in rubber area coverage to 10.1%. Settlement had increased to an area coverage of 3.2%. Wetland covered 3.2%, while exposed waterbodies covered only 0.5%. In 2002, palm in the western part of the landscape (mainly coconut farms) were seen to be disappearing and paving way for shrubland and cropland.

Table 4. Area of land cover category in ha and percentage of change from initial size.

Year	**1986**	**2002**	**2015**	**2020**	**Percentage Change**			
LULC Types	**Ha**	**Ha**	**Ha**	**Ha**	**1986–2002**	**2002–2015**	**2015–2020**	**1986–2020**
Settlement	802.44	1867.41	2282.04	4412.88	132.72	22.20	93.37	449.93
Forest	6341.49	5663.79	5217.66	5315.04	−10.69	−7.88	1.87	−16.19
Rubber	5846.13	5915.88	9309.24	15,939.54	1.19	57.36	71.22	172.65
Palm	18,866.25	14,264.64	17,479.26	11,491.56	−24.39	22.54	−34.26	−39.09
Wetland	1561.32	1869.21	1671.03	1174.86	19.72	−10.60	−29.69	−24.75
Shrub land	16,820.55	18,557.82	8684.55	6676.29	10.33	−53.20	−23.12	−60.31
Cropland	7699.95	9874.35	13,348.80	12,962.43	28.24	35.19	−2.89	68.34
Waterbody	355.59	280.62	301.14	321.12	−21.08	7.31	6.63	−9.69
Total	58,293.72	58,293.72	58,293.72	58,293.72				

Similarly, there was no change in land cover types in 2015, although there were differences in the spatial extent and area proportions of the land cover types. Shrubland had decreased to 14.9%. Palm now covered an area of 30.0%. Cropland had also increased to 22.9%. Rubber had increased to 16.0%, with more rubber trees visible in smaller patches compared with the larger plantation blocks. The smaller patches of rubber trees were seen dominating the western part of the study area. Forest had a slight decrease to 9.0%, with settlement increasing in area coverage to 3.9%. The area increase in settlement is seen in the eastern part of the study landscape. Exposed water bodies remained unchanged while wetland had reduced to 2.9%.

In the same way, there were no new land cover types found in 2020; nonetheless, considerable changes had occurred in the area extent and spatial distribution of the land cover types. Shrubland had significantly decreased to 11.5%. The remaining shrubland on the study landscape dominated the eastern part of the study landscape and shared an immediate border with settlement. Palm had also decreased to 19.7%, with a slight increase in cropland to 22.2%. Rubber had also increased significantly to 27.3%, making rubber the highest dominant land cover type in 2020. The increase in rubber dominated the western part of the study landscape. Forest did not change in area (9.1%). Settlement had also increased to 7.6%, with much dominance in the eastern part of the study landscape.

3.2. Changes in Land Cover Categories, Land Use Trends and Landscape Transitions in AWMA from 1986 to 2020

The stock changes for the entire study period are displayed in Table 4 (percentage change). The entire study period showed varying degrees of changes in all the land cover types in surface areas and coverage. These changes were seen in the area extent and spatial distribution. Settlement increased to more than four times the initial size between 1986 and 2020 (449.93%). Expansions in settlement occurred at 132.72% in 16 years (1986–2002) and 93.37% in only a period of 5 years (2015–2020) (Table 4). The expansion in settlement dominated the eastern part of the study landscape (Figure 4). Rubber, similarly, is the second land cover category that had expanded more than three times the initial size (172.65%), with significant expansions occurring in the period 2002–2015 (57.36%) and 2015–2020 (71.22%) (Table 4). The expansions in rubber dominated the western part of the study landscape (Figure 4). Cropland had also expanded at a little over twice the initial size. All the other land cover categories had reductions in their sizes compared to their initial size, with shrubland losing more than half of its initial size (Table 4).

Table 5 illustrates the landscape transition matrix with the gross gains and gross losses. The transition matrix also details the transfers among the various land cover types/categories over the 34-year study period. The individual study periods are also represented in the appendices (Tables A1–A3). At the end of the 34 years (1986–2020), 59.14% (34476.84 ha) of the landscape had undergone land cover transitions, with 40.86% (23816.88 ha) remaining as persistence. The land cover transition trends for the individual study periods similarly witnessed almost half of the study landscape undergoing land cover transitions (48.73%, 49.74% and 41.05% for 1986–2002, 2002–2015 and 2015–2020, respectively). About two-thirds of the land cover change occurred in palm, shrubland and cropland, with the major land cover transition trend seen in palm changing to cropland/shrubland and later to rubber, palm changing to cropland and later to shrubland, cropland/palm changing to settlement, cropland/shrubland changing to rubber, and shrubland changing to cropland.

At the end of the study period (1986–2020), cropland remained the highest gross gainer on the landscape, gaining 10,777.77 ha (18.49%). On the other hand, cropland lost 5515.29 ha (9.46%), with a net change of 5262.48 ha (9.03%). Changes from cropland were mainly from rubber (3.27%), palm (2.74%), shrubland (2.20%) and settlement (1.10%), while changes to cropland were from shrubland (18.46%) and palm (8.53%). Likewise, rubber became the second largest gainer on the landscape, gaining 10,421.01 ha (17.88%) and losing 327.60 ha (0.56) with a net change of 10,093.41% (17.31%). The major land cover changes to rubber are from palm (7.18%), shrubland (6.58%) and cropland (3.27%). Although cropland was the largest gainer on the landscape, rubber emerged as the largest land cover category with the highest net change (17.31%). This implies that rubber is the first land cover category with the largest extent in land cover changes from other land cover types. Settlement emerged as the land cover category with the third largest extent in land cover changes from other land cover types. Contrary to rubber, cropland and settlement land cover types, with net change values of −17.40% for shrubland and −12.65% for palm, these two land cover types accounted for the first and second land cover categories with the largest extent in land cover change to other land cover types.

Disparities occurred among the individual study periods. Between 1986 and 2002, palm, with a net change of (−7.89%), was the highest land cover category with the largest land cover change to other land cover types (Table A1). In contrast, cropland became the highest land cover category with the largest land change from other land cover types (Table A1). From 2002 to 2015, shrubland accounted for the highest land cover category losing to other land cover types, with 12.87% lost to palm, 7.48% lost to rubber, and 3.87% lost to cropland (Table A2). The period 2015–2020 witnessed net gains in rubber (11.37%) and settlement (3.66%) with net losses in shrubland (−3.45%), palm (−10.27%) and cropland (−0.66%) (Table A3). Land cover change to rubber was mainly from cropland (3.54%), palm (4.02%), and shrubland (3.98%). Land cover change to settlement was mainly from cropland (2.38%), shrubland (1.07%) and palm (0.29%). The other land cover types, forest, wetland and waterbody, contributed marginally to the land cover changes. The landscape experienced high gains and high losses in shrubland, cropland and palm, making them the most dynamic land cover types during the study periods. On the other hand, rubber and settlement recorded higher gains, but losses were very low during the study periods.

Table 5. Cross tabulation matrices for 1986–2020: area in ha (top values), percentage of total land area (bottom value underlined), The diagonal (in bold) values indicates the persistence of land cover types.

	2020										
1986	**Cropland**	**Forest**	**Palm**	**Rubber**	**Settlement**	**Shrubland**	**Waterbody**	**Wetland**	**Initial Total**	**Gross Loss**	**Net Change**
Cropland	**2184.66**	13.14	1599.66	1908.81	640.62	1280.79	7.38	64.89	7699.95	5515.29	5262.48
	3.75	0.02	2.74	3.27	1.10	2.20	0.01	0.11	13.21	9.46	9.03
Forest	312.66	**5225.49**	204.66	452.34	2.88	130.77	1.17	11.52	6341.49	1116.00	−1026.45
	0.54	8.96	0.35	0.78	0.00	0.22	0.00	0.02	10.88	1.91	−1.76
Palm	4972.59	53.46	**6266.16**	4188.24	1179.72	2076.66	3.06	126.36	18,866.25	12,600.09	−7374.69
	8.53	0.09	10.75	7.18	2.02	3.56	0.01	0.22	32.36	21.61	−12.65
Rubber	125.91	3.96	54.90	**5518.53**	80.28	50.13	2.34	10.08	5846.13	327.60	10,093.41
	0.22	0.01	0.09	9.47	0.14	0.09	0.00	0.02	10.03	0.56	17.31
Settlement	41.04	0.09	6.57	5.13	**653.22**	41.13	30.69	24.57	802.44	149.22	3610.44
	0.07	0.00	0.01	0.01	1.12	0.07	0.05	0.04	1.38	0.26	6.19
Shrubland	4933.62	16.92	3335.40	3835.89	1512.18	**3054.33**	5.13	127.08	16,820.55	13,766.22	−10,144.26
	8.46	0.03	5.72	6.58	2.59	5.24	0.01	0.22	28.85	23.62	−17.40
Waterbody	14.40	0.18	0.00	8.91	107.19	0.00	**205.02**	19.89	355.59	150.57	−34.47
	0.02	0.00	0.00	0.02	0.18	0.00	0.35	0.03	0.61	0.26	−0.06
Wetland	377.55	1.80	24.21	21.69	236.79	42.48	66.33	**790.47**	1561.32	770.85	−386.46
	0.65	0.00	0.04	0.04	0.41	0.07	0.11	1.36	2.68	1.32	−0.66
Final total	12,962.43	5315.04	11,491.56	15,939.54	4412.88	6676.29	321.12	1174.86	58,293.72		
	22.24	9.12	19.71	27.34	7.57	11.45	0.55	2.02			
Gross gains	10,777.77	89.55	5225.40	10,421.01	3759.66	3621.96	116.10	384.39			
	18.49	0.15	8.96	17.88	6.45	6.21	0.20	0.66			

3.3. Intensity Analysis of Land Cover Transfers from 1986 to 2020 of AWMA

Analysis at the interval level revealed that the periods 1986–2002 and 2002–2015 experienced slow land cover transitions, while within five years, the period 2015–2020 experienced fast land cover transitions (Figure 5). This implies that, considering the duration of each time period, the rate of land change within five years (third interval) is much faster compared to the rate of land change in the first- and second-time intervals. This makes land cover change in the period 2015–2020 very rapid compared to the previous two time periods (Figure 5).

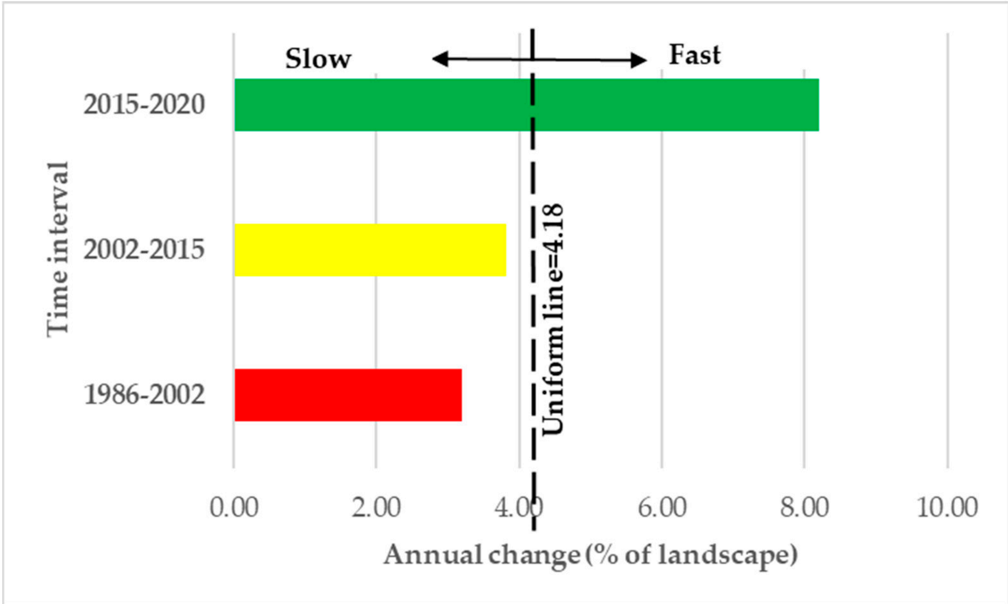

Figure 5. Interval level intensities for 1986–2002, 2002–2015 and 2015–2020.

Figure 6 shows the categories that have undergone active and dormant changes (category level intensity analysis). From 1986 to 2002, gains and losses in rubber, forest, waterbody and wetland were dormant. On the other hand, shrubland and cropland recorded intense active gains and losses. In contrast, land under settlement intensively recorded active gains with dormant losses, while palm had active losses and dormant gains. Between 2002 and 2015, shrubland and cropland were intensively recording active gains and losses, with relatively higher losses in shrubland and relatively higher gains in cropland. In the same period, gains in palm were active, while its losses were dormant. All the other land cover categories experienced dormant gains and losses, with rubber recording the least losses and forest recording the least gains. Similarly, in 2015–2020, active gains and active losses were recorded in shrubland, with a marginal difference between the gains and losses compared to the previous periods (2002–2015). Land under settlement and rubber experienced intense active gains with minimal dormant losses. Palm, in addition to wetland, recorded active losses with dormant gains. Forest remained the single land cover type with the least dormant gains and dormant losses.

Transition intensities observed between land cover categories for 1986–2002, 2002–2015 and 2015–2020 are represented in Figures 7–11. Transition intensities for rubber, settlement, shrubland, cropland and palm were the focus. The hypothetical uniform intensity is represented as vertical dash lines which appear on both sides of the chart. To the left is the uniform intensity explaining the hypothetical uniform value in the intensity of transition that accounted for the losses in the respective land cover category. To the right represent the gains in transition intensity. For example, from 1986 to 2002, the transition to shrubland targeted cropland and palm and avoided the other land cover categories (Figure 11). Similarly, losses in shrubland targeted cropland, palm, and settlement (Figure 11). Expansions in cropland in 2002 targeted palm, shrubland and wetland, while losses in cropland targeted settlement in addition to palm and shrubland (Figure 9). Losses in palm targeted cropland and shrubland (Figure 10), while gains in settlement targeted shrubland, cropland and waterbody (Figure 8). From 2002 to 2015, reductions in shrubland similarly targeted cropland and palm, with expansions targeting cropland and marginally targeting wetland and waterbody. Expansions in cropland in this same period similarly targeted palm and shrubland, while reductions in cropland area targeted shrubland, settlement and slightly targeted wetland. Gains in palm targeted shrubland, while losses targeted cropland.

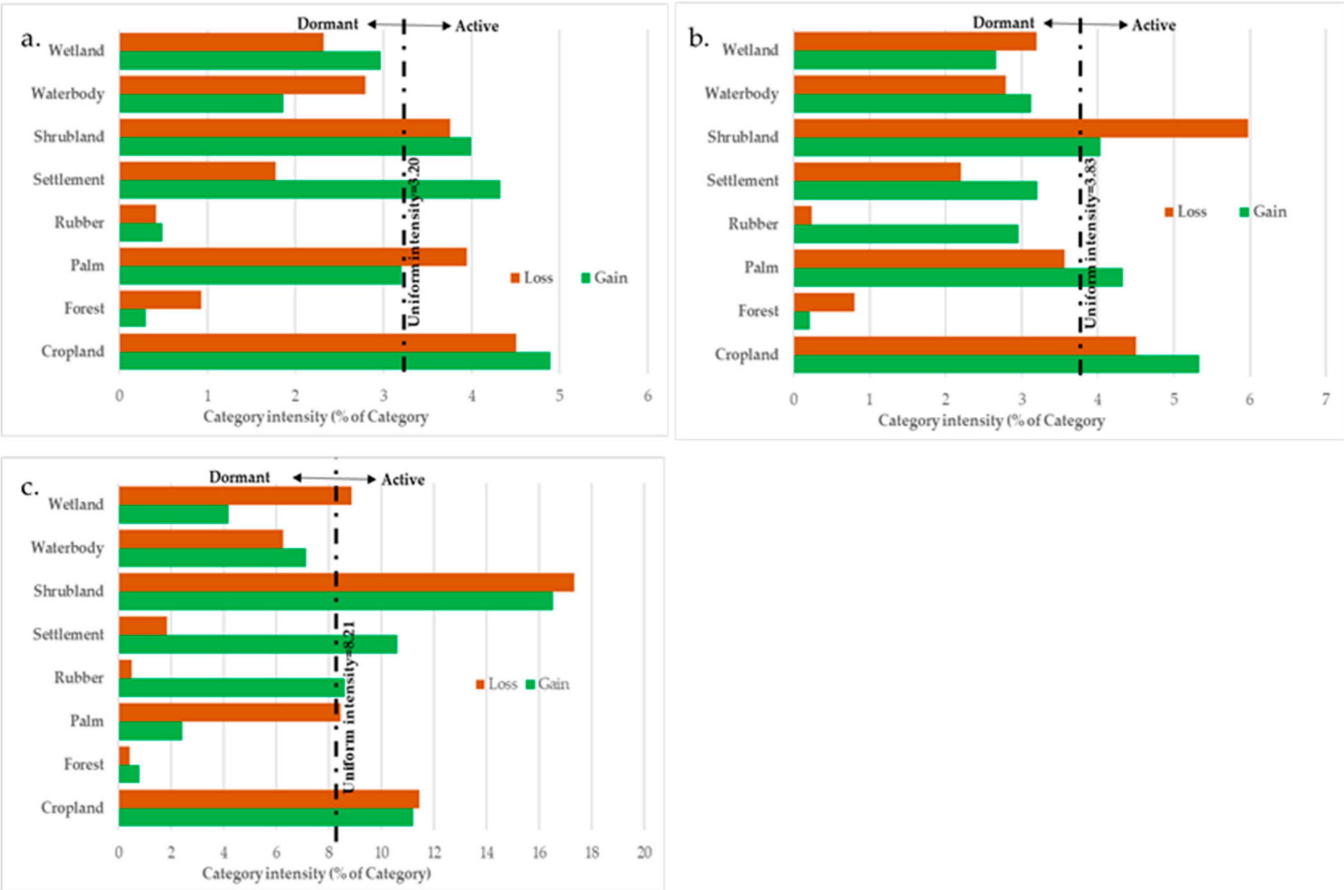

Figure 6. Category level intensities for (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020.

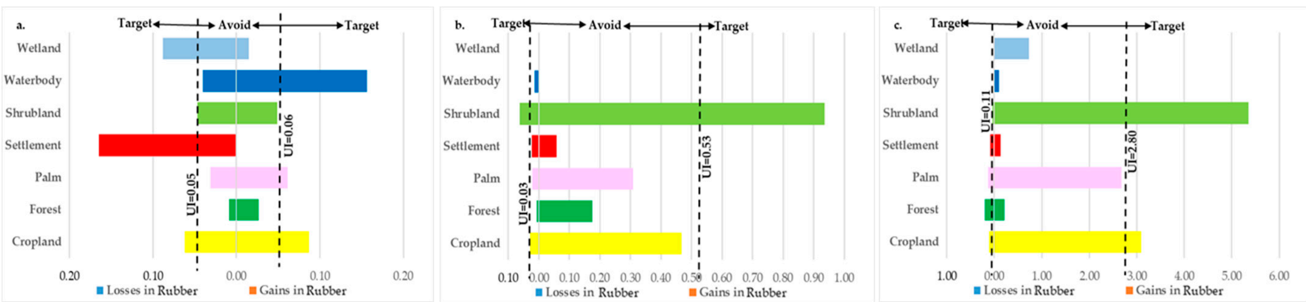

Figure 7. Transition level intensities for rubber for the period (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020 (gains on the right, losses on the left).

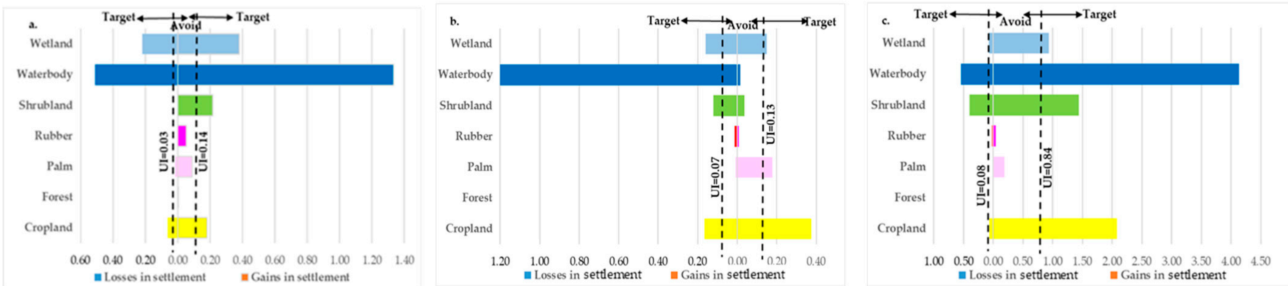

Figure 8. Transition level intensities for settlement for the period (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020 (gains on the right, losses on the left).

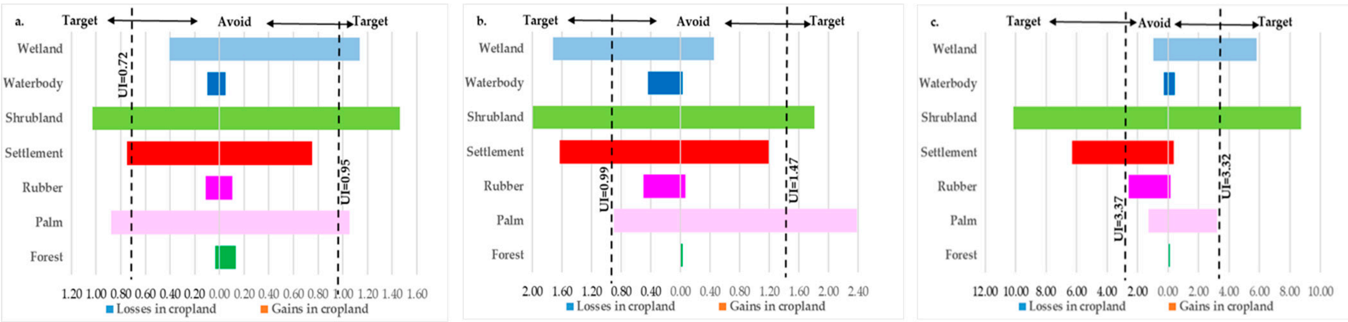

Figure 9. Transition level intensities for cropland for the period (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020 (gains on the right, losses on the left).

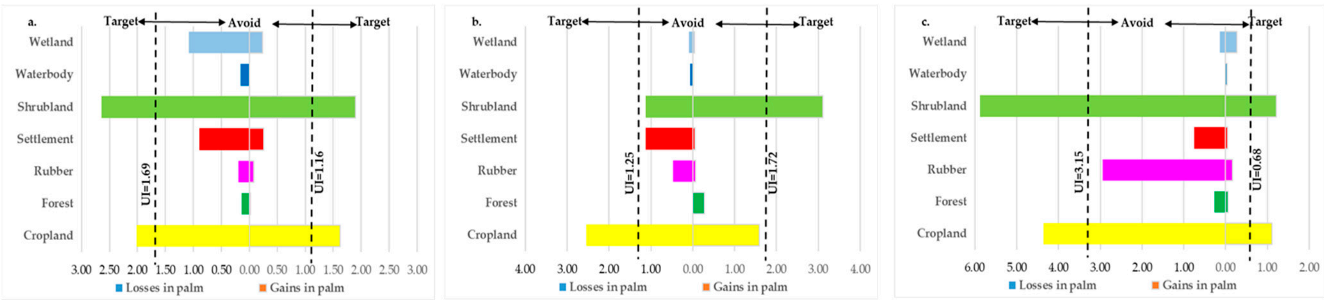

Figure 10. Transition level intensities for palm for the period (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020 (gains on the right, losses on the left).

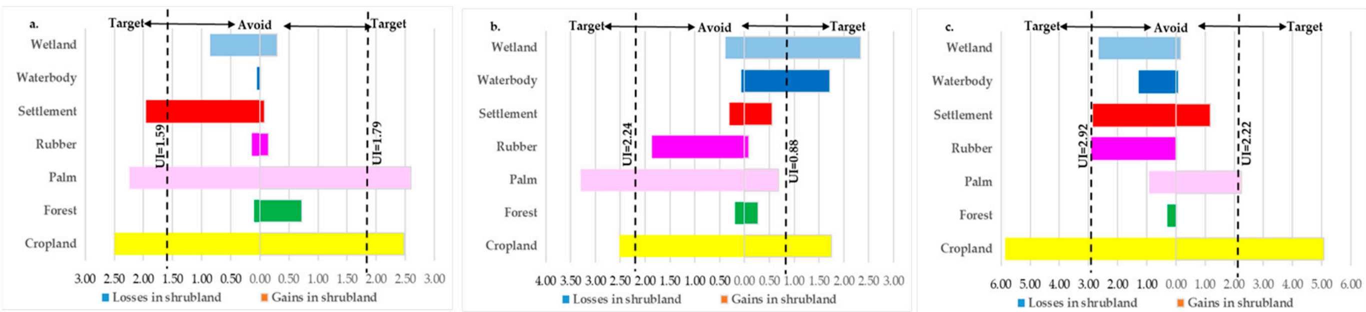

Figure 11. Transition level intensities for shrub land for the period (**a**) 1986–2002, (**b**) 2002–2015 and (**c**) 2015–2020 (gains on the right, losses on the left).

The last five years of the study period (2015–2020) had similar transition intensity trends for cropland, palm and shrubland. In contrast, this period saw expansions in rubber with transition intensity targeting cropland and shrubland and a marginal avoidance in palm (Figure 7). The rubber intensity gain from shrubland was higher than for cropland. Expansion in settlement in this period targeted cropland, shrubland, wetland and waterbody (Figure 8). Losses in settlement targeted the same land cover categories. In both gains and losses for settlement, the intensity was highest in the transition from waterbody and to waterbody (Figure 8).

3.4. Researcher's Observations and Stakeholders' Perceptions on LULC Trends on the Study Landscape

The stakeholders engaged in oral conversations attested that oil palm and coconut farming has been the predominant cash crop cultivation in the study landscape. Coconut trees are grown in the hot wet areas while oil palm occurs on saline soils and in riverine areas. Coconut farming and oil palm occur on smallholder holdings. These crops were grown for economic and household needs such as fuel, indigenous building materials, and raw materials for oil and food. Coconut and oil palm farms are integrated with food-crops such as cassava and vegetables, which increases the profitability of farming. Coconut fruits are consumed locally and are for export to neighboring countries such as Nigeria, while oil palm is cultivated mainly to provide raw materials for the oil palm industry (Norpalm) on the study landscape. The cultivation of coconut and oil palm locks up land during their productive periods. Due to the integration with other food-crops, farmers cultivating coconut and oil palm do not normally switch to other crops.

However, farmers expressed grievances about the compulsory acquisition of oil palm farms with the onset of oil discovery and the need for an oil refinery. The farmers expressed fear of the lack of compensation associated with the compulsory land acquisitions. Farmers could no longer maintain their oil palm farms and switched to seasonal and annual crops until the lands were completely taken over. The chiefs engaged in conversations expressed the amenities that come with urban establishment, such as hospitals, road networks and schools, as the reasons for leasing land for infrastructure purposes to land investors.

The researcher also engaged farmers in the voluntary switching of crop choices to rubber. The farmers expressed higher economic returns in rubber cultivation as the reason for switching crop choices. Specifically, oil palm farmers expressed bad road network and lack of trust with the oil-producing company as the reasons for switching oil palm crops to rubber. Oil palm, when productivity declines, is used in the production of '*akpeteshi*' a locally manufactured alcoholic drink.

Most of the farmers engaged in conversations were of the view to continue to convert any land available in their possession to rubber cultivation. The farmers expect to increase their financial income from rubber cultivation in order to access food and other nature-based needs from the market. The stakeholders expect rubber plantations to dominate the landscape, considering its economic profitability. The farmers are more interested in the financial returns rather than household food sufficiency. The farmers also regard economically rewarding cash crops, such as rubber, as an endowment in the male-headed household. In a male-headed household, men own and control decisions and revenue on land use while the women are responsible for household food security. Any transitions from croplands have setback consequences for the women. All the stakeholders engaged in conversations were more optimistic and never expect a decline in rubber prices. Considering these hopes, further land use transitions at the expense of arable lands are anticipated with household and landscape food security becoming questionable.

4. Discussion

4.1. Land Use/Land Cover Category Mapping in the Structurally Complex Smallholder Mosaic Landscape

The consolidation of manual digitizing of polygons from Google Earth images, the maximum likelihood supervised classification (MLC) and oral discussions with local stakeholders made it feasible to discriminate and map the complex smallholder mosaic land cover types. Google Earth image is, by far, seen to increase the accuracies of image classification with medium resolution satellite images [37,57,58]. The use of digitized polygons from Goggle Earth image assisted in reducing misclassification, a phenomenon highly associated with complex and heterogeneous landscape mapping using medium resolution satellite images. The use of the conventional classification methods enabled a fine-scale land cover mapping in the smallholder complex mosaic landscape and analysis of transfers among the land cover types. The overall accuracies for the 2002, 2015 and 2020 images were higher than the recommended 85% [57–60], mainly due to the manual digitizing of representative land cover types of high resolution Google Earth data that was coupled with intensive field data collection. The high accuracies from manual digitizing agrees with studies such as [34,35]. Clarity challenges associated with historical data from Google Earth may explain the accuracy of the 1986 map falling below the recommended 85% threshold.

The dominant land cover types of the study landscape in 1986 were palm (32.4%) and shrubland (28.9%). However, by 2020, the dominant land cover types were rubber (27.3%), cropland (22.2%) and palm (19.7%). The local stakeholder conversations revealed that palm (coconut and oil palm) has been the major cash crop grown on the landscape for many years. The AWMA also captures coconut and oil palm as the major livelihood activity for the indigenous people in former times in its medium-term development plan (MTDP) [42]. It was also mentioned that the integration of food-crop (e.g., cassava, vegetables) with palm cultivation was contributing to household food security needs, hence, not much land was needed for food-crop establishment. Again, it was emphasized that most of the lands were reserved as fallow lands and uncultivated bushes. However, in recent years, rubber cultivation has transformed most lands on the landscape to rubber farming. The few elderly men on the study landscape who were interviewed were of the view that, lack of alternative livelihood support and low-income levels from crop farming might have contributed to the switch in crop choices to rubber. In addition, young farmers who were also interviewed mentioned rubber as a more profitable farming business, hence its rapid switch from other crops. The young farmers and landowners interviewed were strongly of the view to convert any available land in their possession to the cultivation of rubber with dependence on the market for household food access

4.2. Changes in Landscape Composition and Drivers of Rapid Land Use Change

The study findings revealed a highly dynamic landscape, indicating that the study landscape has undergone substantial land cover changes. This can also be seen from the high change-to-persistent ratio, which recorded almost half of the study landscape under persistence and the remaining half undergoing land cover transitions.

The major land cover types occurring in this dynamic land cover changes were shrubland, cropland, palm, settlement and rubber, occupying areas of 28.9%, 31.8%, 14.9%, 11.5% (shrubland), 13.2%, 16.9%, 22.9%, 22.2% (cropland), 32.4%, 24.5%, 30.0%, 19.7% (palm), 1.4%, 3.2%, 3.9%, 7.6% (settlement) and 10.0%, 10.1%, 16.0%, 27.3% (rubber) for the years 1986, 2002, 2015 and 2020 respectively. A key finding from this dynamic land cover transitions was a cyclical land cover change movement among palm, shrubland and cropland. This means that land cover changes were alternating between palm, cropland and shrubland in the entire study period. Oil palm thrives best in saline conditions ([61], a typical soil condition of the eastern part of AWMA [22]. This may explain the occurrence of oil palm (smallholder and large scale) in the eastern part of the study landscape. The transfer from palm to cropland and shrubland in the western part of the study landscape can be explained by the outbreak of the Cape Saint Paul Wilt disease (CSPWD) in the coastal areas of Ghana in the year 2000. The disease outbreak resulted in the death of many coconut trees [62–64]. The decline in palm (−7.86%) from 1986 to 2002 (Table A1) can be explained by the unproductive coconut trees that were either converted to cropland or left fallow. This is because, according to Danyo [63], farm hygiene, thus the removal of infested coconut trees, was considered the safer means of reducing the spread of the CSPWD disease; therefore, affected coconut trees might have been cleared and converted to other land cover types.

Surprisingly, palm paved its way into the western part of the landscape in the period 2002–2015 (Table A2, Figure 4). This can be explained by the introduction of new crop varieties (coconut hybrid, Malayan yellow dwarf (MYD) × Vanuatu tall tolerance (VTT)) that were resistant to CSPWD [63,65]. This statement can be supported by several studies that reported on the efficacy in the use of resistant varieties to control CSPWD and increase coconut yields [66,67]. The introduction of resistant coconut crop varieties was expected to increase coconut plantations on the landscape; however, the study noticed a reduction in palm in the period 2015–2020 (−10.27%) (Table 5). Palm was losing land areas to cropland, shrubland, rubber and settlement (Table A3). Palm changed to cropland and shrubland were seen in the eastern part of the study landscape. This means that oil palm farms, rather than coconut farms, were losing land areas. The transfer from oil palm to shrubland and cropland was occurring in the areas where settlement is highly dominating. This indicates that land under palm in the eastern part of the study landscape, mainly oil palm, has been acquired for infrastructure purposes with an immediate switch in crop choices to seasonal crops by the farmers, which agrees with [22,68].

Aside the cyclical land cover change that occurred among palm, shrubland and cropland, another key finding from the study was the land cover change from shrubland, palm and cropland, to rubber in the last two study periods. The 172.65% change in rubber area (between 1986 and 2020) accounted for the second highest land cover category in the study landscape (Table 4). As seen from the land cover maps (Figure 4), this expansion in rubber is highly fragmented, indicating that the expansion in rubber farms occurs on smallholder land and not on a large scale. The outgrower scheme launched by the Ghana Rubber Estate Limited (GREL) in 1998, and rolled up in 2000, to engage smallholder farmlands in the cultivation of rubber, is accounting for the vast fragmented expansions in rubber. The outgrower initiative was to increase Ghana's supply of raw material in meeting global markets' high demand for rubber, and this might have resulted in the increased expansions in rubber

Settlement, as the highest land cover type, expanding more than four times (449.93%) its initial size over the 34-year study period (Table 4), was also a key observation made in this study. As seen dominating the eastern part of the study landscape (Figure 4), the expansion in settlement indicates the effects of oil discovery developments and resultant onshore infrastructure activities on the landscape. Since the discovery of oil in commercial quantities in 2007 along the deep Tano basin of south-western Ghana, the need to establish oil refinery and storage facilities by the government of Ghana in AWMA has had greater consequences on land uses in the district [22,69]. The intention to establish an oil refinery and onshore infrastructure developments in the eastern part of the study landscape triggered in-migration and a population increase. It turned the landscape into a hotspot for land speculation and land rush [22]. In-migration and population increase are common phenomena in oil discovery locations and onshore infrastructural developments [70].

The study also noticed that there were not many land changes in forest. The forest block remained within the precinct of the Cape Three Point forest reserve. In Ghana, the laws regulating the establishment and management of national parks and forest reserves, such as the Forest Protection (Amendment 2002) Act 624 and the Forest Act 1927 (CAP 157), forbid any agricultural activities within the forest reserves. This legal protection status may have contributed to the low change rate in the forest block of the study area. The slight decline in forest areas was recorded between the 1986–2002 and 2002–2020 change periods due to off-reserve changes into other land use types.

Interestingly, contrary to other tree-crop (e.g., cocoa) expansion studies that found decreases in cropland area as a result of expansions in the tree-crops [36,58,71], cropland did not decline drastically in this study. During field discussions with farmers growing rubber, it was mentioned that fallow lands and unproductive croplands were first considered for rubber cultivation before the conversion from croplands. In addition, cocoa plantations were introduced on smallholder farms since their establishment in Ghana in the 1870s, compared to rubber, which occurred on large scale plantations with recent introductions into smallholder farms in the last two decades. This may explain why cropland did not decline drastically on the study landscape.

4.3. Intensity Analysis of the Structurally Complex Mosaic Landscape

Findings from the interval level analysis revealed an intensive land cover change in the last time period (2015–2020) compared to the former. However, though slow, change in 1986–2002 was slower than in 2002–2015. This implies that the study landscape has been rapidly undergoing transformation over the last 18 years (2002–2020). The rapid land cover changes correspond with the recent socio-economic activities of increasing rubber on smallholder lands and the influence of oil discovery developments, driving a population increase on the landscape. These rapid land cover changes agree with the findings of Otchere-Darko and Ovadia [27] and Bugri and Yeboah [22]. The GSS [72] report also noted a rapid population increase of 9500 to 13,500, corresponding to 42% in the AWMA between the year 2000 and 2014. Population increase denotes more need for infrastructure developments [71,73,74].

At the categorical level analysis, key findings first revealed cropland and shrubland as both active gainers and active losers. This means that losses and gains in shrubland and cropland occur at intensities above the average intensity of all land cover types in gains and losses. Secondly, palm was an active loser in the 1986–2002 period, an active gainer in 2002–2015, and an active looser again in 2015–2020. The CSPWD on coconut trees that rendered them unproductive, leading to their removal, the introduction of resistance coconut varieties (MYD × VTT hybrid), and the change of palm to settlement can account for the losses, gains and losses status in palm in the periods 1986–2002, 2002–2015 and 2015–2020, respectively. Third, forest remained a dormant gainer and dormant loser in all three study periods due to its legal protection status.

Interestingly, a fourth finding from the categorical analysis, showed that, settlement is a dormant loser and a dormant gainer in 2015–2020. The gains in settlement that occurred at intensities lower than gains in all other land cover types can be explained by the literature stating that, although oil was discovered in 2007, onshore infrastructural activities on the study landscape only began after 2010 [22]. Perhaps, land deals and negotiations were not yet completed during this study period. Lastly, findings revealed how gain intensities in rubber were occurring rapidly, compared to the gain intensities of all other land cover types, especially in 2002–2015 and 2015–2020. From the onset of 2002, rubber expansions on the landscape have been occurring faster due to the introduction of the outgrower schemes. From the discussions held with farmers cultivating rubber, it was mentioned that the incentives associated with rubber cultivation are the driving factors for the rapid rubber expansions.

At transition level analysis, key findings showed palm losses to cropland to be higher in 2002–2015 compared to the losses in palm to the same land cover categories in the other study year periods. During field discussions with farmers, oil palm farmers expressed grievances in the cultivation of oil palm as the major factor for the voluntary switch from oil palm into other land uses. Specific reasons given by the oil palm farmers were: (1) a bad road network to transport oil palm to the oil manufacturing industry resulting in matured oil palm fruit being destroyed on the farm; (2) a feeling of cheating at the weighing scale by agents from the oil-producing company; (3) high labor involved in oil palm production; and (4) the benefit of converting oil palm trees in the preparation of the locally manufactured alcoholic drink, *akpeteshi*. When oil palm trees are felled, the trees are left lying on the ground to produce the local drink *akpeteshi*, while food-crops (e.g., cassava, maize, vegetables) are being planted. This might have accounted for the high loss in palm to cropland in the 2002–2015 change period. Rubber cultivation subsequently followed the land after oil palm trees were removed. The gain in rubber in 2015–2020, though avoided, was higher compared to the gains in rubber from palm in the other study periods. This may agree with the fact that farmers voluntarily converted their oil palm lands for rubber cultivation. Farmers cultivating oil palm expressed the high incentives and economic profitability in rubber cultivation as a reason for oil palm conversion to rubber. The transition of palm to shrubland and cropland in the 2015–2020 change period may be explained by the findings of Bugri and Yeboah [22], which stated that: (1) the switch of oil palm to seasonal crops by farmers was due to lack of compensation under compulsory land acquisition; (2) the acquisition of 243 ha of land for the development of the oil city and 810 ha of land by the Petronia company was for real estate development; and (3) the land rush and land speculation which resulted in in-migration and population increase led to infrastructural demands. The acquisition of 5261 ha of land by speculators in AWMA, including the entire stretch of land on both sides of the 15 km road stretch from Apowa to Agona Nkwanta (Figure 1), agrees with the gains in shrubland in the period 2015–2020 [22]. According to Bugri and Yeboah [22], these acquired lands are meant for the reallocation to investors seeking land for commercial activities, hence the status is likely to be converted to settlement in the future.

Another interesting key finding was seen in the gains in settlement targeting cropland and shrubland and not palm, especially in the 2015–2020 change period. However, gains in settlement instead targeted palm from 2002 to 2015. First, the transition from palm to settlement from 2002 to 2015 is in line with the government's decision to establish an oil refinery on the study landscape after discovering oil in 2007. This decision led to 486 ha of land being compulsorily acquired by the government for onshore infrastructure-related purposes [75,76]. The 486 ha included 405 ha of oil palm smallholder farms [22]. The immediate change of acquired oil palm lands into the establishment of the oil refinery might account for the gains in settlement targeting palm in the year 2002–2015. When the intention of acquiring land for any national development is made, landowners are no longer entitled to use the land for other purposes [77,78]. Hence due to the fear of a lack of compensation for any cash crops, oil palm farmers switched crop choices to seasonal and annual crops until the lands were taken entirely. This may explain the high gains in settlement targeting cropland and shrubland in the last study period.

4.4. Implications of the Rapid Land Use Change on the Study Landscape

Findings from the study indicate the drivers responsible for the rapid land cover changes are rubber and settlement expansions. The cultivation of rubber is associated with many environmental effects such as soil degradation, biodiversity loss and a decline in ecosystem services [79]. As a high sucking plant, rubber also alters the local hydrological cycle, affecting groundwater recharge [80,81]. Contrary to coconut and oil palm, as tree-crops that can be intercropped with other food-crops, rubber, on the other hand, does not support food-crop intercropping. The local farmers interviewed, mentioned the production of a pungent smell associated with the cultivation of rubber that gets infused into food-crops to alter its taste. The onset of oil and gas production and exploration in Ghana has also resulted in a decline in agricultural growth for subsistence use with a high impact of land stress issues experienced in Sekondi-Takoradi and AWMA [27,82].

Expansions in rubber and settlement on the study landscape mean the loss of arable lands with negative impacts on food production [68]. Authors' suggestion from this analysis is the loss of arable land may result in small farms owners' food production. This may likely lead to rural displacement, which can be seen in two ways: enfolding arable lands for food security and a transformation in the economy transformed through technologically oriented industry with less need for the local labor force. The former may lead to a decline in food availability, as also noticed by Bugri and Yeboah [22], who mentioned that the expansions in rubber on the landscapes of south-western Ghana would lead to food insecurity issues. Food security concerns have also become a critical sustainability issue in the coastal landscape of south-western Ghana [27]. Otchere-Darko and Ovadia [27] also found increasing prices in food commodities (cassava, maize, plantain, yam) mainly due to the socio-economic activities on the landscape, which is enfolding arable lands for food security sustainability. As food production declines, demand for food from other regions of the country will increase. Food prices will increase when supply is below demand, thereby affecting local household finances. The local households will be forced to rely on the market for food access. This may lead to an exposure of local dwellers becoming volatile to market price fluctuations. Lack of food prices may affect the quality of food purchased, affecting the nutritional value of food consumed by these local households [83]. Rapid land cover changes in the study landscape can also lead to changes in social organization and attitudes, and loss of adaptive capacity.

5. Conclusions

In conclusion, this study employed a maximum likelihood supervised classification and digitized polygons from Google Earth images to classify the complex heterogeneous mosaic landscape of AWMA for the years 1986, 2002, 2015 and 2020. The study addressed the drivers responsible for the rapid spatial transformations in the local land use system of the smallholder mosaic landscape of AWMA using an intensity analysis. A dynamic landscape was revealed where settlement and rubber expansions were seen as the main drivers of rapid land use transformations occurring at the expense of other land cover categories that support food production (smallholder palm, shrubland and cropland). The causes of the expansions of rubber and settlement are the outgrower scheme to increase rubber to meet the high demands of the global market and the onshore infrastructural developments that drive in-migration and population increase on the landscape, respectively. The study demonstrated that the use of MLC, combined with manual digitizing from high resolution satellite images and discussions with local stakeholders, are good approaches for studying complex heterogeneous mosaic landscapes in the Global South. The findings from this study imply the possible decline in food production factors such as fertile lands and ecosystem services. The consequences of these rapid changes in the local land use system of the study landscape will create food security issues, ecosystem degradation and a possible decline in the nutritional value of local household food consumption. To ensure sustainability in land uses, the enforcement of legislative instruments governing spatial planning and use of land in Ghana, as embedded in the 2016 Land use and Spatial Planning Act, is recommended. Further research is needed to model the future state of the study landscape based on the current rapid land cover changes using local people's perceptions and stakeholder-based models. Land use optimization scenarios are equally needed in further studies for policy actions.

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Appendix A

Table A1. Cross tabulation matrices for 1986–2002 area in ha (top values), percentage of total land area (bottom value underlined); the diagonal (in bold) values indicate the persistence of land cover types.

	2002										
1986	Cropland	Forest	Palm	Rubber	Settlement	Shrubland	Waterbody	Wetland	Initial Total	Gross Loss	Net Change
Cropland	**2147.31**	31.50	2004.39	106.74	223.92	3060.81	4.32	120.96	7699.95	5552.64	2174.40
	3.68	0.05	3.44	0.18	0.38	5.25	0.01	0.21	13.21	9.53	3.73
Forest	134.10	**5392.62**	26.55	26.91	0.09	733.50	0.54	27.18	6341.49	948.87	−677.70
	0.23	9.25	0.05	0.05	0.00	1.26	0.00	0.05	10.88	1.63	−1.16
Palm	3176.46	123.48	**6949.98**	184.77	265.77	7835.13	7.02	323.64	18,866.25	11,916.27	−4601.61
	5.45	0.21	11.92	0.32	0.46	13.44	0.01	0.56	32.36	20.44	−7.89
Rubber	98.10	7.83	71.46	**5453.01**	49.14	138.51	1.80	26.28	5846.13	393.12	69.75
	0.17	0.01	0.12	9.35	0.08	0.24	0.00	0.05	10.03	0.67	0.12
Settlement	96.66	0.18	33.03	0.09	**574.56**	9.99	22.86	65.07	802.44	227.88	1064.97
	0.17	0.00	0.06	0.00	0.99	0.02	0.04	0.11	1.38	0.39	1.83
Shrubland	3934.53	90.09	5118.93	131.76	582.75	**6705.63**	1.98	254.88	16,820.55	10,114.92	1737.27
	6.75	0.15	8.78	0.23	1.00	11.50	0.00	0.44	28.85	17.35	2.98
Waterbody	2.79	0.45	0.00	8.91	75.96	0.63	**196.83**	70.02	355.59	158.76	−74.97
	0.00	0.00	0.00	0.02	0.13	0.00	0.34	0.12	0.61	0.27	−0.13
Wetland	284.40	17.64	60.30	3.69	95.22	73.62	45.27	**981.18**	1561.32	580.14	307.89
	0.49	0.03	0.10	0.01	0.16	0.13	0.08	1.68	2.68	1.00	0.53
Final total	9874.35	5663.79	14,264.64	5915.88	1867.41	18,557.82	280.62	1869.21	58,293.72		
	16.94	9.72	24.47	10.15	3.20	31.84	0.48	3.21			
Gross gains	7727.04	271.17	7314.66	462.87	1292.85	11852.19	83.79	888.03			
	13.26	0.47	12.55	0.79	2.22	20.33	0.14	1.52			

Table A2. Cross tabulation matrices for 2002–2015 area in ha (top values), percentage of total land area (bottom value underlined); the diagonal (in bold) values indicate the persistence of land cover types.

	2015										
2002	**Cropland**	**Forest**	**Palm**	**Rubber**	**Settlement**	**Shrubland**	**Waterbody**	**Wetland**	**Initial Total**	**Gross Loss**	**Net Change**
Cropland	**4099.32**	6.84	2047.86	600.39	482.31	2247.57	17.01	373.05	9874.35	5775.03	3474.45
	7.03	0.01	3.51	1.03	0.83	3.86	0.03	0.64	16.94	9.91	5.96
Forest	21.96	**5076.18**	203.85	129.33	0.09	202.59	0.90	28.89	5663.79	587.61	−446.13
	0.04	8.71	0.35	0.22	0.00	0.35	0.00	0.05	9.72	1.01	−0.77
Palm	4416.39	2.70	**7654.14**	572.13	332.28	1264.95	2.25	19.80	14,264.64	6610.50	3214.62
	7.58	0.00	13.13	0.98	0.57	2.17	0.00	0.03	24.47	11.34	5.51
Rubber	49.59	4.23	49.41	**5733.81**	7.02	71.28	0.54	0.00	5915.88	182.07	3393.36
	0.09	0.01	0.08	9.84	0.01	0.12	0.00	0.00	10.15	0.31	5.82
Settlement	288.63	0.00	14.67	14.13	**1332.36**	136.08	47.07	34.47	1867.41	535.05	414.63
	0.50	0.00	0.03	0.02	2.29	0.23	0.08	0.06	3.20	0.92	0.71
Shrubland	4361.49	127.53	7499.70	2258.82	91.26	**4132.53**	2.43	84.06	18,557.82	14,425.29	−9873.27
	7.48	0.22	12.87	3.87	0.16	7.09	0.00	0.14	31.84	24.75	−16.94
Waterbody	0.99	0.00	0.18	0.09	0.54	62.73	**178.92**	37.17	280.62	101.70	20.52
	0.00	0.00	0.00	0.00	0.00	0.11	0.31	0.06	0.48	0.17	0.04
Wetland	110.43	0.18	9.45	0.54	36.18	566.82	52.02	**1093.59**	1869.21	775.62	−198.18
	0.19	0.00	0.02	0.00	0.06	0.97	0.09	1.88	3.21	1.33	−0.34
Final total	13,348.80	5217.66	17,479.26	9309.24	2282.04	8684.55	301.14	1671.03	58,293.72		
	22.90	8.95	29.98	15.97	3.91	14.90	0.52	2.87			
Gross gains	9249.48	141.48	9825.12	3575.43	949.68	4552.02	122.22	577.44			
	15.87	0.24	16.85	6.13	1.63	7.81	0.21	0.99			

Table A3. Cross tabulation matrices for 2002–2015 area in ha (top values), percentage of total land area (bottom value underlined); the diagonal (in bold) values indicate the persistence of land cover types.

	2020										
2015	**Cropland**	**Forest**	**Palm**	**Rubber**	**Settlement**	**Shrubland**	**Waterbody**	**Wetland**	**Initial Total**	**Gross Loss**	**Net Change**
Cropland	**5705.46**	3.78	740.25	2062.35	1387.98	3388.86	4.32	55.80	13,348.80	7643.34	−386.37
	9.79	0.01	1.27	3.54	2.38	5.81	0.01	0.10	22.90	13.11	−0.66
Forest	33.39	**5108.49**	16.29	54.90	0.09	4.50	0.00	0.00	5217.66	109.17	97.38
	0.06	8.76	0.03	0.09	0.00	0.01	0.00	0.00	8.95	0.19	0.17
Palm	2820.69	71.01	**10,105.83**	2346.12	166.32	1961.10	0.18	8.01	17,479.26	7373.43	−5987.70
	4.84	0.12	17.34	4.02	0.29	3.36	0.00	0.01	29.98	12.65	−10.27
Rubber	73.26	53.82	74.34	**9075.42**	19.89	12.15	0.27	0.09	9309.24	233.82	6630.30
	0.13	0.09	0.13	15.57	0.03	0.02	0.00	0.00	15.97	0.40	11.37
Settlement	42.39	0.00	5.13	15.03	**2072.16**	134.19	8.64	4.50	2282.04	209.88	2130.84
	0.07	0.00	0.01	0.03	3.55	0.23	0.01	0.01	3.91	0.36	3.66
Shrubland	3794.31	77.31	527.04	2322.99	626.31	**1160.55**	20.43	155.61	8684.55	7524.00	−2008.26
	6.51	0.13	0.90	3.98	1.07	1.99	0.04	0.27	14.90	12.91	−3.45
Waterbody	6.93	0.27	0.54	1.53	62.28	1.35	**206.73**	21.51	301.14	94.41	19.98
	0.01	0.00	0.00	0.00	0.11	0.00	0.35	0.04	0.52	0.16	0.03
Wetland	486.00	0.36	22.14	61.20	77.85	13.59	80.55	**929.34**	1671.03	741.69	−496.17
	0.83	0.00	0.04	0.10	0.13	0.02	0.14	1.59	2.87	1.27	−0.85
Final total	12,962.43	5315.04	11,491.56	15,939.54	4412.88	6676.29	321.12	1174.86	58,293.72		
	22.24	9.12	19.71	27.34	7.57	11.45	0.55	2.02			
Gross gains	7256.97	206.55	1385.73	6864.12	2340.72	5515.74	114.39	245.52			
	12.45	0.35	2.38	11.78	4.02	9.46	0.20	0.42			

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