Expanding tree-crop farming

An integrated socio-spatial analysis in a transitioning mosaic landscape in Ghana

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Chapter Three

3. Integration versus segregation: structural dynamics of a smallholder-dominated mosaic landscape under tree-crop expansion in Ghana

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Asubonteng, K., O., Pfeffer, K., Ros-Tonen, M., A., F., Baud, I., Benefoh, D., T., (2020). Integration versus segregation: Structural dynamics of a smallholder-dominated mosaic landscape under tree-crop expansion in Ghana. *Applied Geography* 118:102201. https://doi.org/10.1016/ j.apgeog. 2020.102201. It has been slightly modified for consistency in language and layout throughout the manuscript. Some repetition in the methodology section occurs with the previous chapter, but I decided to keep it in so that this chapter can be read independently.

Abstract

Tree crops like cocoa and oil palm have ecological and socioeconomic significance in tropical landscapes. However, their expansion in tropical landscapes leaves footprints on ecosystem-based livelihoods, forests, and land for food. While policy and research have focused on productivity, markets and land-use transitions, the structural effects of expanding tree crops on landscapes have rarely been assessed. This study investigates changes in landscape structural properties associated with tree-crop expansion in a smallholder-dominated mosaic landscape. It quantifies the degree of integration/segregation in the landscape and the direction in which the landscape evolves on an integration-segregation continuum. Landscape metrics from 1986 and 2015 land-cover maps were used to quantify landscape composition and configuration. Selected metrics were combined into a new composite landscape structural state index (LSSI) to measure the degree of integration/segregation. The study found that landscape composition was relatively stable. However, reduced patch numbers and complexity and increased connectivity and aggregation revealed configurational dynamics: cocoa and oil palm exhibited aggregation tendencies, while food-crop areas became fragmented, and the LSSI indicated a shift towards greater segregation in the landscape between 1986 and 2015. Regarding structure, the smallholder landscape mimics an industrial agrarian landscape with large segregated homogenous cocoa and oil palm areas and a reserved forest area. The study thus reveals changes in structural properties due to tree-crop-led landscape transitions. It suggests considering these aspects when promoting tree crops in mosaic landscapes as they imply adverse effects on food availability and ecosystem services.

Keywords:

FRAGSTATS, landscape composition, landscape configuration, integration/segregation, landscape structural state index (LSSI), sparing/sharing

3.1 Introduction

Single-purpose productive landscapes (e.g. tree-crop plantations of cocoa and oil palm) are considered economically efficient as well as managerially convenient (Brandt, 2003). However, the rapid growth and ultimate dominance of commodity crops in tropical landscapes have led to forest fragmentation and loss of natural habitat, biodiversity and associated livelihoods (Clough et al., 2016; Ordway et al., 2017). Reconciling conservation and production goals in multifunctional landscapes that provide multiple ecosystem services is therefore generally acknowledged as a sustainable choice (van Noordwijk et al., 2011).

Landscape multifunctionality generally refers to the ability of a landscape to concurrently offer multiple ecosystem services. Two commonly debated pathways to achieving landscape multifunctionality are land sharing and land sparing (Phalan et al., 2016; Tscharntke et al., 2012). Land sharing refers to generating various functions from different landscape components concurrently from the same land area (spatial integration); land sparing involves setting aside tracts of land for intensive agriculture development to increase yields while protecting natural areas for biodiversity conservation elsewhere (spatial segregation) (Brandt, 2003; Phalan et al., 2011b). Land-sharing advocates posit that multifunctionality is better achieved by interspersing farmlands with nature areas, generating landscapes with high biodiversity value and relatively lower but more sustainable yields (Perfecto and Vandermeer, 2010; Tscharntke et al., 2012). Contrastingly, under land sparing, the landscape is characterised by both high productivity in the cultivated areas and high conservation outcomes in the protected area.

A fundamental difference between sparing and sharing in landscapes is variation in landscape structural properties. Existing studies (e.g. Perfecto and Vandermeer 2010; Phalan et al. 2011) have mainly addressed the ‘what’ (components and quantities) and ‘for whom’ (benefits and beneficiaries) in landscape sparing and sharing discussions, with little attention to the ‘where’ (location) and ‘how’ (spatial arrangement). Meanwhile, structural dynamics in terms of space and composition are fundamental to the availability and potential generation of ecosystem services. Hence, understanding landscape structure is key to studies focusing on landscape functions and approaches that aim at achieving multifunctionality (Galler et al., 2013; Krováková et al., 2015).

Sometimes, ‘integration and segregation’ and ‘sharing and sparing’ are used synonymously (Dewi et al., 2013; Kremen, 2015; van Noordwijk et al., 2012). However, the former distinction underscores the spatial dimensions. Exclusively assigning a sparing or sharing label to landscapes is overly simplistic and unpractical as it obscures the spatial transformational dynamics in landscape structure between the two extremes over time.

According to the integrate-or-segregate theory proposed by van Noordwijk et al. (2012, 2013), landscape multifunctionality can be achieved over a spatial continuum from extreme integration (e.g. smallholder farming in a forested landscape) to extreme segregation (e.g. nature reserves separated from large-scale agriculture), through deforestation/reforestation resulting in intermediaries of agriculture and forest with varying spatial patterns over time. Several spatial configurations of landscape transitions can evolve along this continuum over time, with each providing different bundles of ecosystem benefits and environmental impacts (Goulart et al., 2016; Lamy et al., 2016; van Noordwijk et al., 2014). If structural patterns are relevant for landscape processes and ecosystem services delivery, it is imperative to understand the spatial configurations of land-cover types in landscapes over time along the integration-segregation continuum.[3]

Research on the expansion of tree crops (cocoa and oil palm) abounds in literature (Benefoh et al., 2018; e.g. Ordway et al., 2017), but insights into structural changes associated with their areal increase in mosaic landscapes are few. Former studies (e.g. Su et al. 2014b; Diwediga et al. 2017) have examined the heterogeneity and fragmentation in landscapes but paid less attention to spatial and temporal transformations towards an integrated or segregated landscape. A few studies (Castella et al., 2013; van Noordwijk et al., 2012) have conceptualised spatial aspects of this continuum but have failed to spatially operationalise them for monitoring. Another effort to characterise the integration-segregation gradient employed edge contrast as a proxy for measuring landscape forest extent, quality and connectivity to typify landscapes (Dewi et al., 2013). However, this single index method does not sufficiently account for the spatial complexities and variations in structural properties in dynamic landscapes during transitions. Edge contrast measures have also been criticised because of the subjectivity in user-defined weighting schemes, which are usually not informed by empirical data and understanding of the landscape under investigation (Wang et al., 2014). Hence there is a need for a new index that quantifies changes in the physical properties of all land-cover types to estimate the degree of segregation in landscapes. This study is the first – to our knowledge – that moves beyond the study of land transitions and intensities to address the spatio-temporal changes in the structure of cocoa and oil palm landscapes over time.

This study characterises a landscape based on its spatial structure on the integration-segregation continuum and tracks structural variations between two moments in time. The specific objectives are, first, to investigate the changes in composition and configuration and, second, to assess the extent of integration or segregation in a landscape based on its structural characteristics and position on the integration-segregation continuum. After explaining the method, this chapter analyses changes in composition and configuration at landscape and class level as well as the degree of integration or segregation. The following discussion interprets the results, compares them with other studies, and addresses the potential and limitations of the composite index developed in this chapter. The conclusion addresses the implications of this research.

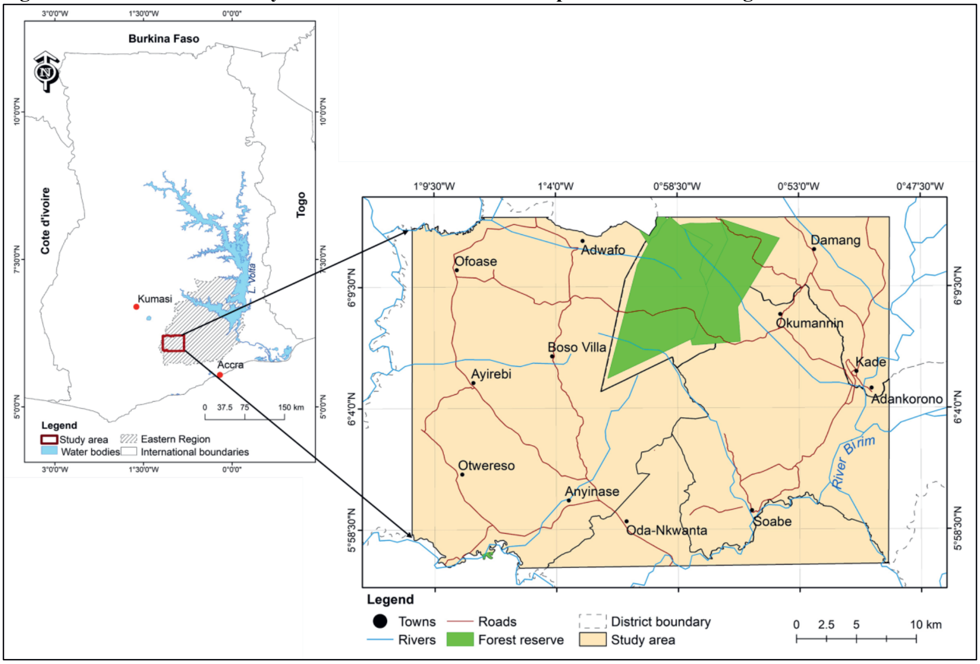
[3] The integrate-or-segregate theory refers to landscape-level analysis at a scale beyond plots and individual land-cover categories, without specifying the scale of the landscape. Landscape scale definition is context-specific, which could be a watershed, sourcing area, or a jurisdictional domain. In this thesis the landscape is defined by the occurrence of both cocoa and oil palm cultivation within a single landscape (see Section 3.1) (Asubonteng et al., 2018).

3.2 Methodology

3.2.1 Description of the study area

The landscape under study is the area stretching across the boundaries of Akyemansa, Denkyembour and Kwaebibirem Districts and Birim Central Municipality of Ghana's Eastern Region and is hereafter referred to as the Akyemansa-Kwaebibrem landscape (Figure 3.1). Historically the Akyemansa-Kwaebibrem landscape was predominantly forest, mixed with swidden agriculture. It is characterised by a bi-modal precipitation pattern with a major season from March-July and a minor season from September-December. Rainfall measurements range between 1,500 mm and 2,000 mm, and annual temperature is around 23.5°C to 33°C, supporting predominantly agrarian livelihoods (MoFA, 2020b, 2020c).

Figure 3.1 Location of the Akyemansa–Kwaebibrem landscape in the Eastern Regions of Ghana

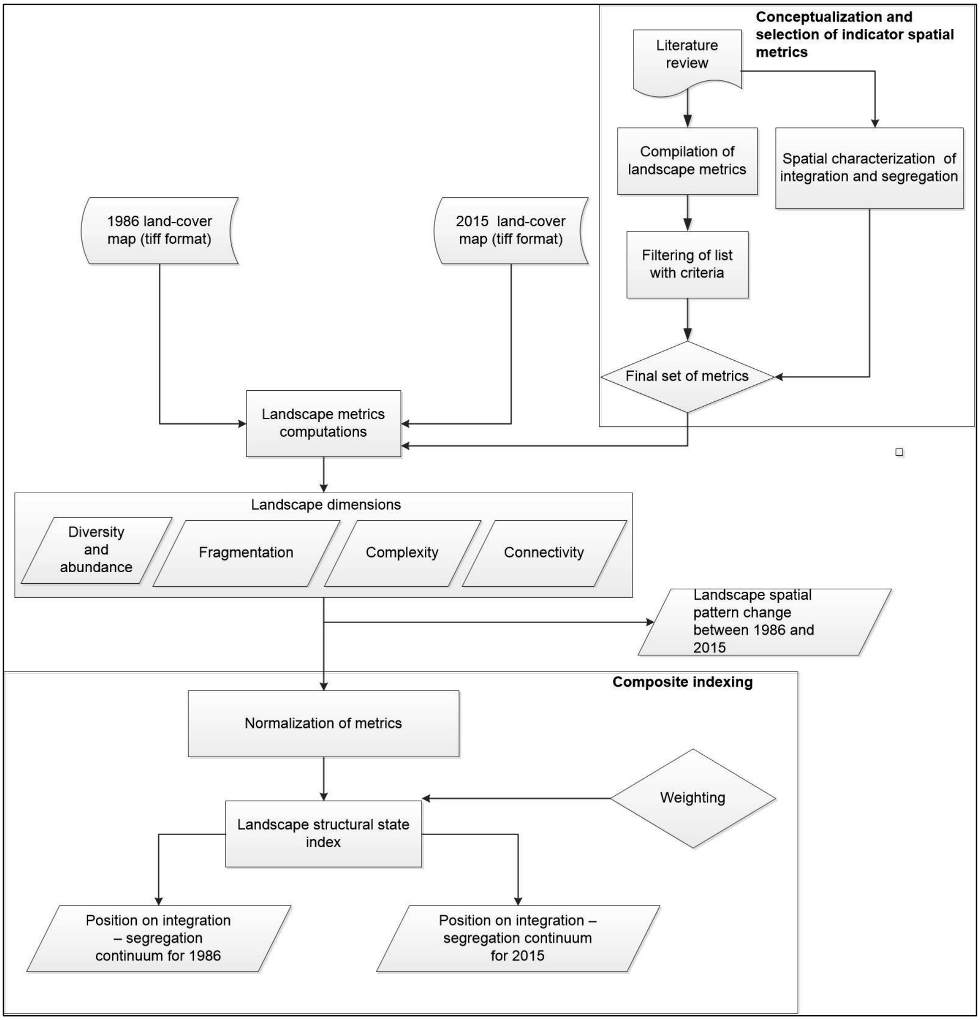


Data source: Ghana Forestry Commission (2019) and GSS (2021).

The requisite microclimatic conditions for cocoa cultivation provided by the forest and tall trees in the area encouraged the establishment of the earliest frontiers of cocoa cultivation and expansion in Ghana. Over the years, the area has seen multiple trajectories of change in some areas, from predominantly cocoa to other tree crops, such as oil palm and citrus (Michel-Dounias et al., 2015). Key factors that drove oil palm development were a combination of landscape suitability, the establishment of a large agroindustry – the Ghana Oil Palm Development Company Limited – in 1975, and the presence of the Oil Palm Research Institute

(Asubonteng et al., 2018, Chapter 2). The landscape is mainly rural, characterised by smallholder agriculture as the source of livelihood for the majority of the population (GSS, 2014b; MoFA, 2020c). The historical stages of transitions in terms of landscape composition and the presence of different agricultural activities make it a suitable landscape to assess the spatial structural dynamics over time.

Figure 3.2 Framework for assessing the spatial dynamics and position of the landscape along the integration-segregation continuum

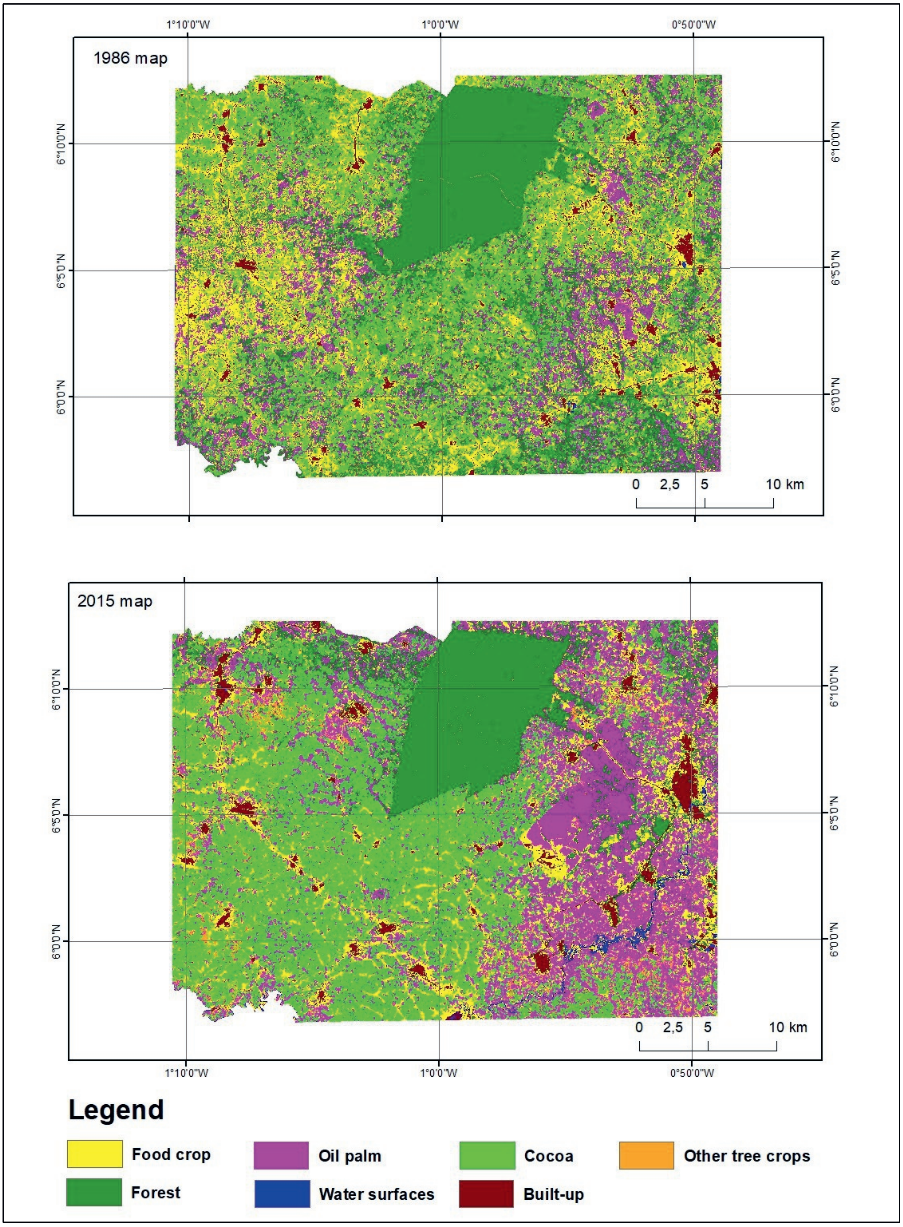


Source: Author's construct.

3.2.2 Methods and data requirements

The study employs land-cover maps derived from satellite images and spatial methodologies to quantitatively characterise the land-cover pattern dynamics in the landscape.

Figure 3.3 Land-cover maps of the Akyemansa-Kwaebibrem landscape in 1986 and 2015



Source: Asubonteng et al. 2018 (see Chapter 2).

Spatial characteristics from land-cover maps are used to explore the changes in structural properties in the Akyemansa-Kwaebibrem landscape to determine the landscape's position on the integration-segregation continuum over time. The spatial attributes of integrated and segregated landscapes are quantified using landscape metrics drawn from existing studies. Selected landscape-level metrics are combined into a composite index for interpretation of the integration-segregation continuum. The details are explained in the following sections and Figure 3.2.

Data

The study employed 1986 and 2015 categorical land-cover maps of the Akyemansa-Kwaebibrem landscape produced by Asubonteng et al. (2018) (Chapter 2) as the main data to assess variation in structural properties of the landscape and to explore the overall shifts along the integration-segregation continuum over the 29-year period (Figure 3.3). Only data from 1986 and 2015 were used because cloud-free satellite images were limited for the study area (see Chapter 2).

In an earlier study by Asubonteng et al. (2018), maps consisting of seven land-cover types (representing the main land categories) were produced from anniversary Landsat 5 and 8 images of 1986 and 2015, respectively (Table 3.1; see Chapter 2).

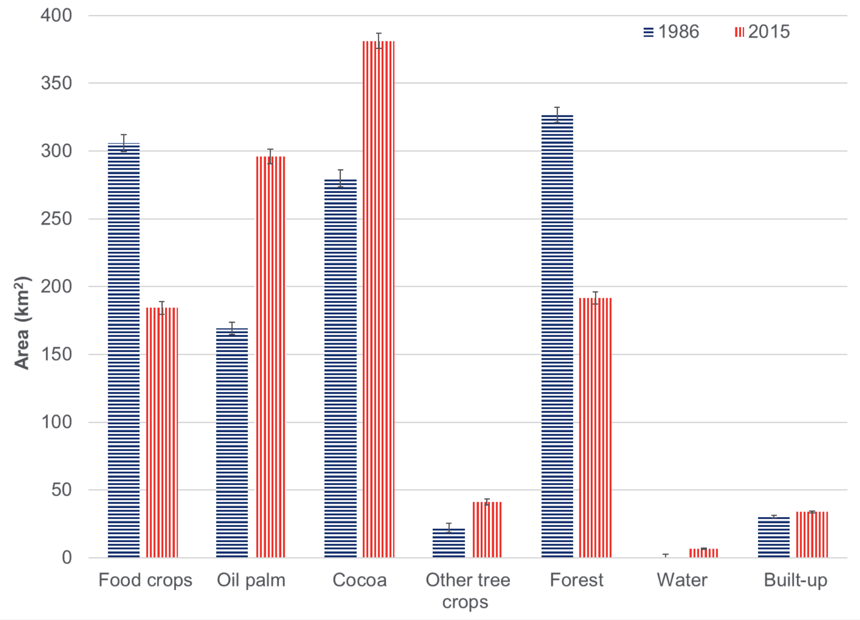
Following atmospheric correction and geometric alignments, the 1986 and 2015 images were classified into thematic land-cover maps employing unsupervised Iterative Self Organising Data Analysis (ISODATA) and supervised Maximum Likelihood Classification (MLC), respectively (Figure 3.3). The classification accuracies of the 1986 and 2015 maps were 91.2% and 78.8%, respectively (Asubonteng et al. 2018 c.f. Section 2.4.1). Using the approach by Olofsson et al. (2014), uncertainties in the land-cover type areas were estimated (Figure 3.4). In addition to the maps, we recorded field observations of visible characteristics of the landscape components and people's perceptions of the landscape through interviews with 30 chiefs and village elders in Ofoase, Ayirebi, Kade and Soabe (Asubonteng et al. 2018; Chapter 2).

Table 3.1 Main land-cover categories identified in the Akyemansa-Kwaebibrem landscape

Land-cover classes	Description
Food crops	Land that is primarily available for food production, both annual and bi-annual. It also includes natural vegetation areas that oscillate between production and fallow periods in a food production cycle. The fallows consist of grasses and shrubs.
Oil palm	Small- to large-scale palm farms of different shade intensities and age categories. Includes naturally occurring palms along water bodies.
Cocoa	Small- to large-scale cocoa farms of different shade intensities and age categories
Other tree crops	Comprises all other tree-crop plantations in the landscape, mainly rubber and citrus.
Forest	Naturally growing woody tree vegetation clusters with stems reaching 5 m high. This includes bamboo clusters and timber plantations.
Water surface	All forms of exposed water surfaces, including rivers, reservoirs, and ponds.
Built-up	Areas with high and low intensities of infrastructural development and exposed soil surfaces with little or no capacity to support plant life. This class includes roads (tarred and untarred), towns, wastelands and rock outcrops.

Source: Asubonteng et al. (2018) (see Chapter 2).

Figure 3.4 Error bars showing area estimate uncertainties of the 1986 and 2015 land-cover maps



Source: Author's compilation based on Table 2.3.

Landscape structural analysis

The land-cover maps cover an area of 1,134.51 ha at a spatial resolution of 30 x 30 m. FRAGSTATS 4.2 software, developed for spatial pattern analysis, was used to compute the spatial metrics. It is capable of computing a wide range of landscape metrics at patch, class and landscape levels (McGarigal, 2015). We selected metrics that quantitatively characterise the landscape, namely diversity and abundance, fragmentation, connectivity and complexity. An initial list of landscape metrics was compiled from the literature (Gulcin and Yilmaz, 2017; Plexida et al., 2014; Zhang and Gao, 2016) (see Appendix 1). The list was reduced by adopting the following criteria: metrics should communicate information about different aspects of landscape dimensions and exhibit low redundancy (Su et al. 2014). Metrics information redundancy was reduced by dropping one of a pair of metrics with a class-level correlation coefficient of 0.9 and above. Patch richness (PR), Shannon diversity index (SHDI), Shannon's evenness index (SHEI), and Simpson's diversity index (SIDI) were added based on their usage in previous studies (Plexida et al., 2014; Su et al., 2014b) (Appendix 1).

Primarily two levels of metrics – landscape and class level – were computed from both land-cover maps (1986, 2015). The landscape-level analysis is based on the premise that the landscape is a whole (regardless of different land-cover types), while class-level analysis focuses on the spatial characteristics of individual land-cover types constituting the landscape and their respective patches (McGarigal, 2015).

FRAGSTATS 4.2 software allowed direct loading of the categorical maps in tiff formats from ENVI 5.0. FRAGSTATS' analysis parameters were set to use the four neighbouring cells rule and a cell size of 30 m, which is inherent in the source satellite image. The analysis was executed for both the 1986 and 2015 land-cover maps (Figure 3.3) to generate values of each indicator metric for the landscape for both years. Changes in landscape structural patterns that have occurred over the 29 years were assessed, focusing on diversity and abundance, fragmentation, connectivity, and complexity dynamics at both landscape and class levels (Table 3.2).

Table 3.2 List of landscape metrics used for describing structural properties of the Akyemansa-Kwaebibrem landscape

Landscape metric	Level[a]	Interpretation
Composition		
Diversity		
Patch richness (PR)	L	The number of different land-cover types present in the landscape.
Shannon diversity index (SHDI)	L	The number of different land-cover types and their proportional abundance in the landscape.
Shannon's evenness index (SHEI)	L	The similarities in the proportional abundance of the different land-cover types making up the landscape.
Simpson's diversity index (SIDI)	L	The likelihood that any two cells selected randomly from the landscape would be from a different land-cover type.
Percentage of landscape (PLAND)	C	The proportional abundance of each land-cover type in the landscape.
Configuration		
Fragmentation		
Number of patches (NP)	C, L	The total number of patches counts in a land-cover type or the entire landscape, depending on the scale of application.
Mean patch area (AREA_MN)	C, L	The total of areas of the patches of a land-cover type is divided by the number of patches of the same land-cover type.
Largest patch index (LPI)	C, L	The percentage of total landscape area occupied by the largest patch.
Contagion index (CONTAG)	L	A measure of dispersion (the spatial distribution of a land-cover type) and interspersion (the intermixing of units of different land-cover types) in a landscape based on cell adjacency. It is used as a measure of aggregation sometimes.
Interspersion and Juxtaposition Index (IJI)	C	A measure of the intermixing of units of different land-cover types based on patch adjacencies.
Aggregation index (AI)	C, L	The percentage of the observed number of like adjacencies relative to the maximum possible number of like adjacencies using the single-count method.
Connectivity		
Patch cohesion (COHESION)	C, L	A measure of physical connectedness of the corresponding land-cover type.
Complexity		
Perimeter-area fractal dimension (PAFRAC)	C, L	A measure of patch shape complexity across a wide range of spatial scales based on the perimeter-area relationship of patches in the landscape.

[a] C = Class level; L = Landscape level. Source: McGarigal (2015).

3.2.3 Operationalising integration and segregation

Landscapes can be seen as clusters of individual land-cover types (ecosystems) arranged in patterns and interacting with each other (Forman and Gordron, 1986; Perfecto et al., 2009). The type of clusters and their arrangements constitute the structure, while the functions of the landscape are derived from the existing ecosystems and their interactions. The segregate-or-integrate theory (van Noordwijk et al., 2013, 2012) suggests that multifunctionality in a landscape can be achieved across a spectrum, depending on the spatial arrangement of landscape components such as food crops, plantations and natural forest.

Advances in landscape ecology have resulted in a variety of different landscape metrics that characterise the structural properties of landscapes intrinsically associated with ecological processes (McGarigal, 2013; Turner and Gardner, 2015; Wu, 2012). Applying landscape metrics to measure the complexities and variations in spatial patterns resulting from continuous transitions provides indicator scores that can be combined to quantitatively characterise shifts on the integration-segregation continuum. Such a composite quantitative measure can serve as an overall indicator of the structural state of the landscape. However, landscape metrics are multidimensional, quantified over diverse scales, and have different units (McGarigal, 2015).

Composite indices have gained currency as an approach to integrating complex and multidimensional datasets into a single quantitative value indicating the phenomenon of interest (Nardo et al., 2005; Talukder et al., 2017). They are used in research and decision-making to synthesise complex real-life phenomena. Constructing composite indices involves the mathematical integration of indicators that together explain a dimension of the complex system under study (Nardo et al., 2005; Talukder et al., 2017). Indicators are selected based on the objectives and conceptual framing of the phenomenon. Mathematically, a composite index (CI) (Talukder et al., 2017) is generically represented as:

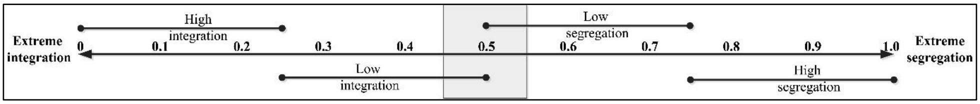
$$\mathrm{CI} = \sum_{i=1}^{n} W_i \, X_i \qquad \text{Equation 3.1}$$

Where *Xi* is the normalised selected indicator (as many as are needed); *n* is the population of selected indicators; and *Wi is the* weights assigned to each *Xi* (with weights ranging between 0 and 1).

Multi-sourced and multidimensional indicators tend to be scaled differently (interval, normal, ordinal, ratio). Therefore, to combine indicators, normalisation is required to convert original data values to standard value ranges devoid of their original scales and units for easy comparison and integration (Nardo et al., 2005). Weighting is normally used to indicate the importance attached to an individual indicator relative to others in contributing to the final index (Greco et al., 2019).

The combination of dimensions and their indicators into a composite index provides an estimate of the position of a landscape on the integration-segregation continuum. The index that measures landscape compositional and configurational dimensions will hereafter be referred to as the landscape structural state index (LSSI). The resultant value of the landscape structural state index ranges between 0 and 1. The index values are interpreted on the integration-segregation continuum in four ranges: 0-0.25 (high integration), 0.26-0.5 (low integration), 0.51-0.75 (low segregation) and 0.76-1 (high segregation) (Figure 3.5). The range between 0.45-0.55 of the continuum is seen as a dynamic range and considered transitory over time. Within this range, a landscape can swing between integration and segregation without external efforts. However, beyond the dynamic range, a landscape can be considered as trending towards either of the extreme ends.

Figure 3.5 Scale for assessing the direction of change in landscape's structural state on an integration-segregation continuum



Source: Author's construct.

Computing the landscape structural state index of the Akyemansa- Kwaebibrem landscape for 1986 and 2015

Drawing on the changing properties of landscape components along the model integration-segregation continuum (van Noordwijk et al., 2012) and using descriptive attributes of integrated and segregated landscapes (Primdahl, 1990), landscape-level metrics were regrouped into four dimensions based on the structural properties in the operationalisation section (Table 3.3). These include diversity and abundance of land-cover types (D), fragmentation (F), connectivity (C) and complexity (N). A final set of metrics was sampled from the initial selection based on the finiteness of their value range for normalisation. The number of patches was included, although it varies as a function of the patch sizes in a given landscape. Its inclusion was based on assumptions that allowed for defining definite value limits (explained in the next section).

Data normalisation

In order to create the composite index for determining the landscape's position along the integration-segregation continuum during a particular time interval, the results of the selected metrics, having different value ranges and meanings, were normalised. As only two datasets from 1986 and 2015 were available, we used min-max normalisation to normalise the metric values with a defined minimum and maximum values between 0 and 1. For landscapes of equal extent, when a high value of a metric suggests segregation (e.g. aggregation index), the forward normalisation (Equation 3.2) was applied to rescale the data range (Martinez-Salvador et al., 2007). Equation 3.3 was applied when a low value of a metric suggested segregation (e.g. number of patches) (Ibid).

$$NM = (x_i - minR)/(maxR - minR) \qquad \text{Equation 3.2}$$

$$NM = (maxR - x_i)/(maxR - minR) \qquad \text{Equation 3.3}$$

Where *NM* is the normalised metrics value rescaled to a range between 0 and 1; *maxR* is the highest possible value (upper limit) of the metrics; *minR* is the lowest possible value (lower limit) of the metrics; and x_i is the original landscape metric value generated from FRAGSTATS.

Table 3.3 Characterisation of integrated and segregated landscapes with structural dimensions

Integration	Segregation	Measurable attributes	Landscape dimensions	Structural properties
Heterogonous (fields of different crops and components)	Homogeneous (small, scattered bushes and others and large commodity crop)	• Variety of land-cover types present • Area proportions of land-cover types	Diversity and abundance of land-cover types	Composition
Small to medium size	Large field size	• Size of each land-cover type relative to the entire landscape • Occurrence of different patch sizes • Number of patches occupying a unit area	Fragmentation	Configuration
Many plots or landholdings in an area	Few land holdings in an area	• Areal extent of the largest and smallest patch units • Patch clustering or mixing up • Spatial distribution of patch types		
High degree of interactions	Low degree of interactions	• Separation distance and the effects on landscape process and functions	Connectivity	
Extensification (nature driven)	Intensification (mechanized)	• Extent of naturalness and orderliness	Complexity	

Source: Based on Duarte et al. (2018), McGarigal (2013), and Primdahl (1990).

We make the following assumptions to determine the landscape-specific value range for the number of patches. First, we assume that the least number of patches a predefined landscape can have equals 1, i.e. when the entire landscape is composed of one land-cover unit. Second, the maximum number of patches for the landscape is determined by the smallest possible patch size in the landscape. Hence the estimated maximum number of patches in the landscape (*PNmax)* is a function of the total landscape area and smallest patch size and computed as:

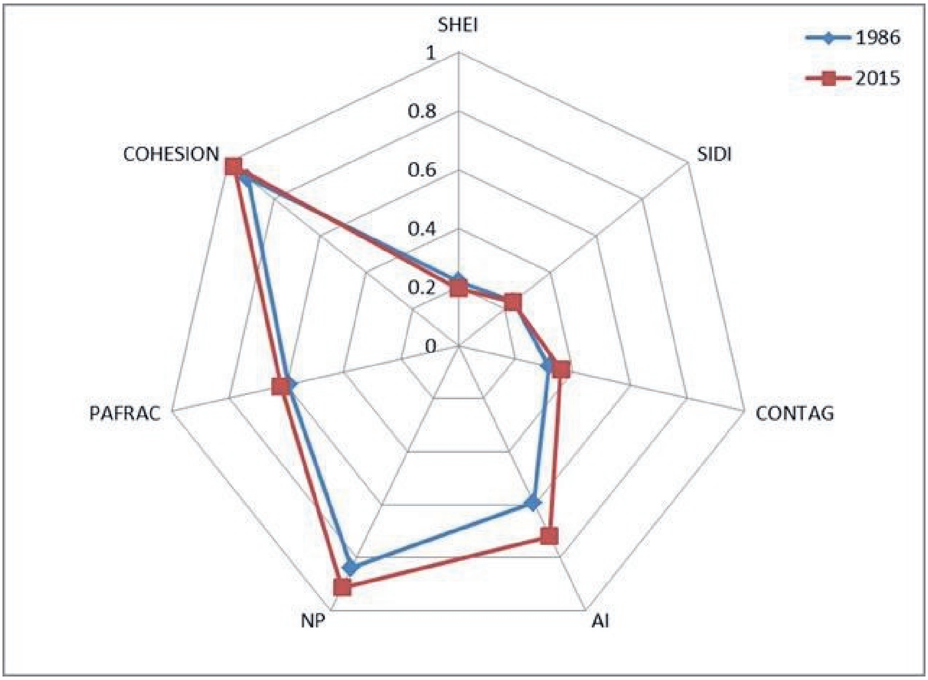
$$PNmax = aL/aSp \qquad \text{Equation 3.4}$$

Where *aL* is the area of the entire landscape in hectares (ha), and *aSp* is the size of the smallest patch in the landscape for the years under study in ha.

Weighting and aggregation

Weighting and aggregation have an immense influence on the final score of the index. There are limited guidelines based on theoretical underpinnings or expert agreement to indicator weighting (Greco et al., 2019). Regardless of the approach taken to weighing indicators, transparency is paramount. For this chapter, initially equal weighting of 0.25 was assigned to the normalised metrics for the four landscape dimensions and the final aggregation. These were later adjusted to 0.1 for the diversity/abundance dimension while allocating 0.3 to the other dimensions. The lower weight assigned to the diversity/abundance dimension is justified by its low contribution to the landscape structural properties in both 1986 and 2015 (see radar diagram in Figure 3.6).

Figure 3.6 Radar diagram showing the variance between the metrics for 1986 and 2015



Source: Author's construct based onlandscape metrics.

The landscape structural state index (LSSI) was computed using the geometric aggregation (multiplicative function) through the application of Equation 3.5. The multiplicative function was chosen for its minimum levels of compensability even when the values of some indicators are lower (Nardo et al., 2005).

$$\mathrm{LSSI} = \prod_{i=1}^{n} \mathrm{D}^{1/wd} \times \prod_{i=1}^{n} \mathrm{F}^{1/wf} \times \prod_{i=1}^{n} \mathrm{C}^{1/wc} \times \prod_{i=1}^{n} \mathrm{N}^{1/wn} \qquad \text{Equation 3.5}$$

Where *D* is the diversity and abundance dimension; *wd* is the weight allocated to *D*; *F* is the fragmentation dimension; *wf* is the weight allocated to *F*; *C* is the connectivity dimension; *wc* is the weight allocated to *C*; *N* is the complexity dimension; and *wn* is the weight allocated to *N.* The resultant LSSI value from Equation 3.5 marks the position of the landscape on the integration-segregation continuum at a specific time, here 1986 and 2015.

Table 3.4 Landscape metrics and their interpretation on the segregation-integration continuum

	Indicator	Units	Value range	Meaning of the indicator
	Diversity & Abundance			
1	Simpson's Diversity Index (SIDI)	None	$0 \leq SIDI < 1$	SIDI approaches 0 when the number of patches is reducing and shifts towards 1 with an increasing number of different patches and uniform area distribution. SIDI = 0 means segregation and greater than zero is an indication of increasing integration.
2	Shannon's Evenness Index (SHEI)	None	$0 \leq SHEI < 1$	SHEI = 0 means area distribution of the different patch types is uneven, an indication that some patch types are dominating. SHEI = 1 indicates perfect uniform area distribution among the different patch types. On an integration -segregation scale, SHEI = 0 means complete segregation and SHEI = 1 complete integration.
	Fragmentation			
3	Number of Patches (NP)	Count	$1 \leq NP < PNmax$	$PS \geq 1$
4	Aggregation Index (AI)	%	$0 \leq AI \leq 100$	At high disaggregation, AI = 0, whereas AI approaches 1 when the landscape is increasingly aggregated. AI = 0 (maximum integration); AI = 1 (maximum segregation).
5	Contagion index	%	$0 \leq CONTAG \leq 100$	CONTAG approaches 0 when the patch types are maximally disaggregated and interspersed (integration). CONTAG = 100 when all patch types are maximally aggregated (segregation).
	Connectivity			
6	Patch cohesion Index (COHESION)	None	$0 < COHESION < 100$	COHESION approaches 0 if the proportion of the landscape comprised of the focal class decreases and becomes increasingly subdivided and less physically connected. COHESION = 0 means patches of respective classes are not clumped together (i.e., integration), while a COHESION = 1 indicates that respective class patches are aggregated.
	Complexity			
7	Perimeter-area Fractal Dimension (PAFRAC)	None	$1 \leq PAFRAC \leq 2$	FRAC approaches 1 when shapes are simple as squares and approaches 2 for shapes with highly convoluted boundaries.

Source: Authors compilation based on McGarigal (2015).

Based on the characteristics of typical integrated and segregated landscapes in studies such as Primdahl (1990), Perfecto et al. (2009), and Noordwijk et al. (2012), we identified landscape structural properties that are measurable directly or by proxy with metrics (see Table 3.4 for value ranges). These metrics capture diversity and abundance of land-cover types, degree of fragmentation, connectivity between land-cover types, and complexity as an indicator of the degree of naturalness in the landscape.

3.3 Results

3.3.1 Changes in landscape composition and configuration between 1986 and 2015

Landscape-level analysis

Structural analysis at the landscape level revealed marginal compositional variation over the 29 years, while configuration (the spatial arrangement) experienced marked changes in several aspects (Table 3.5).

Patch richness has remained the same, meaning that the land-cover types listed in Table 3.1 were the same in both 1986 and 2015. Also, both Simpson's Diversity Index and Shannon's Evenness Index showed minimal differences between 1986 and 2015 (Table 3.5).

Table 3.5 Summary of landscape-level statistics

	Diversity			Fragmentation					Connectivity	Complexity
	PR	SHDI	SHEI	NP (,000)	AREA_MN	LPI	CONTAG	AI	COHESION	PAFRAC
1986	7	1.52	0.78	203.97	0.56	10.58	31.72	59.29	91.59	1.41
2015	7	1.57	0.81	109.98	1.03	10.21	35.91	71.98	97.81	1.38

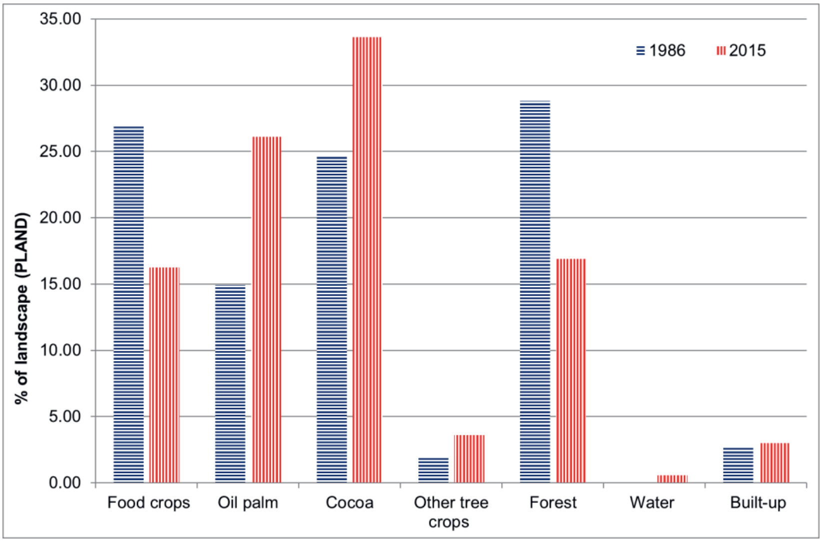
Source: Author's computations based on landscape metrics.

Several changes occurred in the configuration of land-cover types. First, there was a decrease in the number of patches (NP) from 203,969 in 1986 to 109,977 in 2015 and a concomitant increase in average patch size (AREA_MN) from 0.56 ha to 1.03 ha in the same period, suggesting increasing patch agglomeration. This is, however, not reflected in the largest patch index (the proportion of the largest patch size of total area), which has marginally declined from 10.58% to 10.21%. Second, clustering has increased as indicated by the increase in both the contagion index from 31.72% to 35.91% and in the aggregation index from 59.29% to 71.98%. However, the generally low CONTAG for both years suggests that although patches of some land-cover types are expanding, smaller different land-cover types are separating the larger ones. Third, connectivity measured by the patch cohesion index (COHESION) increased from 91.59 to 97.81, confirming increasing patch connectivity and clumping in the landscape. Fourth, perimeter-area fractal dimension (PAFRAC) has decreased marginally, from 1.41 in 1986 to 1.38 in 2015, revealing a trend towards landscape patches becoming less convoluted and simple. These changes suggest increasing high human impact in the landscape.

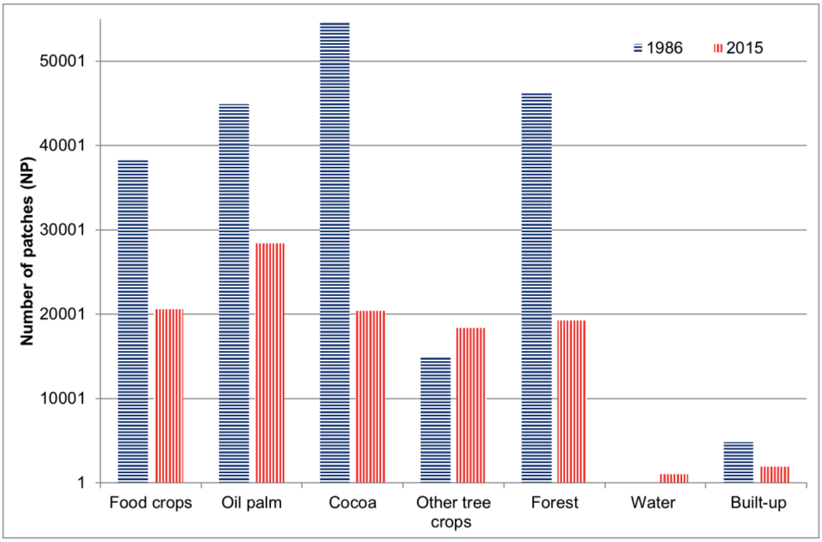
Analysis at class level

Composition at class level was analysed employing a percentage of landscape (PLAND; Table 3.2). PLAND had increased in all land-cover types by 2015 except for food-crop and forest areas, which had declined by 10.7% and 11.9%, respectively (Figure 3.7a). Oil palm recorded the largest increase in PLAND, followed by cocoa with 33.6% and 26.1%, respectively. PLAND reveals that land proportion dominance has switched from forest, cocoa and food crop in 1986 to cocoa and oil palm in 2015.

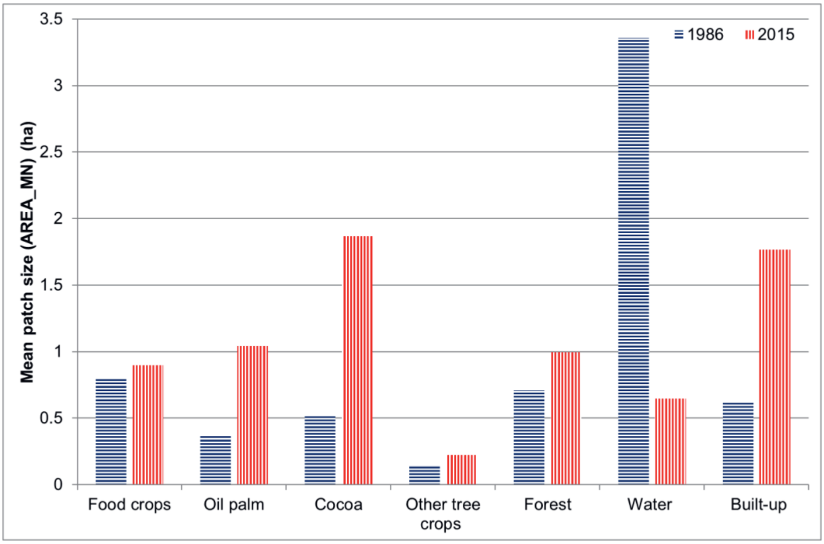
Figure 3.7 Distribution of (a) percentage of landscape occupied, (b) number of patches (c) mean patch size and (d) largest patch index of each land-cover type in 1986 and 2015

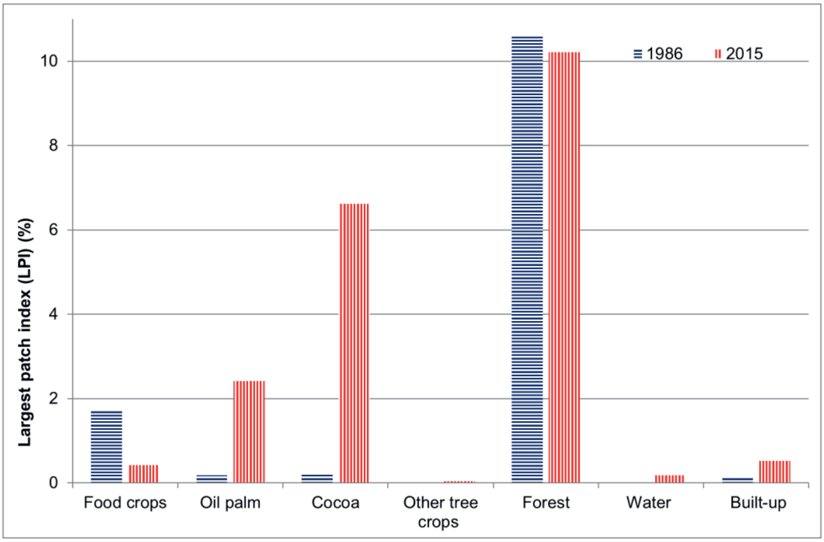


a)



b)

c) 

d) 

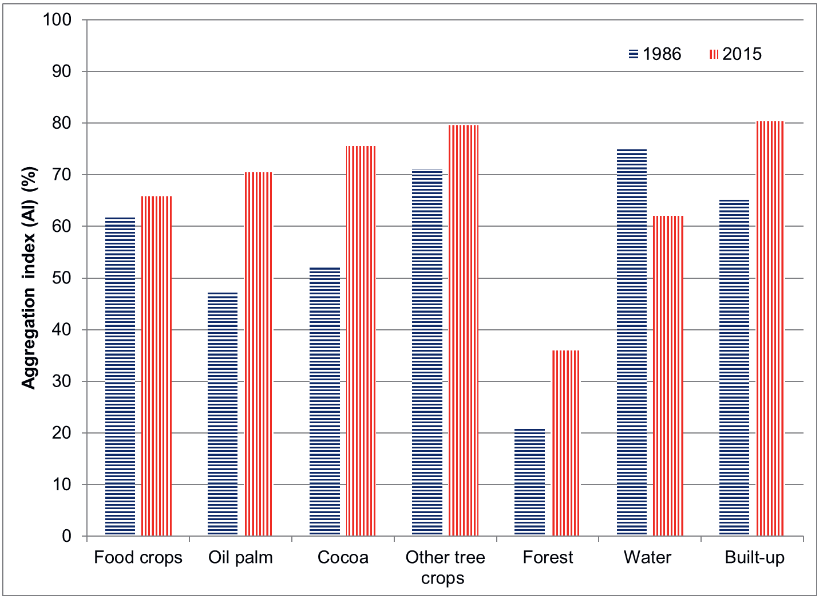
Source: Author's compilation based on landscape metrics

Class-level configuration was expressed by patch properties of the land-cover types and interactions in the landscape in 1986 and 2015 (Table 3.2). Figure 3.7b shows that all land-cover types had more patch numbers (PN) in 1986 than in 2015 except for water surfaces and other tree-crop areas, which had a reverse trend. In 2015, the PN of cocoa had dropped by 62.71%, the highest in the period. PNs of built-up, forest, food crop and oil palm also declined by 60.56%, 58.25%, 46.38% and 36.73%, respectively. The decreasing PNs suggest aggregation of patches or outright loss of patches in the five land-cover types. The increasing number of patches in water surface and other tree crops in Figure 3.7b shows that the existing patches of land-cover types are breaking into smaller patches, or new smaller plots are springing up in the landscape. Figure 3.7c illustrates trends in average patch size (AREA_MN) of the different land-cover types in 1986 and 2015. Average patch sizes increased in 2015 for all land-cover types except for water surface, which had a smaller average area. Cocoa and oil palm recorded larger increases in average patch sizes by 1.3 ha and 0.7 ha, respectively, in 2015. AREA_MN for forest, other tree crops and food crops also showed increases, but least for food crops. Built-up also increased in average patch size, indicating growing settlements. Thirdly, the distribution of the largest patch index (LPI), which shows trends in the biggest patch of each land-cover type relative to the landscape area in both years, confirms the growth in patch areas in 2015 (Figure 3.7d). The LPI for the different land-cover types had increased in 2015 except for forest and food crops that decreased. The LPI for forest reduced marginally from 10.52% in 1986 to 10.21% in 2015, while food crop LPI decreased from 1.74% to 0.42%, respectively. Contrastingly, the LPI for cocoa and oil palm increased from about 0.19% to 6.6% and 0.18% to 2.4%, respectively. The trends in AREA_MN and LPI point to the expansion of cocoa, oil palm, built-up and other tree-crop patch areas in the period between 1986 and 2015. For the same period, the average patch size of forest and food crops also increased, but their largest patches decreased. This implies that the increase in AREA_MN experienced in food crops and forest is due to the conversion of smaller patches to other land-cover types.

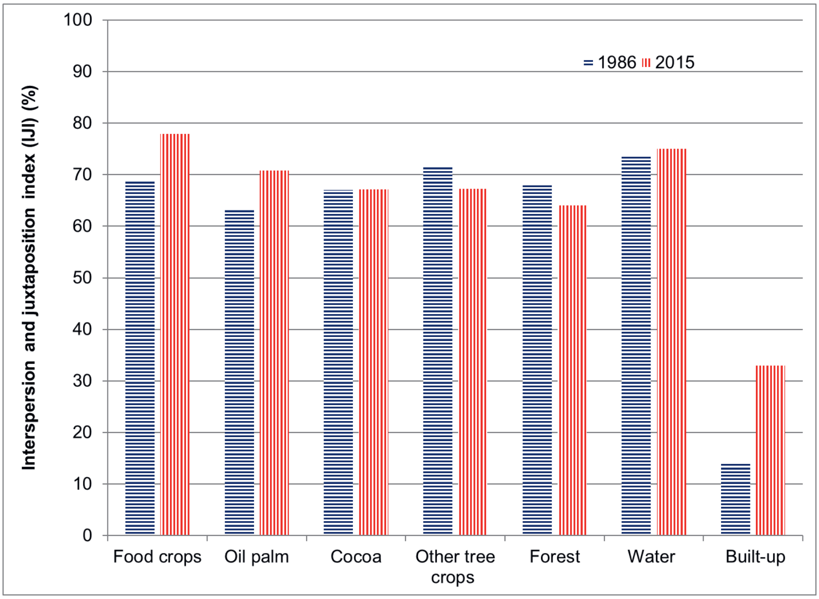
The AI was higher for all land-cover types in 2015 except for water surface. This indicates that similar land-cover types clustered more in 2015 than they did in 1986 (Figure 3.8a). The low clustering seen in water surfaces in 2015 is attributed to the presence of isolated ponds of water due to siltation and forest clearing as well as the increased presence of scattered mine pits filled with water. In the period between 1986 and 2015, large increases in AIs were found in built-up and other tree crops, particularly in cocoa and oil palm (about 23% each). The expansive nature of cocoa and oil palm in the landscape is the cause of the high clustering levels. The AI for forest also increased substantially due to the high conversion rate in off-reserve forest fragments, leading to the concentration of forest in forest reserves.

Unlike the AI, trends in IJI were mixed in both years (Figure 3.8b). As a metric based on patch adjacency, it is not influenced by the increasing patch sizes but rather by the frequency of patch types lying side-by-side. In 2015, while IJI increased in built-up, food crop, oil palm and water, it decreased in forest and other tree crops and stabilised in cocoa. The higher IJI in 2015 indicates that built-up, food crops, oil palm and water increasingly shared borders evenly with other land-cover types compared to1986. The decreased IJI in forest reflects a disproportionate adjacency in the focal land-cover types. The rather stable IJI in cocoa indicates that cocoa farms maintained the land-cover types with which it shares boundaries.

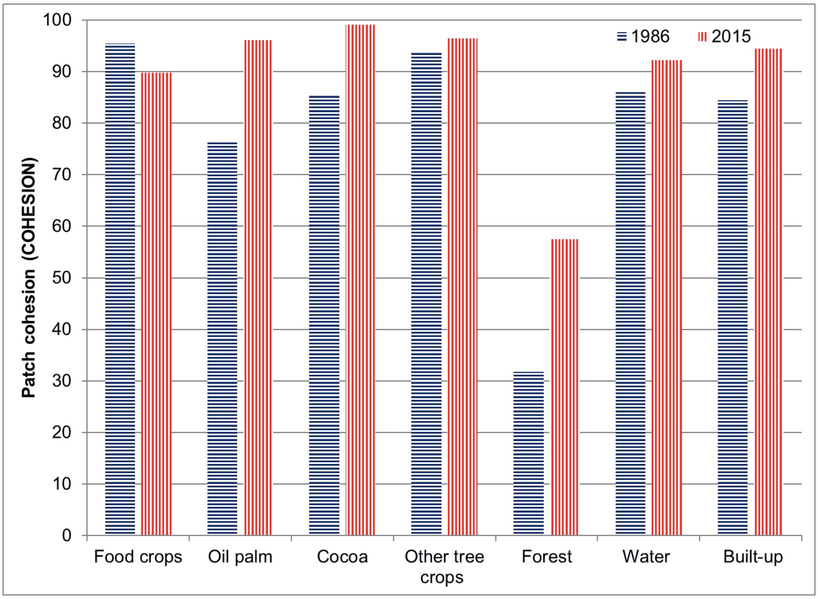
Figure 3.8 Distribution of (a) aggregation index, (b) interspersion and juxtaposition, (c) patch cohesion index and (d) perimeter-area fractal dimension index for land- cover types in 1986 and 2015

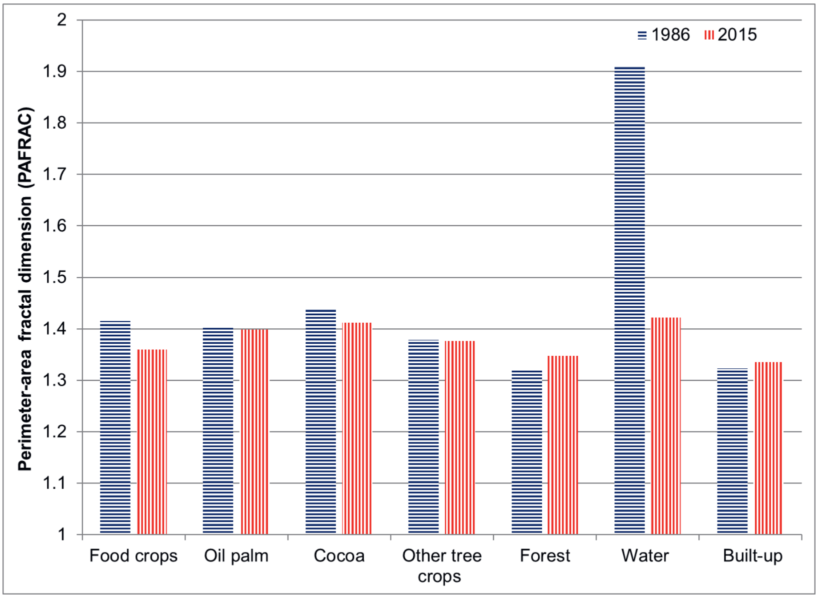


a)



b)

c) 

d) 

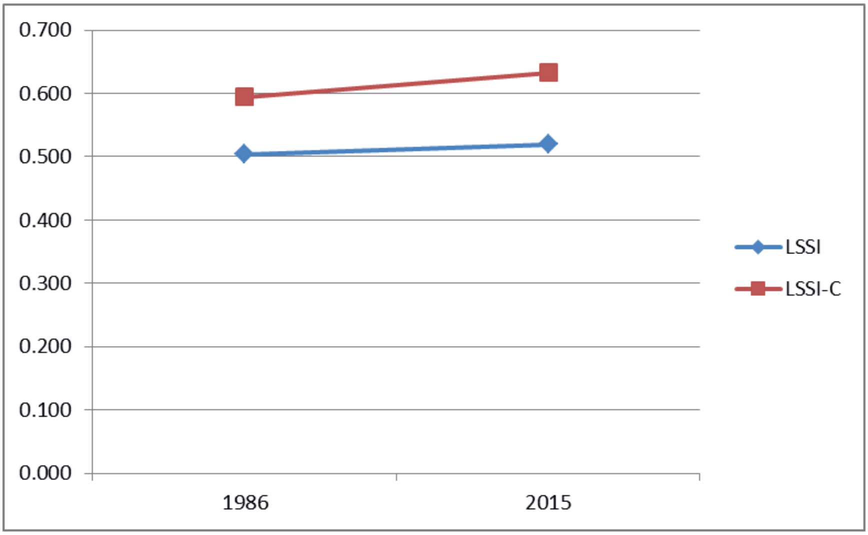
Source: Author's compilation based on the landscape metrics.

Connectivity, measured by COHESION was higher for all land-cover types in 2015 except for food crops (Figure 3.8c). The 5.7 decline in food crop COHESION is because of the isolation effect from cocoa and oil palm expansion on it. Forest COHESION increased from 31.7 in 1986 to 57.5 to become the most connected land cover in 2015 due to the aforementioned concentration of forest in a connected forest reserve block. Oil palm and cocoa followed forest with a 19.9 and 13.7 increase in COHESION for the same period. Whilst the increase in connectedness among oil palm is due to the increasing area of industrial plantations and establishment of new smallholder farms (including outgrower schemes), the increased connectedness in cocoa is mainly driven by new farm establishment and expansion of old farms to capture adjoining non-cocoa areas.

Patch shape complexity as measured by perimeter-area fractal dimension (PAFRAC) (Table 3.2) declined in all land-cover types between 1986 and 2015 except for forest and built-up (Figure 3.8d). The low values of PAFRAC in 2015 indicate that patches are assuming regular shapes. It signifies simplification in the landscape due to human influence. The extreme simplification observed in water surface is due to increased farming activities along waterways.

The increased complexity in forest and built-up areas in 2015 can be attributed to the uncoordinated conversion of portions of off-reserve forest to other uses and the unregulated manner of creating and expanding built-up areas, respectively.

Figure 3.9 Landscape structural state index (LSSI) for the landscape in 1986 and 2015 using equal weights (LSSI) and budget allocated weights (LSSI-C)



Source: Author’s compilation based on Landscape Structural State Index.

3.3.2 Degree of integration or segregation: the landscape structural state index

The landscape structural state index (LSSI) was computed for the Akyemansa-Kwaebibrem landscape for 1986 and 2015 to assess the direction of change on the integration-segregation continuum. Initially, when equal weight was given to all dimensions, the LSSI increased from 0.50 in 1986 to 0.52 in 2015 (Figure 3.9). This indicates that the landscape tends towards segregation, even though it lies within the dynamic range and could be transient.

A radar diagram assessment and a second run of the LSSI (LSSI-C) based on a budget allocation of weights resulted in 0.59 in 1986 and 0.63 in 2015. The radar diagram (Figure 3.6) shows that the diversity dimension of the landscape (measured with SHEI and SIDI) contributed less to the variance in spatial diversity. The two measures also remained almost the same in1986 and 2015. This is due to the stable numbers of land-cover types.

Placing more weight on configuration than on composition increased the index for both years as well as the difference between them. The new results situate both 1986 and 2015 landscapes at the low segregation portion of the continuum, implying that the landscape is at the early stages of a trajectory towards becoming a segregated landscape characterised by large separated areas for different land-use types. This can be attributed to the expansion of industrial oil plantations and the aggregation effect of smallholder cocoa farms, coupled with the presence of a block of forest reserve in the landscape.

3.4 Discussion

3.4.1 Structural dynamics in tree-crop dominated mosaic landscapes

The analysis of landscape structural dynamics between 1986 and 2015 (first objective) showed that the landscape consisted of the same land-cover types in both years (Table 3.5 and Figure 3.7a). This confirms Michel-Dounias et al.'s (2015) historical account of the presence of cocoa and oil palm in the Akyemansa-Kwaebibrem landscape prior to 1986. Although not mapped separately, a new entrant in the landscape is rubber (field observation), which occurred in very small patches, hence was merged with citrus that was present in small patches in 1986 (Asubonteng et al., 2018 Chapter 2). The analysis further revealed that patches are taking on regular shapes, revealing a tendency towards greater simplification and a more homogenised landscape dominated by cocoa and oil palm in 2015 compared to 1986 (Figure 3.7d). The increase in areas of the two main tree crops in the landscape is due to the high rate of land transfers, mainly from forest and food-crop areas (Asubonteng et al., 2018 Chapter 2); a trend also reported for the Western Region in Ghana by Benefoh et al. (2018). The conversion of forest lands, particularly off-reserve forest, into agriculture is common practice in Ghana's high forest zone. Hence there is a need to characterise the structural changes resulting from the process (Addo-Fordjour and Ankomah, 2017; Koranteng et al., 2016; Kusimi, 2015).

The higher aggregation levels in the landscape as evidenced by increased mean patch area, contagion, aggregation index, and patch cohesion and reduced number of patches (Table 3.5, Figures 3.7c,3.8a, 3.8c and 3.7b) indicates that the mosaic character of the landscape has reduced. Also, the dynamics of the land-cover types pointed to increased aggregation, driven mainly by the expansion of cocoa and oil palm at the cost of off-reserve forest and food-crop areas. High cohesion and lower IJI were also associated with farmland expansion in China (Sun and Zhou, 2016). Cocoa and oil palm have become the first- and second-largest land-cover type in the study area in 2015 (Figure 3.7a and 3.7d).

New cocoa farms were established next to old cocoa farms by replacing remnant forest patches that served as natural boundaries between cocoa farms in the past with food crops and ultimately with cocoa (Asubonteng et al., 2018 see Chapter 2). Studies on cocoa landscapes barely acknowledge the ecosystem functions of these forest fragments and fail to discuss their disappearance in landscapes, focusing instead on shade trees integrated into cocoa farms and their role in increasing climate change resilience (e.g. Abdulai et al., 2018; Middendorp et al., 2018). However, such old forest patches serve as functional corridors between habitats in landscapes (Asare et al., 2014). They are occasionally replaced with a row of ornamental plants under the closed canopies (field observations).

Low financial returns are causing a decline in food-crop areas, which are being replaced with commodity crops (Benefoh et al., 2018; Vongvisouk et al., 2016). The few remaining food-crop areas are highly interspersed in cocoa and oil palm areas (Figure 3.8b). This implies that patches are becoming larger and vegetation (food and forest) separating the patches is disappearing, suggesting declining food production and loss of ecosystem services (Clough et al., 2016). Equally, the oil palm area is also increasing due to large-scale oil palm plantations, both industrial and by aggregating smallholdings in smallholder and out-grower schemes (Asubonteng et al., 2018). In addition to expansion, adopting an equilateral triangle planting design for oil palm farm establishment (Bonneau et al., 2018) has contributed to the regular edge shapes. This contradicts the increased complexity associated with farmland expansion reported by Sun and Zhou (2016).

The implication of declining off-reserve forest is reducing pollinating services and worsening the microclimate for cocoa production due to the declining availability of shade trees for cocoa (Tscharntke et al., 2012). Decreasing heterogeneity also implies a declining habitat for wildlife (Ibid). Hence, whereas the cocoa-oil palm landscape is smallholder-dominated by ownership (GSS, 2014b; MoFA, 2020c), the landscape is structurally similar to a landscape dominated by industrial plantations. The decline in biodiversity and other ecosystems services and the need for high yields have led to increased farm sizes and application of herbicides, pesticides, and fertilisers (Fianko et al., 2011) and, in recent times, human-assisted pollination (Dapatem, 2017).

3.4.2 Integration and segregation in the landscape

Results regarding the degree of integration and segregation and the temporal direction into which the landscape is developing (second objective) show that the landscape was already at the early stages of segregation in 1986 and moved further in the direction of more segregation in 2015. These tendencies are attributed to the high participation of farmers in cocoa and oil palm farming, coupled with the adoption of intensification leading to aggregation, connectedness and declining patch shape complexity and patch numbers in both crops. Built-up areas are also expanding, leaving the other vegetation types as small patches and usually isolated in the landscape, except for the protected forest reserve that appears as a contiguous block. This corroborates the findings of the structural analysis with the landscape metrics, which suggest increased levels of aggregation, connectedness and declining patch shape complexity and patch numbers (Table 3.5), all of which are characteristics of a segregated landscape.

Application of the landscape index helped us to quantify these transitions, adding a temporal dimension to spatial landscape analysis. Until now, integration and segregation have been quantified in landscapes employing edge contrast measures (Dewi et al., 2013). This study provides a multidimensional index to quantify and monitor the state of a landscape. This provides proof of concept for measuring transformations in landscapes over time.

The LSSI provides a simple but intuitive approach to generate information about the state and changes in the structure of the components in the landscape, considering the diversity, abundance, fragmentation, connectivity and complexity dimensions of landscapes. Although we agree with Dewi et al. (2013) that segregation is influenced more by landscape configuration, we disagree with the exclusion of composition. A focus on configuration is relevant for landscapes with a stable composition, but this hardly applies to mosaic landscapes that undergo conversion to new land uses. Both composition and configuration properties are relevant for the availability of multiple ecosystem functions that landscapes provide (Lamy et al., 2016). In a landscape, several different land-cover types (composition) have to be present before consideration can be given to their arrangement (configuration).

Commodity crops (including tree crops) continue to transform landscape structure at varying rates and periods as observed in western Ghana (Benefoh et al., 2018) and across the tropics (Castella et al., 2013; Dewi et al., 2013; Vongvisouk et al., 2016). Applying the LSSI in these landscapes will facilitate the tracking of manifestation of land sharing and sparing for apt decision-making. The standardised nature of the LSSI makes it easier to monitor and interpret landscape dynamics without technical expertise in spatial analysis. It can be a useful tool to engage a broad range of stakeholders in discussions about the state of the landscape. This could serve as a basis for stakeholder negotiations in integrated landscape approaches (Arts et al., 2017; Reed et al., 2016; Ros-Tonen et al., 2018) Understanding the state of the landscape and its spatial trajectory is also relevant for predicting the availability and quality of certain landscape services in the distant future. Such knowledge can form the point of departure for developing context-relevant landscape policies.

3.4.3 Limitations

Despite the successful characterisation of the landscape with the landscape metrics and the state of the landscape with a single quantitative value, the LSSI, we acknowledge some limitations of the study. First, adjusting the aggregation of weights based on the difference observed in the radar diagram of the structural dimensions for the period between the two years suggests that the weights will vary for different landscapes. Therefore, we recommend that future studies focus on developing empirical coefficients for weighting through Analytic Hierarchy Process (AHP).

Second, challenges with data acquisition and period of availability and data quality constrained the analysis in two ways:

- Merging of citrus, a land-cover type present in 1986 on a very small scale, with recently introduced rubber, reduced the thematic resolution of the landscape and hence the computation of some landscape dimensions, especially the diversity dimension. This implies that there is a need to seek a balance between the spatial resolution of satellite images and the thematic resolution of the maps derived from them.

- The limited availability of cloud-free satellite images between the two time points made it challenging to identify concrete trends in structural landscape changes based on landscape metrics. Available data allows the observation of tendencies in broad strokes but not a refined analysis of the actual trend. In the absence of rich temporal datasets, the development of the LSSI was constrained as the sensitivity and robustness of the approach could not be tested.

3.5 Conclusions

This chapter characterised changes in spatial patterns associated with the evolution of tree crops in the forest mosaic landscape of eastern Ghana between 1986 and 2015. It further explored how landscape metrics can be used to determine the degree of integration and segregation in landscapes. First, the findings reveal that landscape-level composition was relatively stable with the same land-cover types and a slight increase in the evenness over time. This situation could have been slightly different if the emerging small area of rubber was separated from citrus. The patchy and complex configuration of the landscape is transitioning into one with a few large connected and regularly shaped patches, which is a sign of simplification. The two major tree crops – cocoa and oil palm – have similar trends regarding increasing land coverage, mean patch areas, connectivity, aggregation and decreasing complexity. On the other hand, food-crop areas have seen reduced land areas, connectivity and increased intermixing with other vegetation cover types. Forest became more connected and less fragmented through the conversion of off-reserve forests and deforestation at the edges of the forest reserve. In summary, food-crop land and forest outside reserve areas have been squeezed out by the expansion of cocoa and oil palm and, to a lesser extent, by built-up areas. The smallholder-dominated landscape exhibits structural characteristics similar to those in industrial plantations, namely high patch connectivity, aggregation, and simplification.

This has significant implications for ecosystem services such as natural disease, pest control, and pollination dependent on biodiversity. Moreover, we showed that the landscape was already in the early stages of segregation on the integration-segregation continuum in 1986 and is now sliding towards greater segregation. The observed expansive tendencies in cocoa and oil palm have led to the loss of land-sharing attributes and the transitioning of the landscape into a ‘spared’ landscape, characterised by fewer land-cover types with limited interactions and multifunctionality.

These tendencies call for practitioners and government to consider the effects of segregation processes for the availability of ecosystems services and the livelihoods that depend on them when planning for increased yields and farmer participation in tree-crop value chains. Further trials of the LSSI are needed in landscapes under the influence of different socioeconomic drivers and with data covering several years to assess both the sensitivity of the landscape structural index to change and the robustness of the approach.