

# Integration versus segregation: Structural dynamics of a smallholder-dominated mosaic landscape under tree-crop expansion in Ghana

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## ARTICLE INFO

### Keywords:

FRAGSTATS

Landscape composition

Landscape configuration

Integration/segregation

Landscape Structural State Index (LSSI)

Sparing/sharing

## ABSTRACT

Tree crops like cocoa and oil palm have ecological and socio-economic 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 to 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), as a measure to determine 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.

## 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 has led to forest fragmentation and loss of natural habitat, biodiversity and associated livelihoods (Clough et al., 2016; Ordway, Asner, & Lambin, 2017). Reconciling conservation and production goals in multifunctional landscapes that provide multiple ecosystem services is therefore

generally acknowledged as a sustainable choice (van Noordwijk, Hoang, Neufeldt, Oborn, & Yatich, 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

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<https://doi.org/10.1016/j.apgeog.2020.102201>

Received 14 November 2019; Received in revised form 18 March 2020; Accepted 28 March 2020

Available online 4 May 2020

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natural areas for biodiversity conservation elsewhere (“spatial segregation”) (Brandt, 2003; Phalan, Onial, Balmford, & Green, 2011). Land-sharing advocates posit that multifunctionality is better achieved by interspersing farmlands with nature areas, which generates landscapes with high biodiversity value and relatively lower, but more sustainable yields (Perfecto & Vandermeer, 2010; Tschamtket et al., 2012). Contrastingly, under land sparing the landscape is characterized 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 & 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 an understanding of landscape structure is key to studies focusing on landscape functions and approaches that aim at achieving multifunctionality (Galler, Haaren, & Albert, 2013; Krováková, Semerádová, Mudrochová, & Skaloš, 2015).

Sometimes ‘integration and segregation’ and ‘sharing and sparing’ are used synonymously (Dewi, van Noordwijk, Ekadinata, & Pfund, 2013; Kremen, 2015; van Noordwijk, Tata, Xu, Dewi, & Minang, 2012). However, the former distinction underscores the spatial dimensions. Assigning exclusively sparing and sharing labels 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, Carvalho-Ribeiro, & Soares-Filho, 2016; Lamy, Liss, Gonzalez, & Bennett, 2016; van Noordwijk et al., 2014). If structural patterns are relevant for landscape processes and ecosystem services delivery, then it is imperative to understand the spatial configurations of land-cover types in landscapes over time along the integration-segregation continuum.<sup>1</sup>

Research on the expansion of tree crops (cocoa and oil palm) abounds in literature (e.g. Benefoh et al., 2018; Ordway et al., 2017), but insights into structural changes associated with their areal increase in mosaic landscapes are few. Former studies (e.g. Diwediga, Agodzo, Wala, & Le, 2017; Su, Wang, et al., 2014b) 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 conceptualized spatial aspects of this continuum, but have failed to spatially operationalize them for monitoring. Another effort to characterize 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). This single index method, however, does not sufficiently account for the spatial complexities and variations in structural properties in dynamic

landscapes during transitions. Edge contrast measures have also been criticized 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, Blanchet, & Koper, 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 characterizes 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 paper 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 and compares them with other studies and addresses the potential and limitations of the composite index developed in this paper. The conclusion addresses the implications of this research.

## 2. Methodology

### 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-Kwaebibirem landscape (Fig. 1). Historically the Akyemansa-Kwaebibirem landscape was predominantly forest, mixed with swidden agriculture. It is characterized 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–33 °C, supporting predominantly agrarian livelihoods (MoFA, 2020a and 2020b).

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, Steer, Giry, Jannot, & Kalms, 2015). Key factors that drove oil palm development was 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, Pfeffer, Ros-Tonen, Verbesselt, & Baud, 2018). The landscape is mainly rural, characterized by smallholder agriculture as the source of livelihood for the majority of the population (Ghana Statistical Service, 2014; MoFA, 2020). The historical stages of transitions in terms of landscape composition and presence of different agricultural activities make it a suitable landscape to assess the spatial structural dynamics over time.

### 2.2. Data and methods

The study employs land-cover maps derived from satellite images and spatial methodologies to quantitatively characterize the land-cover pattern dynamics in the landscape. Spatial characteristics from land-cover maps are used to explore the changes in structural properties in the Akyemansa-Kwaebibirem 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 (McGarigal, 2015, pp. 1–182). Selected landscape-level metrics are combined into a composite index for interpretation of the integration-segregation continuum.

<sup>1</sup> 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 paper 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).

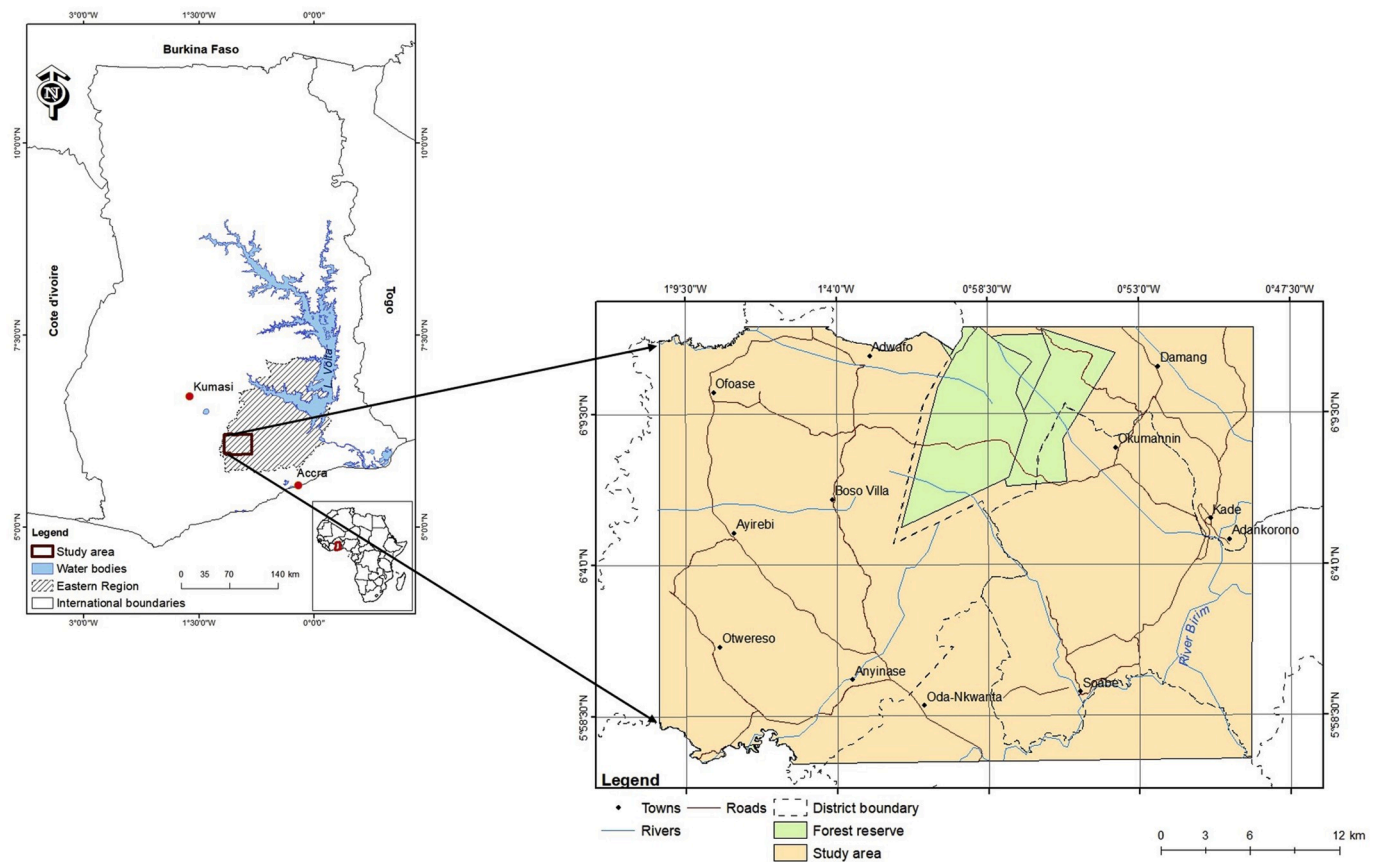


Fig. 1. Location of the Akyemansa–Kwaebibrem landscape in the Eastern Regions of Ghana.

The details are explained in the following sections (Fig. 2).

### 2.2.1. Data

The study employed 1986 and 2015 categorical land-cover maps of the Akyemansa-Kwaebibrem landscape produced by Asubonteng et al. (2018) as the main data for assessing variation in structural properties of the landscape and to explore the overall shifts along the integration-segregation continuum over the 29-year period (Fig. 3). Data for only 1986 and 2015 were used because cloud-free satellite images were limited for the study area (Asubonteng et al. (2018)).

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 1).

Following atmospheric correction and geometric alignments, the 1986 and 2015 images were classified into thematic land-cover maps employing unsupervised Iterative Self Organizing Data Analysis (ISO-DATA) and supervised Maximum Likelihood Classification (MLC), respectively (Fig. 3). The classification accuracies of the 1986 and 2015 maps were 91.2% and 78.8%, respectively (Asubonteng et al., 2018). Using the approach by Olofsson et al. (2014), uncertainties in the land-cover type areas were estimated (Appendix 1). 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, Kadé and Soabe (Asubonteng et al., 2018).

### 2.2.2. 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, pp. 1–182). We selected metrics that quantitatively characterize the landscape, namely diversity and abundance, fragmentation, connectivity and complexity. An initial list of landscape metrics was compiled from the literature (Gulcin & Yilmaz, 2017; Plexida, Sfougaris, Ispikoudis, & Papanastasis, 2014; Zhang & Gao, 2016). The list was reduced by adopting the following criteria: metrics should communicate information about different aspects of landscape dimensions and exhibit low redundancy (Su, Wang, 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, Wang, et al., 2014).

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, pp. 1–182).

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 (Fig. 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 2).

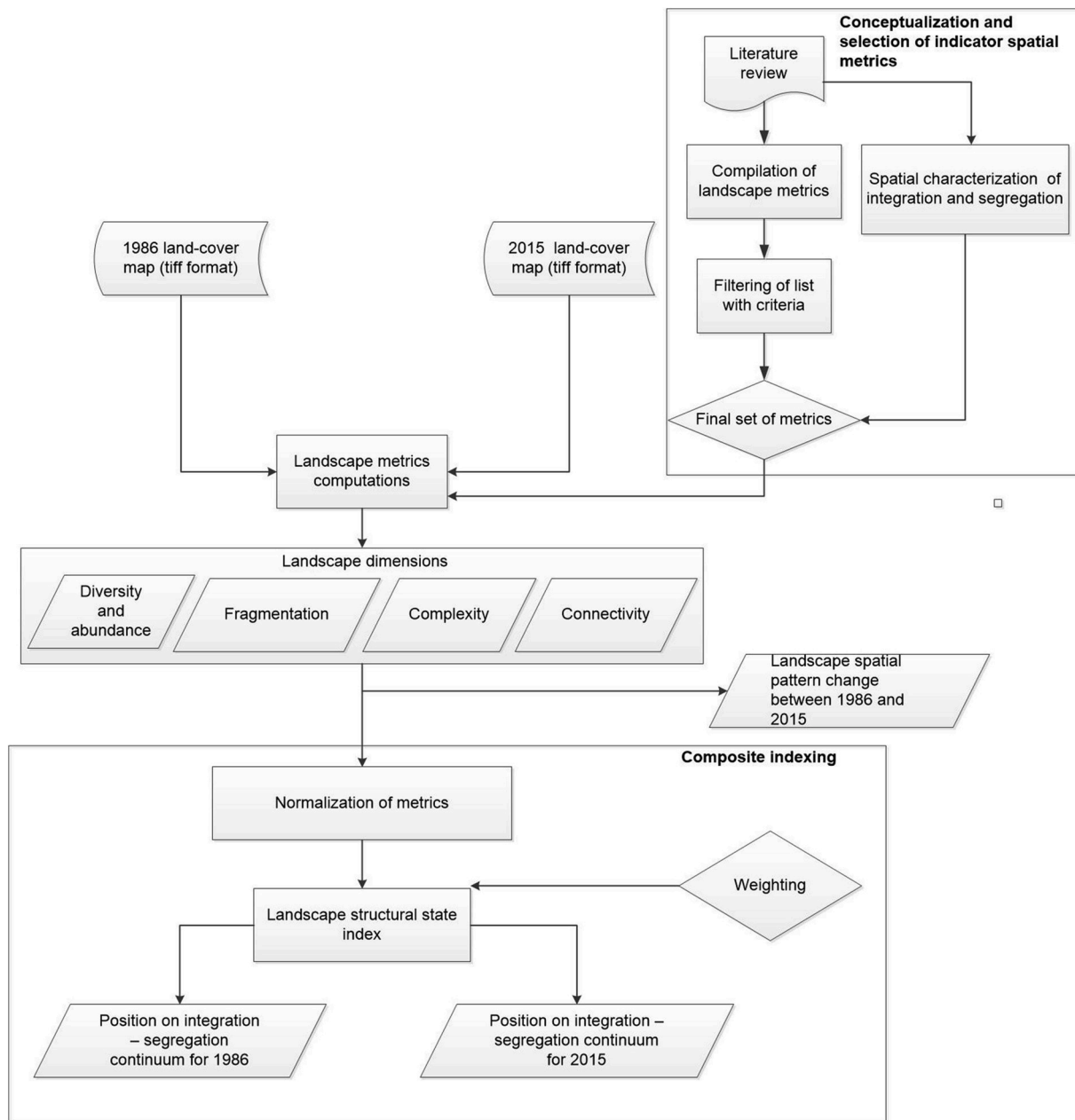


Fig. 2. Framework for assessing the spatial dynamics and position of the landscape along the integration-segregation continuum.

### 2.3. Operationalizing integration and segregation

Landscapes can be seen as clusters of individual land-cover types (ecosystems) arranged in patterns and interacting with each other (Forman & Gordron, 1986; Perfecto, Vandermeer, & Wright, 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., 2012, 2013) 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 characterize the structural properties of landscapes intrinsically associated with ecological processes (McGarigal, 2013; Turner & 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 characterize 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, pp. 1–182).

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, Saisana, Saltelli, & Tarantola, 2005; Talukder, Hipel, & van Loon, 2017). They are used in research and decision-making to synthesize 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:

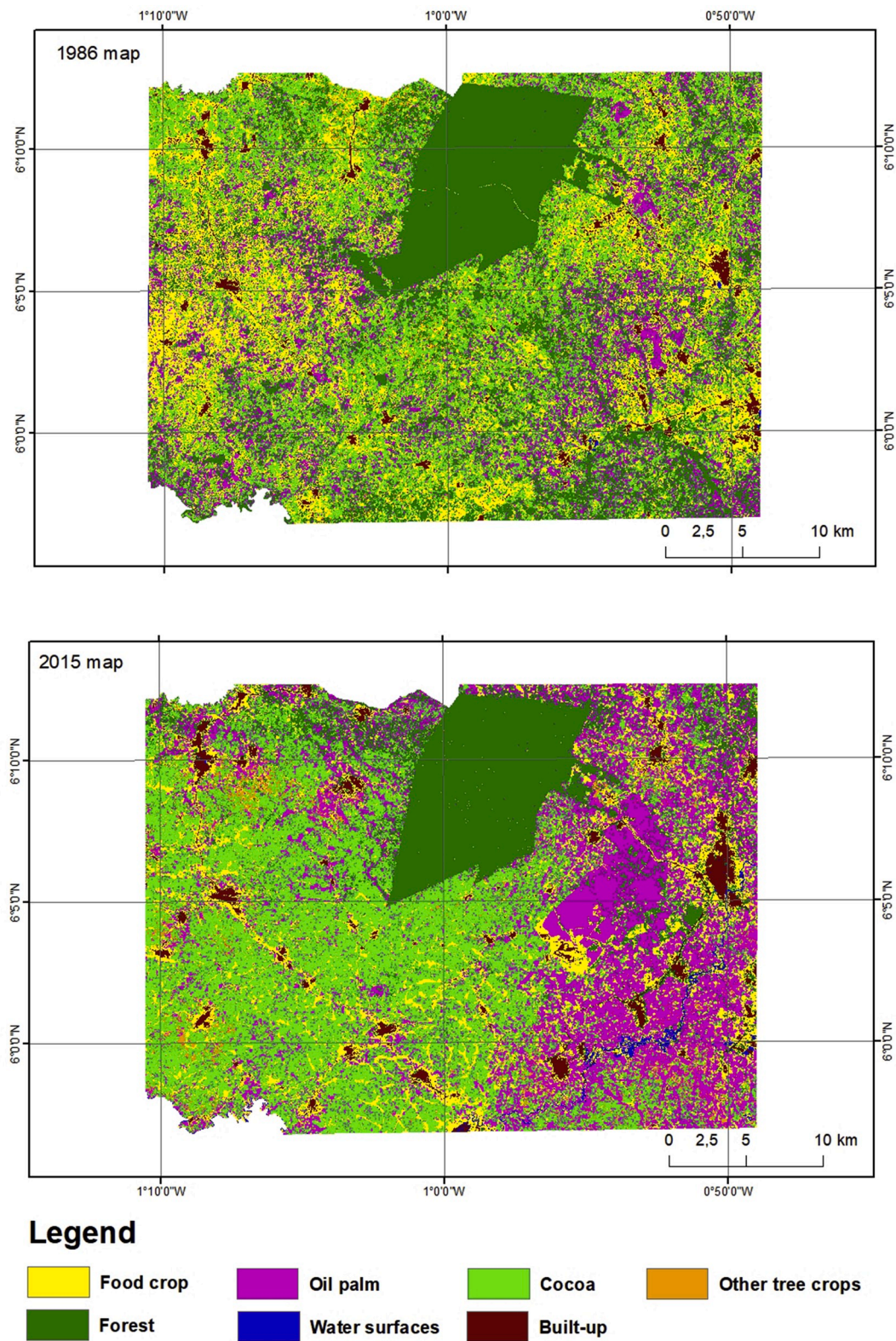


Fig. 3. Land-cover maps of the Akyemansa-Kwaebibrem landscape in 1986 and 2015.

$$CI = \sum_{i=1}^n W_i X_i \tag{1}$$

where  $X_i$  is the normalized selected indicator (as many as are needed);  $n$  the population of selected indicators and  $W_i$  the weights assigned to each  $X_i$  (with weights ranging between 0 and 1).

Multisourced and multidimensional indicators tend to be scaled differently (interval, normal, ordinal, ratio). Therefore, to combine indicators, normalization 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

**Table 1**

Main land-cover categories identified in the Akyemansa-Kwaebibrem landscape (adapted from Asubonteng et al., 2018).

Land-cover classes	Description
Food crops	Land primarily available for the production of food, mainly annual and biannual. It also includes natural vegetation areas that oscillate between production and fallow periods in a food production cycle. The latter are predominantly 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. Bamboo clusters and timber plantations are included.
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, waste lands and rock outcrops.

relative to others in contributing to the final index (Greco, Ishizaka, Tasiou, & Torrisi, 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 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) (Fig. 4). The range between 0.45 and 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.

### 2.3.1. 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 operationalization section (Table 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 normalization. The number of patches was included although it varies as 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).

### 2.3.2. Data normalization

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 normalized. As only two datasets from 1986 to 2015 were available, we used min-max normalization to normalize the metric values with 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),

**Table 2**

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

Landscape metric	Level	Interpretation (McGarigal, 2015, pp. 1–182)
<b>Composition</b>		
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 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 at random 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.
<b>Configuration</b>		
Fragmentation		
Number of patches (NP)	C, L	Total number of patch counts in a land-cover type or in 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 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 interspersions (the intermixing of units of different land-cover types) in a landscape based on cell adjacency. It is sometimes used as a measure of aggregation.
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.
<b>Connectivity</b>		
Patch cohesion (COHESION)	C,L	A measure of physical connectedness of the corresponding land-cover type.
<b>Complexity</b>		
Perimeter-area fractal dimension (PAFRAC)	C, L	A measure of patch shape complexity across a wide range of spatial scales based on perimeter-area relationship of patches in the landscape.

<sup>a</sup>C = Class level; L = Landscape level.

the forward normalization (Equation (2)) was applied to rescale the data range (Martinez-Salvador et al., 2007). Equation (3) was applied when a low value of a metric suggested segregation (e.g. number of patches) (Martinez-Salvador et al., 2007).

$$NM = (x_i - \min R) / (\max R - \min R) \quad (2)$$

$$NM = (\max R - x_i) / (\max R - \min R) \quad (3)$$

where *NM* is the normalized 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<sub>i</sub>* is the original landscape metric value generated from FRAGSTATS.

To determine the value range for the “number of patches”, which is landscape specific, we make the following assumptions. First, we assume that the least number of patches a predefined landscape can have is equal to “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

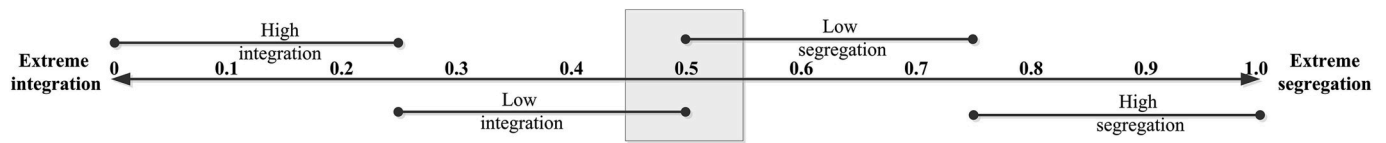


Fig. 4. Scale for assessing the direction of change in landscape's structural state on integration-segregation continuum.

Table 3

Characterisation of integrated and segregated landscapes with structural dimensions (based on Duarte, Santos, Cornelissen, Ribeiro, & Paglia, 2018; McGarigal, 2013; Primdahl, 1990).

Integration	Segregation	Measurable attributes	Landscape dimensions	Structural properties
Heterogenous (fields of different crops and components) Small to medium size	Homogeneous (small, scattered bushes and others and large commodity crop) Large field size	<ul style="list-style-type: none"> <li>Variety of land-cover types present</li> <li>Area proportions of land-cover types</li> <li>Size of each land-cover type relative to the entire landscape</li> <li>Occurrence of different patch sizes</li> <li>Number of patches occupying a unit area</li> </ul>	Diversity and abundance of land-cover types Fragmentation	Composition Configuration
Many plots or land holdings in an area	Few land holdings in an area	<ul style="list-style-type: none"> <li>Areal extent of the largest and smallest patch units</li> <li>Patch clustering or mixing up</li> <li>Spatial distribution of patch types</li> </ul>	Connectivity	
High degree of interactions	Low degree of interactions	<ul style="list-style-type: none"> <li>Separation distance and the effects on landscape process and functions</li> </ul>	Complexity	
Extensification (nature driven)	Intensification (mechanized)	<ul style="list-style-type: none"> <li>Extent of naturalness and orderliness</li> </ul>		

the estimated maximum number of patches in the landscape ( $PN_{max}$ ) is a function of the total landscape area and smallest patch size and computed as:

$$PN_{max} = aL/aSp \tag{4}$$

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.

### 2.4. Weighting and aggregation

Weighting and aggregation have 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 paper, initially equal weighting of 0.25 was assigned to the normalized 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 Fig. 5).

The landscape structural state index (LSSI) was computed using the geometric aggregation (multiplicative function) through the application of Equation (5). The multiplicative function was chosen due to its minimum levels of compensability even when the values of some indicators are lower (Nardo et al., 2005).

$$LSSI = \prod_{i=1}^n D^{1/wd} \times \prod_{i=1}^n F^{1/wf} \times \prod_{i=1}^n C^{1/wc} \times \prod_{i=1}^n N^{1/wn} \tag{5}$$

where  $D$  is the diversity and abundance dimension,  $wd$  the weight allocated to  $D$ ,  $F$  the fragmentation dimension,  $wf$  the weight allocated to  $F$ ,  $C$  the connectivity dimension,  $wc$  the weight allocated to  $C$ ,  $N$  the complexity dimension and  $wn$  the weight allocated to  $N$ . The resultant LSSI value from Equation (5) marks the position of the landscape on the integration-segregation continuum at a specific time, here 1986 and 2015.

Based on the characteristics of typical integrated and segregated

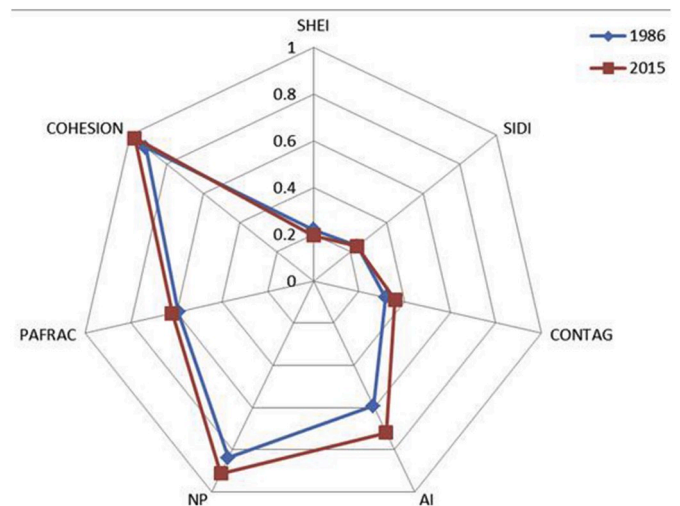


Fig. 5. Radar diagram showing the variance in the metrics for 1986 and 2015.

landscapes in studies such as Primdahl (1990), Perfecto et al. (2009), and van Noordwijk et al. (2012), we identified landscape structural properties measurable directly or by proxy metrics (see Appendix 3 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. Results

### 3.1. Changes in landscape composition and configuration between 1986 and 2015

#### 3.1.1. Landscape level analysis

Structural analysis at landscape level revealed marginal compositional variation over the 29 years, while configuration (the spatial arrangement) experienced marked changes in several aspects (Table 4).

**Table 4**  
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

Patch richness has remained the same, meaning that the land-cover types listed in Table 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 4).

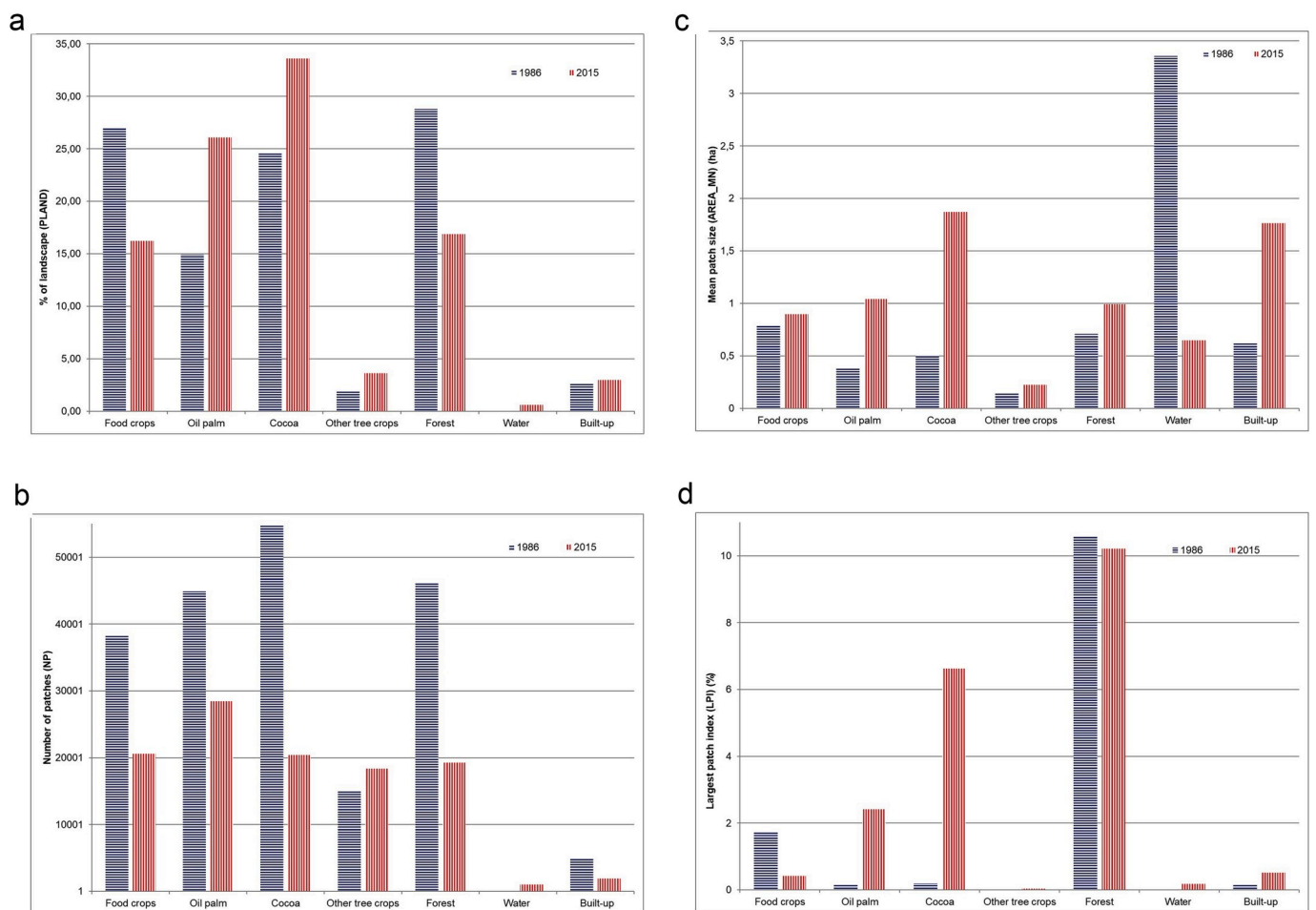
Several changes occurred in the configuration of land-cover types. First, a decrease in number of patches (NP) from 203,969 in 1986 to 109,977 in 2015 and concomitant increase in average patch size (AREA\_MN) from 0.56 ha to 1.03 ha in the same period suggest increasing patch agglomeration. This is however 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 both the increase of contagion index from 31.72% to 35.91% and 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, there are smaller different land-cover types 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.

3.1.2. Analysis at class level

Composition at class level was analysed employing percentage of landscape (PLAND; Table 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 (Fig. 6a). 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.

Class-level configuration was expressed by patch properties of the land-cover types and interactions in the landscape in 1986 and 2015 (Table 2). Fig. 6b 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



**Fig. 6.** 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.

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 Fig. 6b shows that the existing patches of land-cover types are breaking into smaller patches or new smaller plots are springing up in the landscape.

Fig. 6c 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 largest patch index (LPI), which shows trends in biggest patch of each land-cover type relative to the landscape area in both years, confirms the growth in patch areas in 2015 (Fig. 6d). The LPI for the different land-cover types had increased in 2015 except for forest and food crop 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 0.18%–6.6% and 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 average patch size of forest and food crop also increased, but their largest patches decreased. This implies that the increase in AREA\_MN experienced in food crop 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 are clustering more in 2015 than they did in 1986 (Fig. 7a). 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 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, and 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 concentration of forest in forest reserves.

Unlike the AI, trends in IJI were mixed in both years (Fig. 7b). 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 stabilized in cocoa. The higher IJI in 2015 indicates that built-up, food crop, oil palm and water increasingly shared borders evenly with other land-cover types compared to 1986. 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.

Connectivity, measured by COHESION was higher for all land-cover types in 2015 except for food crops (Fig. 7c). 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

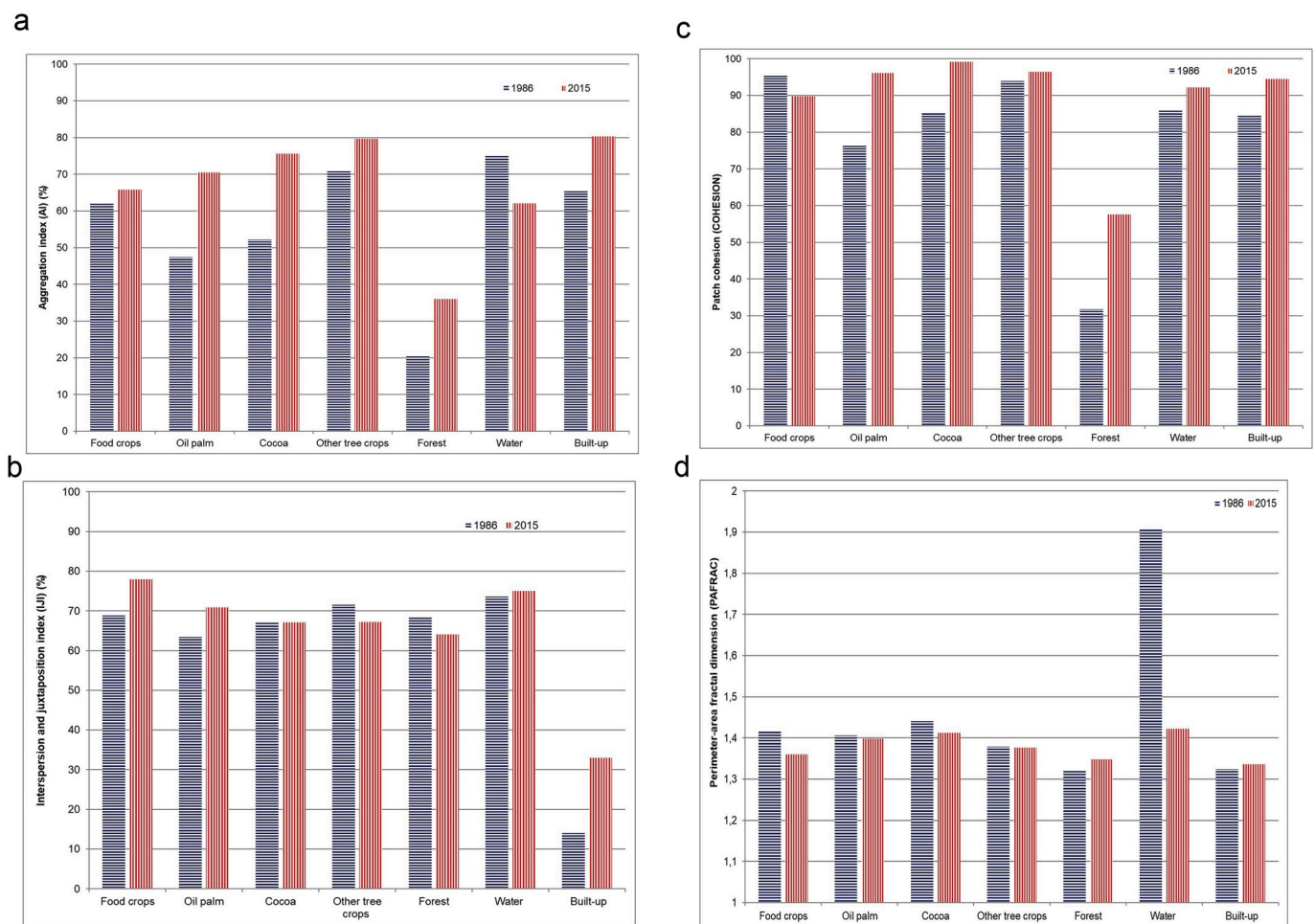


Fig. 7. Distribution of (a) aggregation index, (b) interspersion and juxtaposition, (c) patch cohesion index and (d) perimeter-area fractal dimension index for land-cover types in 1986 and 2015.

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 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 2) declined in all land-cover types between 1986 and 2015 except for forest and built-up (Fig. 7d). 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.

### 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, LSSI increased from 0.50 in 1986 to 0.52 in 2015 (Fig. 8). 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 (Fig. 5) 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 in 1986 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

characterized 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.

## 4. Discussion

### 4.1. Structural dynamics in tree-crop dominated mosaic landscapes

The analysis of landscape structural dynamics between 1986 and 2015 (objective 1) showed that the landscape consisted of the same land-cover types in both years (Table 4 and Fig. 6a). 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). The analysis further revealed that patches are taking on regular shapes, revealing a tendency towards greater simplification and a more homogenized landscape dominated by cocoa and oil palm in 2015 compared to 1986 (Fig. 6d). 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); 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 characterize the structural changes resulting from the process (Addo-Fordjour & Ankomah, 2017; Koranteng, Zawila-Niedzwiecki, & Adu-Poku, 2016; Kusimi, 2015).

The higher aggregation levels in the landscape as evidenced by increased mean patch area, aggregation index, contagion and patch cohesion and reduced number of patches (Table 4, Figs. 5b, 6a and 6c and 5c) 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 & Zhou, 2016). Cocoa and oil palm have become the first and second largest land-cover type in the study area in 2015 (Fig. 5a and d).

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

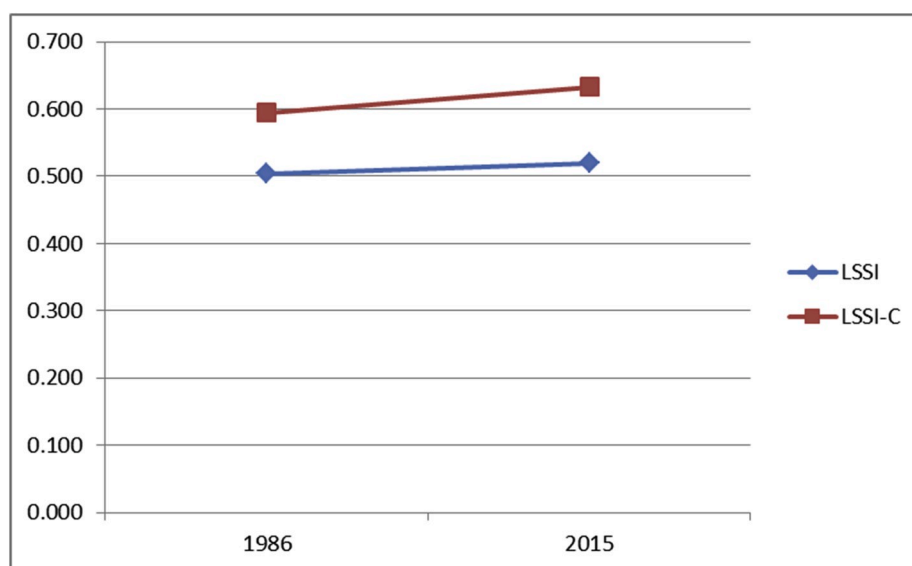


Fig. 8. Landscape structural state index (LSSI) for the landscape in 1986 and 2015 using equal weights (LSSI) and budget allocated weights (LSSI-C).

(Asubonteng et al., 2018; interviews with village elders). 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 in cocoa farms and their role in increasing climate change resilience (e.g. Abdulai et al., 2018; Middelndorp, Vanacker, & Lambin, 2018). However such old forest patches serve as functional corridors between habitats in landscapes (Asare, Afari-Sefa, Osei-Owusu, & Pabi, 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, Broegaard, Mertz, & Thongmanivong, 2016). The few remaining food-crop areas are highly interspersed in cocoa and oil palm areas (Fig. 7b). 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, the adoption of equilateral triangle planting design for oil-palm farm establishment (Bonneau, Impens, & Buabeng, 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 a reduction in pollinating services and a worsening microclimate for cocoa production due to declining availability of shade trees for cocoa (Tschardt et al., 2012). Decreasing heterogeneity also implies a declining habitat for wildlife (Tschardt et al., 2012). Hence, whereas the cocoa-oil palm landscape is smallholder-dominated by ownership (Ghana Statistical Service, 2014; MoFA, 2020), 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 fertilizers (Fianko, Donkor, Lowor, & Yeboah, 2011) and, in recent times, human-assisted pollination (Dapatem, 2017).

#### 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 (objective 2) 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 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, with the exception of 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 4), 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 configuration in landscapes, we disagree with the exclusion of composition. A focus on configuration holds true in landscapes with a stable composition, but this hardly applies to mosaic landscapes that undergo conversion to new land uses. Composition and configuration properties are both relevant for the availability of multiple ecosystem functions that landscapes provide (Lamy et al., 2016). In a landscape, a number of 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 land sharing and sparing for apt decision making. The standardized 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, Van Vianen, Deakin, Barlow, & Sunderland, 2016; Ros-Tonen, Reed, & Sunderland, 2018). An understanding of 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.

##### 4.2.1. Limitations

In spite of the successful characterization 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. We therefore recommend future studies to focus on developing empirical coefficients for weighting through Analytic Hierarchy Process (AHP).<sup>2</sup>

Second, challenges with data acquisition and period of availability and data quality also 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 absence of rich temporal datasets, the development of the LSSI was constrained as sensitivity and robustness of the approach could not be tested.

## 5. Conclusions

This study characterized 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 study reveals that landscape-level

<sup>2</sup> A mathematically structured technique for comparing pairs of variables in a hierarchical manner (Saaty, 1987).

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. Food-crop area, on the other hand, has 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 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 and pest control and pollination dependent on biodiversity. Moreover, we showed that the landscape was in the early stages of segregation on the integration-segregation continuum already 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 which is characterized 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 are needed in landscapes under the influence of different socio-economic 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.

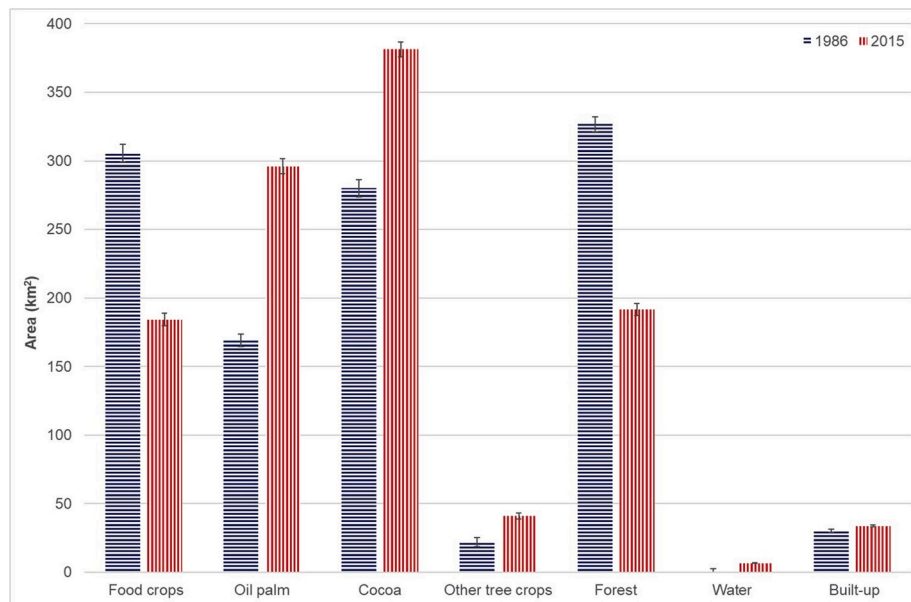
**Author statement**

With this statement, we the Authors have seen and approved the manuscript entitled “Integration versus segregation: structural dynamics of a smallholder-dominated mosaic landscape under tree-crop expansion in Ghana” being submitted to Applied Geography. We confirm that this manuscript is original and has not been published or submitted elsewhere. We further confirm that all authors listed on the title page have contributed sufficiently to the development of the manuscript. On behalf of all co-authors, the corresponding author shall bear full responsibility for the submission.

**Acknowledgements**

This study is part of a research programme on inclusive value chain collaboration with tree-crop farmers in Ghana and South Africa, financed by WOTRO Science for Global Development of the Netherlands Organization for Scientific Research (NWO) (project number W08.250.2013.122).

**Appendix 1. Error bars showing area estimate uncertainties of the 1986 and 2015 land-cover maps**



**Appendix 2. Initial list of landscape metrics extracted from literature for screening**

Landscape metrics	Units	Value range	Plexida et al. (2014)	Kumar, Denis, Singh, Szabó, and Suryavanshi (2018)	Zhang and Gao (2016)
1 Patch Richness (PR)	None	PR ≥ 1, without limit	*	*	*
2 Patch Richness Density (PRD)	Number per 100 ha	PRD > 0, without limit	*		
3	Information	SHDI ≥ 0, without limit	*		*

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Landscape metrics	Units	Value range	Plexida et al. (2014)	Kumar, Denis, Singh, Szabó, and Suryavanshi (2018)	Zhang and Gao (2016)
Shannon's Diversity Index (SHDI)					
4 Simpson's Diversity Index (SIDI)	None	$0 < SIDI < 1$	*		*
5 Modified Simpson's Diversity Index (MSIDI)	None	$MSIDI \geq 0$ , without limit	*		
6 Shannon's Evenness Index (SHEI)	None	$0 < SIDI < 1$	*		
7 Simpson's Evenness Index (SIEI)	None	$0 < SIDI < 1$	*		
8 Modified Simpson's Evenness Index (MSIEI)	None	$0 < SIDI < 1$	*	*	
9 Largest Patch Index (LPI)	Percent	$0 < LPI \leq 100$	*	*	*
10 Patch size (PS)	Hectare	$1 < PS < PS_{max}$	*		
11 Patch Density (PD)	Counts per 100 ha	$PD > 0$ , constrained by cell size	*	*	*
12 Aggregation Index (AI)	Percent	$0 \leq AI \leq 100$	*		*
13 Interspersion and Juxtaposition Index (IJI)	Percent	$0 \leq IJI \leq 100$	*	*	
14 Mean Shape index (MN_SI)	None	$1 \leq SI \leq MN\_Simax$			
15 Fractal Index Distribution (FRAC)	None	$1 \leq FD \leq 2$			
16 Landscape shape index (LSI)	None	$LSI \geq 1$ , without limit		*	*
17 Patch cohesion Index (COHESION)	None	0–100			
18 Connectance Index (CONNECT)	Percent	0–100			
19 Perimeter-Area Fractal Dimension (PAFRAC)	None	$1 \leq PAFRAC \leq 2$	*		
20 Contagion index (CONTAG)	Percent	$0 \leq CONTAG \leq 100$	*		*
21 Effective Mesh Size (MESH)	Hectare	ratio of cell size to landscape area 5 MESH 5 total landscape area (A)			
22 Landscape Division Index DIVISION	Proportion	$0 \leq DIVISION \leq 100$	*		*
23 Splitting Index (SPLIT)	None	$1 \leq SPLIT \leq$ number of cells in the landscape area squared	*		*
24 Patch Cohesion Index (COHESION)	None	$0 \leq COHESION \leq 100$ (unknown at the landscape level hence assumed to behave similarly as the lass level)	*		
25 Percentage of Landscape-PLAND	Percent	$0 \leq PLAND \leq 100$		*	
26 Number of Patches-NP	None	$NP \geq 1$ , without limit		*	*
27 Connectance index (CONNECT)	Percent	$0 \leq CONNECT \leq 100$		*	

The list was compiled based on the metrics used in characterizing landscape by Kumar, Denis, Singh, Szabó, and Suryavanshi (2018); Plexida et al. (2014) and; Zhang and Gao (2016). We excluded all edge, core area and contrast metrics. The computation of these groups of metrics required user-defined proportion of the landscape boundary, edge depth, and edge contrast respectively. However, neither empirically nor expert-determined values were available for the landscape in context. Hence their exclusion for the list. The criteria for selecting the final list used for the study were:

- any other metric that required user defined variables were also excluded (i.e. Connectance Index);
- metrics that quantitatively characterize diversity and abundance, fragmentation, connectivity and complexity of landscapes were included;
- one of a pair of metrics with correlation coefficient above 0.80 was selected;
- metrics without a definite value range were neither selected unless assumptions could be made to estimate the upper and lower limits (i.e. patch number).

### Appendix 3. Landscape metrics and their interpretation on the segregation-integration continuum

Indicator	Units	Value range	Meaning of the indicator
<b>Diversity &amp; Abundance</b>			
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 increasing number of different patches and uniform area distribution. SIDI = 0 means segregation and greater than zero is 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.
<b>Fragmentation</b>			
3 Number of Patches (NP)	Count	$1 \leq NP < PN_{max}$	$PS \geq 1$
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	%	$0 \leq CONTAG \leq 100$	

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Indicator	Units	Value range	Meaning of the indicator
			CONTAG approaches 0 when the patch types are maximally disaggregated and interspersed (integration). CONTAG = 100 when all patch types are maximally aggregated (segregation).
<b>Connectivity</b>			
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) whereas a COHESION = 1 indicates that respective class patches are aggregated.
<b>Complexity</b>			
7 Perimeter-area Fractal Dimension (PAFRAC)	None	1 ≤ PAFRAC ≤ 2	FRAC approaches 1 when shapes are simple as squares and approaches 2 for shapes with highly convoluted boundary.

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