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Archetypes of remnant West African forest patches, their main characteristics and geographical distribution

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ABSTRACT

Remnant West African forest patches provide crucial ecosystem functions and services while contributing to sustaining the livelihoods of vast numbers of people. The vast majority lie outside of protected areas, although relatively few are managed as sacred forests, which limits their access and use. This lack of protection, together with a growing demand for arable land and forest resources, have accentuated their fragmentation, degradation, and deforestation. There is therefore an urgent need to generate knowledge on their social-ecological characteristics and change pressures to support their conservation. This study investigates what are i) the main biophysical and social-ecological characteristics of remnant forest patches, and ii) the potential change pressures and drivers. Within this scope, we apply archetype analysis to discern processes affecting remnant forest patches. Biophysical and socio-ecological indicators were selected from a published dataset via expert consultation, and nine archetypes were developed by applying a cluster analysis. Evaluating the results in relation to ecoregions and landscape features using high resolution imagery, we identify common underlying social-ecological change pressures and characteristics. The most common archetype (2) is characterized by being close to protected areas and having a low average annual precipitation and cluster along the northern fringe of the study area. The second most common archetype (5) is characterized by lying in highly disturbed landscapes, having undergone biomass losses, and widely distributed throughout central and western Nigeria. Patches of archetype 8 found predominantly in mangrove and swamp forests, exhibit positive above-ground biomass changes and greening trends; we propose that these vegetation changes could benefit conservation measures and carbon sequestration programs. In contrast, archetype 10 patches show both forest and biomass losses and gains and are often encompass fragmented forests in urban/arable landscapes. Identifying such common patterns of anthropogenic and ecological change provides a means of prioritizing regionalized strategies for their conservation and sustainable use.

1. Introduction

Remnant West African forest patches are home to a wealth of biodiversity and provide crucial ecosystem functions and services with implications from local to global scales; simultaneously they contribute to sustaining the livelihoods of a great number of people across a vast area (Fischer et al., 2021; Laurance & Bierregaard, 1997; Neuenschwander et al., 2015). Although relatively few are managed as sacred forests, which severely restricts their access and use and thereby benefits biodiversity and ecosystem functioning, many such patches lie outside of protected areas. Here, they are embedded in arable or semi-urban landscape mosaics where they are subject to a range of degradation pressures, chief among them being widespread deforestation and forest fragmentation (Neuenschwander & Adomou, 2017; Wingate, Akinyemi, Iheaturu, & Speranza, 2022).

Forests set in arable or semi-urban landscape mosaics are increasingly conceived as social-ecological systems (SESs), with various socio-cultural, institutional, economic, and ecological factors as well as their interactions, determining their characteristics (Fischer, 2018). Thus, understanding forests and their outcomes requires an integrative social-ecological approach (Vogt, 2020). This enables accounting for the many factors affecting forest outcomes in research, and in their governance, management, and sustainable use (Ostrom, 2009). While these numerous factors are acknowledged in social-ecological frameworks (Ostrom, 2009), an overview of generalizable factors and factor constellations driving forest characteristics and outcomes is necessary. This

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study therefore applies archetype analysis to pinpoint such salient factors to gain a better understanding of west African remnant forest patches as social-ecological systems.

Archetypes are often used in sustainability research to represent models of social–ecological interactions. They enable a better understanding of processes and factors that determine the sustainability of SESs and the underpinning recurrent patterns of biophysical variables and social-ecological processes, across distinct spatial locations and time scales (Oberlack et al., 2019). These include the drivers and outcomes pertaining to livelihoods and land-use (Sietz et al., 2019), but also to describe biophysical disturbance processes (Balling et al., 2021; Eisenack et al., 2019). For example, "land system archetypes" have been used to represent land-use intensity, environmental conditions, and socioeconomic factors that are globally common to all ecosystems (Václavík et al., 2013); while "Archetypes of tropical fire-related forest disturbances" were proposed to study fire disturbances (Balling et al., 2021). Thus, results of archetype analysis can reveal diverse sequences of underlying social-ecological characteristics and change pressures. Subsequently, such results can facilitate the selection of representative sample sites for empirical analysis or, help inform studies on land management (Karrasch et al., 2019; Sietz et al., 2019; Adenle & Ifejika Speranza, 2020).

This study focuses on the remnant forest patches in the West African countries of Togo, Benin, Nigeria, and Cameroon, lying outside of protected areas and spanning the Guineo-Congolian forest and the Guinea Savannah biomes (Fig. 1).

Here, agricultural expansion and urbanization, a raising population as well as increased resource extraction pressures, together with variable or non-existent conservation strategies, are resulting in wide-spread forest losses and accelerating forest fragmentation, while the remaining fragments are being increasingly degraded (R. Fischer et al., 2021; Poorter et al., 2004). Considering these changes, a knowledge of the location, characteristics and types of disturbances and changes remnant forest patches are subject to, is key to furthering our understanding of their response to environmental change and thereby better support their conservation and sustainable use (Wingate, Akinyemi, Iheaturu, & Speranza, 2022).

For example, in the Dahomey Gap, which spans the eastern border of Ghana across to Benin, humid forests remain restricted to small patches containing a rich floral and faunal species diversity originating from both the Congo and Guinea block (Robbins, 1978; Sinsin et al., 2010). In the Benin part of this region, these remnant forest patches mostly comprise about 1000 sacred forest groves of roughly 1 ha, which local inhabitants have maintained and limited the use and access over generations (Neuenschwander et al., 2015). Remnant forest patches cover only a small fraction of the land surface (in the case of Benin, only 1%). They often lie outside of state-protected areas and are found in densely populated, agricultural, and peri-urban landscapes, with >200 people per km^2 (Neuenschwander et al., 2015). Despite this situation, they generally harbour a large proportion of endangered species and a high species richness (Adomoui et al., 2010; Neuenschwander et al., 2011). Thus, knowing the location, condition, and pressures, which these remnant forest patches are subject to, can contribute toward designing better conservation strategies (Neuenschwander & Adomou, 2017). Lastly, due to their rapid rate of change, there is therefore an urgent need to implement strategies that maintain ecosystem functions and services and promote their sustainable use (Wingate, Akinyemi, Iheaturu, & Speranza, 2022).

Conversion of natural land cover leads to fragmentation (Fahrig, 2003), which also impacts biodiversity similarly to habitat loss. Often, habitat fragments have smaller species populations (Connor et al., 2000), which are isolated from populations in neighbouring fragments (Fahrig, 2003; Laurance et al., 2014; Wilson & MacArthur, 1967). The increased edge effect results in the loss of specialized species (Laurance et al., 2011) and an increase in generalist species (Gascon et al., 2000). Together, these impacts generally change the ecosystem functioning of fragments (Cardinale et al., 2006) and as a result, the ecosystem services they provide (Cardinale et al., 2012).

To address these issues, we propose creating West African remnant forest patch archetypes; this approach is expected to provide a basis for a better understanding of the ecological and anthropogenic change processes they are subject to, while concurrently allowing conservation priority regions to be defined, and thereby providing valuable information for their conservation and sustainable use. We define forest patch archetypes (FPAs) as presenting a given combination of social-ecological and environmental indicators and occurring recurrently across the study area. In mapping FPAs, our overarching aims are to identify both their biophysical and social-ecological characteristics, as

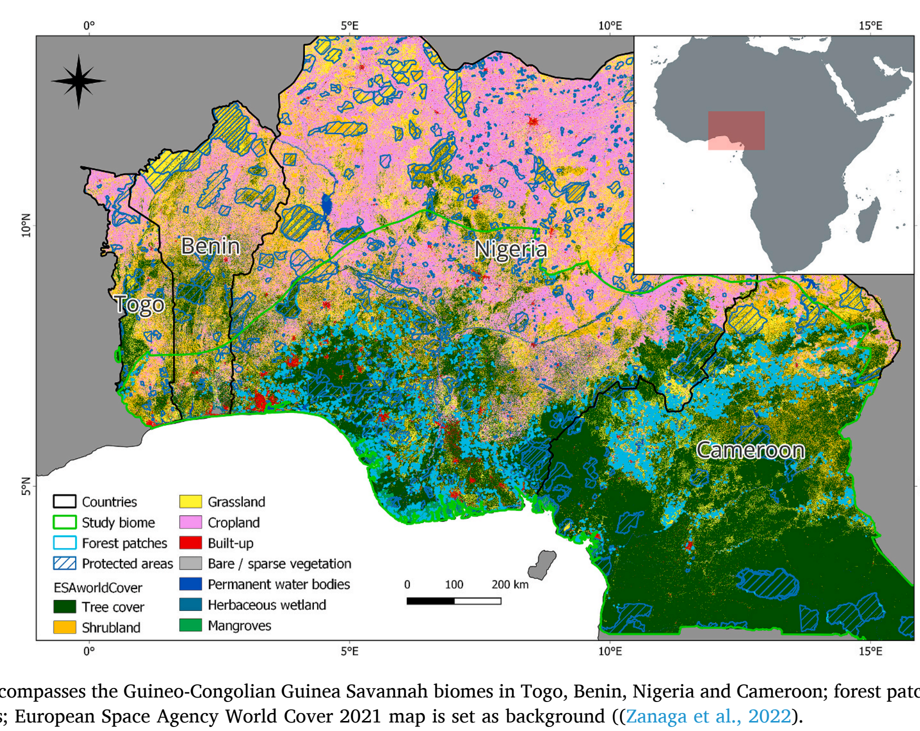

Fig. 1. The study area encompasses the Guineo-Congolian Guinea Savannah biomes in Togo, Benin, Nigeria and Cameroon; forest patches sampled for this study lie outside of protected areas; European Space Agency World Cover 2021 map is set as background ((Zanaga et al., 2022).

well as describe key factors driving changes in their land-use and land cover. Thus, the specific objectives are to i) develop FPAs reflecting (dis) similarities between indicators characterising forest patches; ii) describe FPAs according to predominant indicators; and iii) evaluate FPAs in the context of their geographical situation, including in which biome it is found, whether it is close to an urban area, or if it is found at high elevation or close to a water body, although we omit an analysis of specific adjacent land-uses. We leverage a recently published inventory of forest patches which provides a range of indicators describing their dynamics (Wingate, Akinyemi, Iheaturu, & Speranza, 2022). A sample of these are selected and evaluated using visual interpretation of high-resolution aerial imagery. Lastly, we discuss the ecological and anthropogenic change processes the FPAs are subject to and their relation to the study area ecoregions (Dinerstein et al., 2017).

2. Methodology

2.1. Data

A total of 7784 forest patches ranging from 1 to 10 km^2 were sampled at 30 m spatial resolution across the study area (Wingate, Akinyemi, Iheaturu, & Speranza, 2022). Forest is defined as having a tree cover ≥ to 30%, and a tree height of ≥5 m (Hansen et al., 2020). A panel of 8 experts selected 20 indicator variables deemed pertinent as input to develop forest patch archetypes (Table 1); these variables were thought by the panel to be the most representative biophysical metrics available.

2.1.1. Social-ecological indicators

Population growth and density are associated with deforestation, for instance, through agricultural expansion (Ngwira & Watanabe, 2019), which occurs due to local and external demands on forest resources (Geist & Lambin, 2002). Population data in this study is derived from the Worldpop dataset, which provides global high-resolution, up-to-date data on human population distributions (Linard et al., 2012). Area describes the mapped forest patch areal extent in km^2; the size of a forest patch may affect differently the capacity of the patch to provide ecosystem services, for instance, smaller forest patches may be more susceptible to more fragmentation and edge effects (R. Fischer et al., 2021; Hansen et al., 2020).

Table 1
The indicators used in the archetype analysis, and available for each forest patch.

	Abbreviation	Description
1	Area	Area of the forest patch in m^2
2	Biomass_18	Average AGB Mg ha^{-1} in 2018 (Santoro & Cartus, 2021)
3	BiomassDif	Difference in AGB Mg ha-1 2018–2010 (Santoro & Cartus, 2021)
4	D_IUCN	Distance (m) to a protected area (UNEP-WCMC, 2019)
5	D_roads	Distance (m) to roads (Warszawski et al., 2017)
6	D_settle	Distance (m) to settlements (Marconcini et al., 2020)
7	D_water	Distance (m) to water JRC Global Surface Water Mapping Layers, v1.4 (Pekel et al., 2016)
8	Elevation	Elevation in meters above sea level (m.a.s.l) (Farr et al., 2007)
9	Gain_area	Total area of forest gain (Hansen et al., 2013)
10	gHM	Global Human Modification (gHM) (C. M. Kennedy et al., 2019)
11	LAI_2021	Leaf Area Index (V3) (Kobayashi et al., n.d.).
12	Loss_area	Total area of forest loss (Hansen et al., 2013)
13	MannKendal	Mann-Kendall trend statistic (Wingate, Akinyemi, Iheaturu, & Speranza, 2022)
14	population	WorldPop (Linard et al., 2012)
15	Precp_anom	Precipitation anomaly climatology CHIRPS (Funk et al., 2015)
16	Precp_mean	CHIRPS (Funk et al., 2015)
17	Precp_sum	CHIRPS (Funk et al., 2015)
18	TheilSen	Theil-Sen trend statistic (Wingate, Akinyemi, Iheaturu, & Speranza, 2022)
19	treecover	Average percentage tree cover (Hansen et al., 2013)
20	treeheight	Average tree height GEDI (Potapov et al., 2021a)

2.1.2. Proximity indicators

Distance to protected areas is included as an indicator of how protected the landscape surrounding the patch is, and we assume that a landscape with few protected areas could benefit from more formal protection, while protected area benefit species conservation by providing corridors and refuges (Brennan et al., 2022; Donaldson et al., 2021; Saura et al., 2018; Ward et al., 2020). It is the distance (m) to the nearest protected area, as mapped by the World Database on Protected Areas (WDPA) (UNEP-WCMC).

Similarly, roads act as barriers to species movement and fragment forests (Kleinschroth et al., 2019; Marcantonio et al., 2013). Proximity to roads can be an indicator of deforestation (Akinyemi & Ifejika Speranza, 2022; Kleinschroth et al., 2019; V. Wingate et al., 2016). *Distance to roads* is the distance (m) to the nearest road, as mapped by the Global Roads Open Access Data Set, Version 1 (gROADSv1) (Ubukawa et al., 2014). Settlements may be indicators of anthropogenic disturbances (Cotillon & Tappan, 2016), hence, *Distance to settlements* was computed from the World Settlement Footprint (WSF) 2015, which is a 10 m resolution dataset mapping the extent of human settlements globally (Marconcini et al., 2020). The *global Human Modification* dataset (gHM) provides a cumulative measure of human modification of terrestrial lands globally at 1 km^2 resolution (Kennedy et al. 2019, 2020).

2.1.3. Change metrics

Tree cover gain or loss indicates improvements or degradation of forest patches. *Tree cover loss/gain* refers to the areal extent of loss and gain as computed in the Hansen Global Forest Change v1.9 (2000–2021) dataset (Hansen et al., 2013). *Theil-Sen* refers to trend statistics computed using the Theil-Sen slope which shows whether canopy greenness of individual forest patches is increasing or decreasing, and is applied to a Landsat 5, 7 and 8 harmonized NDVI time-series, for which growing season maximum NDVI images were computed by temporal compositing (Wingate, Akinyemi, Iheaturu, & Speranza, 2022).

Changes in forest biomass are key contributors to the global carbon balance (Houghton, 2005). *Biomass Change* comprises the difference in AGB measured in 2010 and 2018 as measured by Santoro and Cartus (2021) (Santoro & Cartus, 2021). This dataset was calculated as the difference between estimates of forest above-ground biomass for the years 2018 and 2010, which were derived from Copernicus Sentinel-1 mission, Envisat's Advanced Synthetic Aperture Radar instrument and the Japan Aerospace Exploration Agency Advanced Land Observing Satellite (ALOS-1 and ALOS-2). The product consists of four AGB 100m spatial resolution maps for the periods 2010, 2017, 2018 and 2020 (Santoro & Cartus, 2021).

2.1.4. Biophysical variables

Forest patches are characterised by a variable forest structure, resulting from their diverse management strategies and is therefore key to their characterisation (Neuenschwander & Adomou, 2017). Remote sensing-derived biophysical metrics known to be indicators of forest structure and condition were included; we use the *Enhanced Vegetation Index (EVI) 2021, which* refers to the mean annual EVI value derived from the MODIS MYD13A1 product (*https://lpdaac.usgs.gov)*. Leaf Area Index (*LAI) 2021* refers to the mean LAI derived from the GCOM-C/SGLI L3 Leaf Area Index (V3), which is the sum of the one-sided green leaf area per unit ground area (Honda et al., 2006).

Environmental conditions such as precipitation and elevation are controls of forest type, hence, precipitation climatologies and elevation were included (Cotillon & Tappan, 2016). *Precipitation mean* refers to the mean annual rainfall for the period from 1981 to 2020, while the Precipitation anomaly refers to the difference in mean rainfall for 2021 relative to the average 1981–2020 period; the anomaly was computed for 2021 since patches were mapped then, and anomalies are expect to affect map results. The data is derived from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), which is an over 30-year global rainfall dataset, incorporating 0.05° resolution satellite imagery with in-situ station data, resulting in a gridded rainfall time-series for trend analysis and seasonal drought monitoring (Dinku et al., 2018). *Elevation* (meter above sea level) is derived from the Shuttle Radar Topography Mission (SRTM) (Farr et al., 2007); this dataset provides elevation models on a near-global scale and is provided by NASA JPL at a resolution of approximately 30 m. *Tree cover mean (%)* refers to the average tree cover derived from the Hansen dataset (Hansen et al., 2013). *Tree height mean (m)* refers to the mean tree height for each forest patch as derived from the most recent high-resolution Global Ecosystem Dynamics Investigation (GEDI) dataset (Potapov et al., 2021b).

2.2. Analysis

To develop a map of forest patch archetypes the following workflow is applied (Fig. 2). The data were first scaled with "centering" using the scale function in R, to allow for comparing different datasets measured in distinct ways; here, the normalizing is undertaken using the mean value and standard deviation values (Peres-Neto & Jackson, 2001; Scott, 1990). To identify the optimal number of clusters that best characterise the resulting dataset, we apply the "Total Within sum of Squares" method which revealed an optimal number of 10 clusters (Gordon & Henderson, 1977; Schubert & Rousseeuw, 2019). We then applied the Partitioning Around Medoids (PAM) algorithm, based on the k-mean clustering algorithm (Schubert & Rousseeuw, 2019) using a vector of integer indices specifying initial medoids. This unsupervised, data-driven method was selected as it enables effective clustering of large multidimensional datasets with no need to define expert rules or pre-defined classification thresholds. The resulting clusters were then transferred to geographical space, with each forest patch being assigned to a given cluster.

Lastly, we describe and characterise the archetypes, by identifying the most prominent variables in each cluster, namely the variables with the highest or lowest medoid values. These variables are taken to comprise the primary predictors of each archetype. Specifically, the weights of each variable are described by the medoid value, and this in turn indicates the similarity or dissimilarity to the other archetypes. Correspondingly, to further facilitate the interpretation of the archetypes, we reduce the number of archetypes by qualitative merging based on expert opinion those which have a) specific variables in common, and b) which have variables which would logically combine, or which are associated with one another in the literature; for example, low tree height and low mean annual precipitation are associated with each other in tropical latitudes (Shackleton and Scholes 2011).

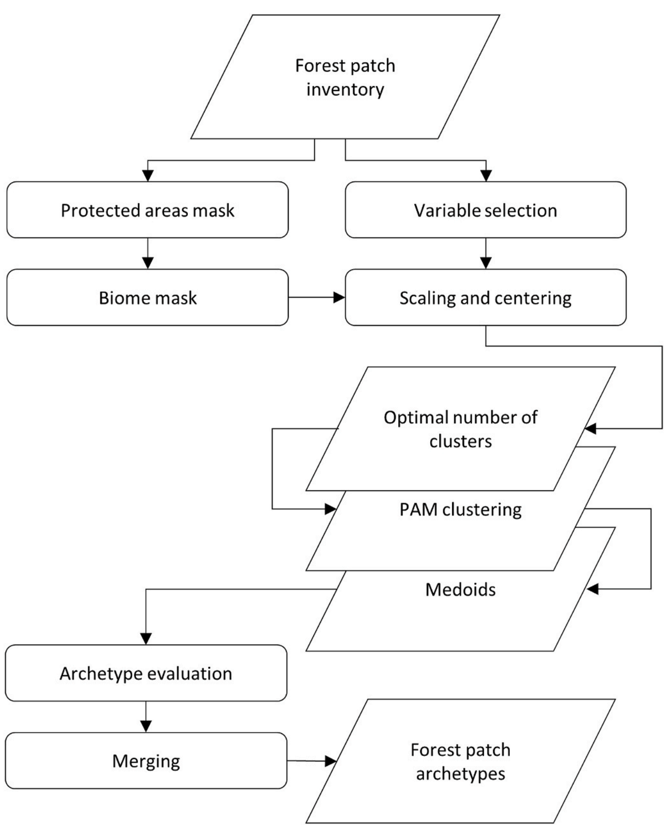

Fig. 2. Workflow diagram highlighting the main processing steps taken to archetype forest patches.

3. Results

3.1. Archetype evaluation

The resulting map of remnant West African forest patch archetypes shows geographically grouped patterns, based on social-ecological indicators (Fig. 3). Their geographical location allows for identifying common underlying anthropogenic pressures and ecological characteristics, in relation to the major ecoregions (Dinerstein et al., 2017; Olson et al., 2001). For example, archetype 2 clusters along the northern boundary of the study area, which is sub-humid and consists mainly of savannah vegetation; in contrast, archetype 9 clusters along the Nigerian coastline, which is humid and comprises mostly mangrove forest.

The 10 archetypes are characterized by a given combination of indicators (variables); for instance, we find that in cluster 10 (Fig. 4), the variables with the highest and lowest medoid values –therefore the variables defining the archetype – are *"Gain_area"*, and *"LAI_2021"*, respectively. Thus, forest patches grouped into this archetype exhibit a particular combination of especially high or low values of these variables, relative to other archetypes.

To assess the performance of the archetype classification, we randomly sampled a single forest patch from each archetype and visually evaluated it in relation to the predominant landscape features and adjacent forest patches using Bing Aerial imagery (Bing Maps, 2021). Specifically, we assessed the geographical location, relation to other archetype clusters, vegetation type, and visible anthropogenic features, such as proximity to urban areas. Concurrently, we evaluated the values of the defining predictor variables (i.e., if the variable AGB was prominent, the value for the said forest fragment is reported). Reporting the indicator values observed for each forest patch was found to help with defining the archetypes and discussing their implications. The results are presented in the 10 plates (A-J) of Fig. 5.

3.2. Archetype description

Archetype 1 – Found in sparsely modified landscapes distant from protected areas; with 960 individual forest patches (12%), this archetype comprises fragments which are distant from any protected area (High D_IUCN), and far from anthropogenic land-use/land cover disturbances (Low gHM), and with increasing greenness (high Theil-Sen trend statistic). Geographically, the patches cluster mainly along the north-eastern part of Cameroon (Fig. 3). Fig. 5 Plate A (Cameroon, Adamaoua) shows a densely wooded, riparian or gallery forest patch, bordering a river; very little human modification is apparent in the landscape (few small-scale arable fields), in accordance with a low gHM (0.2), and it is 60 km from a protected area, and exhibits a positive greening trend.

To evaluate the greening trend further, Fig. 6A plots the average Theil-Sen trend statistic value for each archetype; here we find that archetypes 7 and 9 also exhibit elevated greening trend statistic values. Fig. 6B then plots these values for each ecoregion; it is apparent from the results that the Central African mangrove and Niger Delta swamp forest (Fig. 6C) exhibit the most pronounced greening trends.

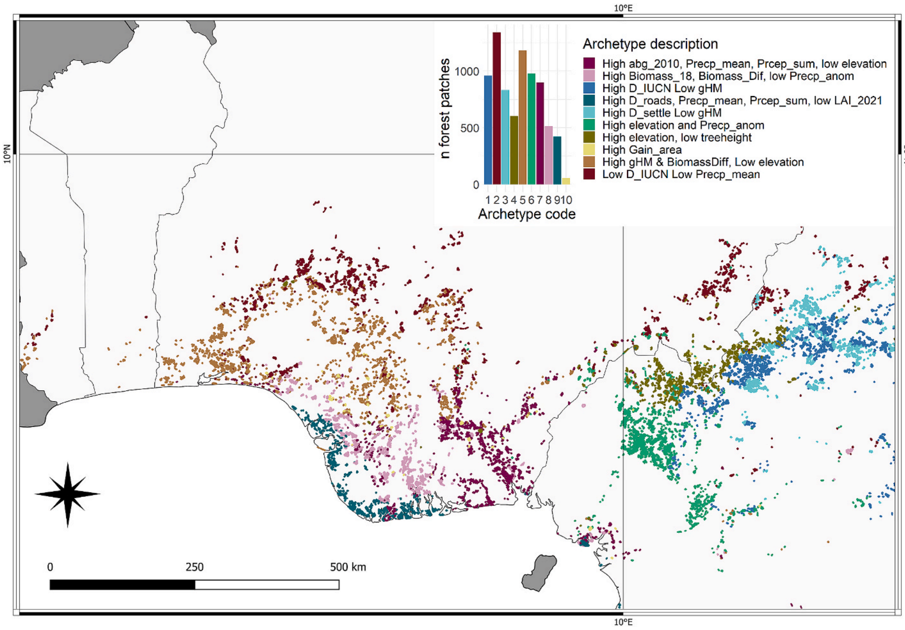

Fig. 3. Remnant forest patch archetypes, their main characteristics and geographical distribution; the map serves to highlight patches with spatially grouped patterns of social-ecological interactions.

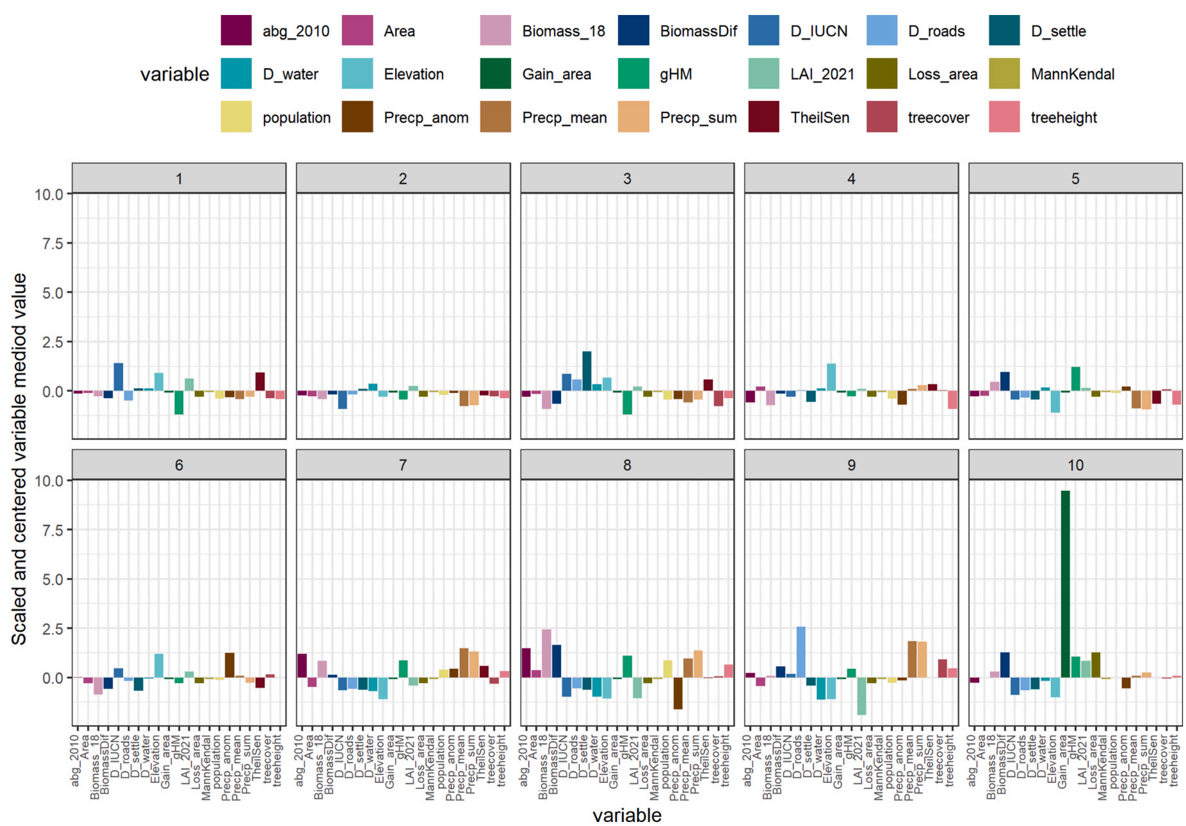

Fig. 4. Identifying the most prominent variables in each cluster (archetype), namely the variables with the highest medoid value. Here for example, cluster 10 has an especially high medoid value for the variable "Gain_area", and as such, this variable serves to characterise the archetype.

Archetype 2 – Savanah landscapes close to protected areas with low rainfall; with 1342 mapped forest fragments (17%), this archetype is the most common throughout the study area. It is characterized by patches being primarily close to protected areas (Low D_IUCN) and having a low average annual precipitation (Low Precp_mean), although we find it to be highly variable due to the spatially widespread nature of the archetype. Geographically, the patches cluster mainly along the northern fringe of the study area (Fig. 3); this region is also expected to have a lower precipitation mean (Maidment et al., 2014). The forest patch in Fig. 5 Plate B (Nigeria, Ekiti) is only 18 km from a protected area (Low D_IUCN), and its average annual precipitation is 1475 mm (Low Precp_mean). Human influence is mainly in the form of small-scale

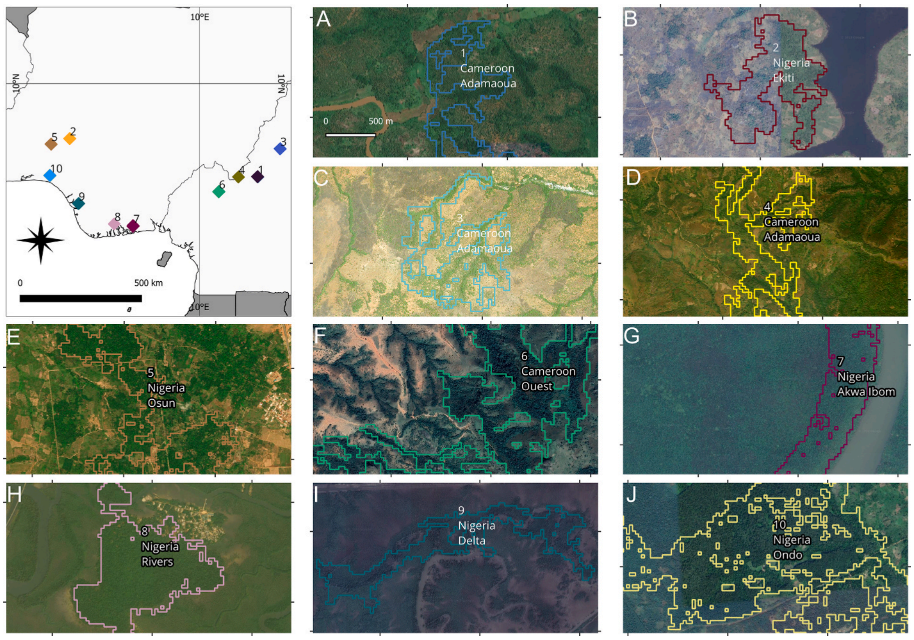

Fig. 5. To evaluate the performance of the archetype classification, a random sample of 10 forest patches from archetypes 1–10, were visually evaluated in relation to the landscape; results are presented in plates A-J.

agriculture and is apparent across the landscape surrounding the forest patch, which itself appears to be heavily utilized and degraded, and is in fact classified as degraded forest (Cotillon & Tappan, 2016). The patch is in a mosaic arable and wooded savannah landscape, bordering a lake. Medoid values for most indicators of this archetype (except D_water and LAI_2021) are negative, signifying that the actual values of each indicator are relatively low compared to the remaining patches. Since forest patches of this archetype are most often found on the northern fringes of the study area, which are drier, it is expected that they exhibit lower values for biophysical indicators (i.e., NDVI) and climatological rainfall measures (i.e., mean precipitation).

Archetype 3 – Remote from settlements and low human landscape modification; with 834 fragments (11%), this archetype encompasses forest patches which are mainly characterized as being distant from settlements (High D_settle) and concurrently exhibiting a low human disturbance (Low gHM). The patches cluster in a geographically similar way to archetype 1, in the north-eastern portion of Cameroon, but also in the central-eastern part of the country (Fig. 3). Fig. 5 Plate C (Cameroon, Adamaoua) shows a forest fragment comprising a gallery forest, adjacent to open woodland savannah with no signs of human land-use except potential burn scars. The closest settlement is over 22 km away (High D_settle), and the gHM is 0.1 (Low gGM).

Archetypes 4 and 6 – Relatively high elevations in the sub-humid Guinea savannah; comprising 602 fragments (8%), patches of this archetype are relatively few; they are characterized as being found in highlands (High_elevation) and exhibiting a low average tree height (Low_treeheight). Geographically, they are located along the border between Cameroon and Nigeria (Fig. 3). The forest patch in Fig. 5 Plate D (Cameroon, Adamaoua) reveal a sparely forested, open woodland savannah valley forest patch in a montane area, and the patch appears surrounded by small-scale arable fields and is highly fragmented, suggesting it is exploited for timber or charcoal. In addition, the region has clear signs of arable farming, roads, and villages. The fragment has an elevation of 1492 m above sea level (a.s.l) (High_elevation), and its average tree height of 8 m (Low_treeheight).

Archetype 6, with 980 mapped patches (13%), is characterized as being found in the highlands (High_elevation) and experiencing pronounced rainfall anomalies (High Precp_anom). Geographically, the forest fragments are found in the north-western part of Cameroon (Fig. 3). The fragment in Fig. 5 Plate F (Cameroon, Ouest) consists of gallery/valley forests in a sparely forested montane landscape, comprising mainly open savannah and gallery forest with little or no human activity. The elevation is 1748 m a.s.l, (High_elevation), and the rainfall anomaly is −20 mm (High Precp_anom).

Archetypes 4 and 6 were merged as they have in common the variable "elevation"; in addition, the variables "high precipitation anomalies" (archetype 4) and "low tree height" (archetype 6) are indicators which can readily be associated with one another (Shackleton and Scholes 2011). Moreover, both archetypes are geographically adjacent. Finally, a visual examination of high-resolution aerial imagery suggests they both comprise comparable gallery or riparian forests in open savannah or arable landscapes.

Archetype 5 – Highly human-modified landscapes with biomass losses; harbouring 1180 forest patches (15%), this archetype is the second most common and is widespread throughout the study area. This archetype is characterized by being found in highly disturbed landscapes (High_gHM), having undergone changes in AGB in the period 2010–2018 (High_BiomassDiff), and being in low-lying areas (Low_elevation). Geographically, they are widely distributed throughout central and western Nigeria (Fig. 3). Fig. 5 Plate E (Nigeria, Osun) reveals a fragmented and sparely forested patch, in a highly human-modified arable landscape with numerous villages and roads, and near a major urban centre. It has a gHM index value of 0.7 (High_gHM), and a negative BiomassDiff value of −46 Mg ha^{-1} (High_BiomassDiff) while its elevation is 310 m (a.s.l) (Low_elevation). Such values may be expected as we anticipate that highly human-modified landscapes could result in forest biomass losses.

Archetype 7 – Lowland, high biomass, humid forest landscapes; consisting of 897 forest fragments (12%), this archetype is characterized as having a high AGB (High abg_2010), high average and cumulative precipitation (High Precp_mean, high Prcep_sum), and a low elevation (Low_elevation). Geographically, the archetypes cluster in south-eastern Nigeria in a region of extensive swamp forests (Fig. 3). The fragment in Fig. 5 Plate G (Nigeria, Akwa Ibom) presents a densely wooded fragment of riparian swamp forest. It borders a large water body (river) and is adjacent to a village in an arable farmed landscape. Deforestation signs

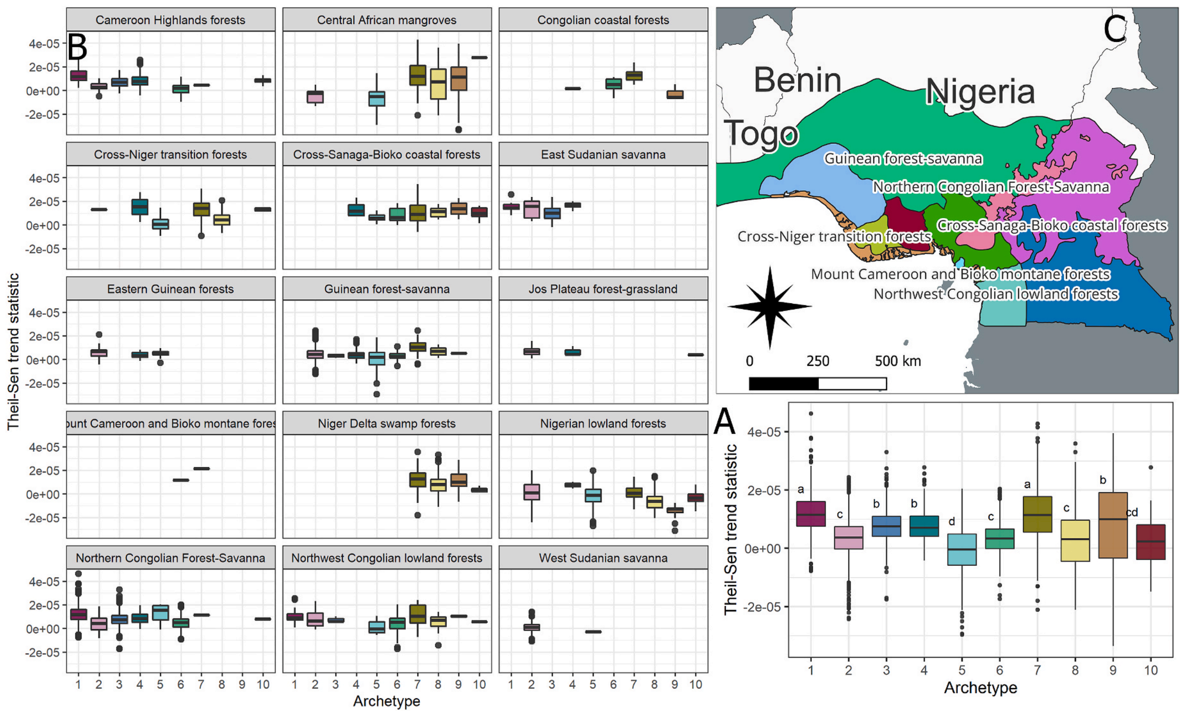

Fig. 6. (A) Significantly different (ANOVA) values (signified by letters) for the Theil-Sen trend statistic, compared to other archetypes, with an average value of (0.0000120). (B) Plot of trend values for each ecoregion; results suggest that the Central African mangrove and Niger Delta swamp forest (C) exhibit the most pronounced greening trend.

are prevalent in adjacent riparian forests, suggesting these forests are increasingly exploited for timber. The average AGB in 2010 was 66 Mg ha^{-1} (High abg_2010), and the average and cumulative precipitation are 2818 mm and 2664 mm, respectively, (High Precp_mean, high Prcep_sum), while the elevation is only 16 m a.s.l.

Archetype 8 – Lowland, positive biomass changes, humid forest landscapes; with only 514 classified fragments (7%), this archetype is the third smallest. It is characterized as having a high AGB in 2018 (High Biomass_18), having undergone positive AGB changes (Biomass_Dif), and experienced negative precipitation anomalies (Low Precp_anom). Geographically, they are mostly located adjacent to and north-west of archetype 7, and often found in the Niger Delta swamp forests and are often riparian (Fig. 3). The forest patch in Fig. 5 Plate H (Nigeria, Rivers) is located in a mangrove forest (Cotillon & Tappan, 2016) adjacent to a small village and surrounded by waterways and rivers, with other little-visible anthropogenic disturbances. Its AGB in 2018 was 153 Mg ha^{-1} (High Biomass_18), it exhibited a positive AGB difference between 2010 and 2018 of 0.5 Mg ha^{-1} and the precipitation anomaly was −361 mm.

Archetype 9 – Remote, lowland, humid forests with often low Leaf Area Index; consisting of 420 patches (5%), this archetype is the second least common. It is characterized by a high distance to roads (High D_roads) and pronounced average and cumulative rainfall (High Precp_mean, High Prcep_sum) and a low LAI (low LAI_2021). Geographically, this archetype is located mainly in the Central African mangrove forests of Nigeria (Fig. 3). The forest patch in Fig. 5 Plate I (Nigeria, Delta), lies in a densely forested mangrove landscape with numerous and dense rivers and waters ways, and only minimal visible human infrastructure. The distance to the nearest road is 20 km (High D_roads), and the mean and cumulative rainfall are 2911 mm and 3251 mm, respectively; finally, the average LAI in 2012 was only 382 units (low LAI_2021), potentially due to the extensive flooding occurring in the region. Since rainfall climatologies seem to play a key role in characterizing this archetype, we evaluate average rainfall further. Fig. 7 A plots average rainfall (Prcp_mn) (mm yr^{-1}) for all archetypes; we find significantly different (ANOVA) values for average rainfall between archetypes, with an average value of 2985 mm yr^{-1} for archetype 9. Similarly, Fig. 7 B plots average precipitation values for each archetype and every ecoregion; here we see that archetype 9 exhibits high mean rainfall values especially in the Central African mangrove ecoregion.

Archetype 10 – Changing forests undergoing forest and biomass loss and gain; consisting of only 55 forest patches (1%), this archetype is primarily characterized by high forest gain values (km^2) (High Gain_area) and a positive biomass difference between 2010 and 2018 (BiomassDiff), and finally high Loss_area values. Geographically, this archetype is sparsely distributed across the Nigerian lowland forests of western Nigeria (Fig. 3). The fragment in Fig. 5 Plate J (Nigeria, Ondo), consists at least partly of plantation forest, which may explain why this forest patch has a positive gain value of 1 km^2 (High Gain_area), and a positive biomass difference value of 38 Mg ha^{-1}. However, this archetype is also characterized by High Loss_area. In effect, when plotting mean forest loss (km^2) per archetype, we find that most forest loss is significantly higher in archetype 10 than in the remaining archetypes, with an average value of 1.76 km^2 (Fig. 8 A); and when examining these results in terms of ecoregion (Fig. 8 B, C), it is apparent that forest loss is most pronounced for archetype 10 in the Nigerian lowland forests and Cross-Niger transition forest.

4. Discussion

4.1. Common underlying characteristics

Mapping landscape features, such as forest patches, into archetypes of social-ecological interactions to inform conservation and sustainable management, is an important challenge in the domain of land system science (Oberlack et al., 2019; Sietz et al., 2019; Václavík et al., 2013). In effect, classifications based only on biophysical variables with little attention to social-ecological indicators may be inadequate to holistically characterise coupled social–ecological systems (Verburg et al., 2009). Addressing these deficiencies is critical since the sustainable

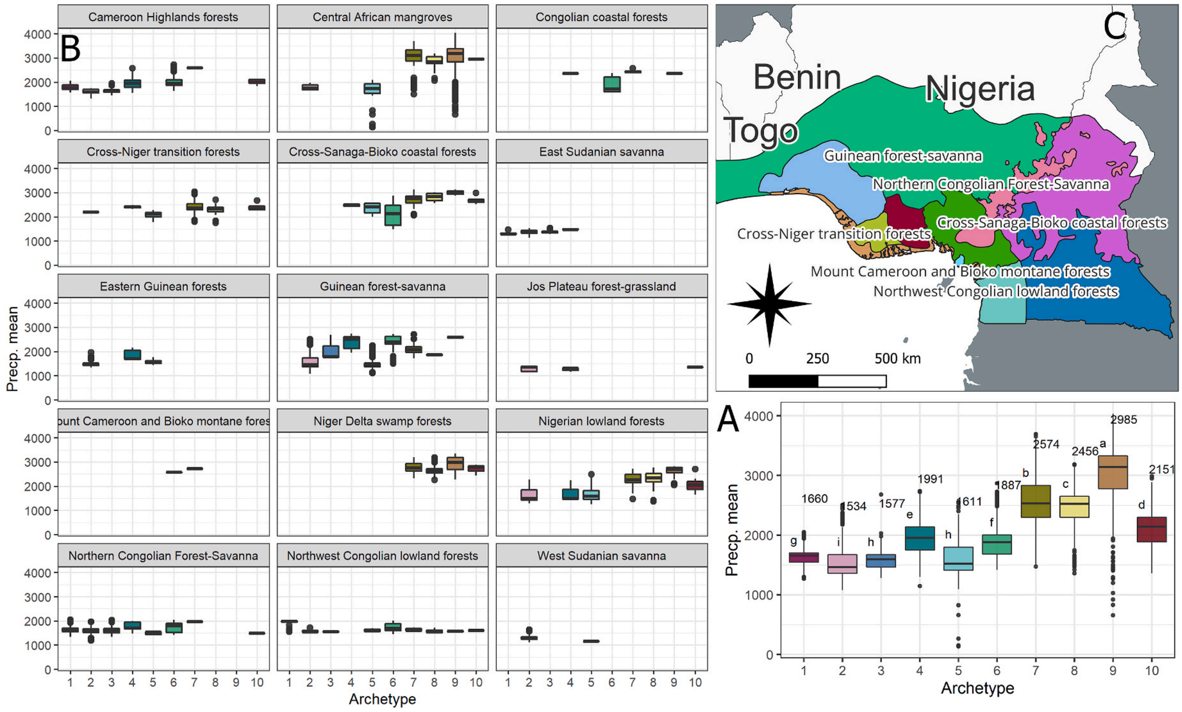

Fig. 7. (A) Significantly different (ANOVA) values (signified by letters) for average rainfall (Prcp_mn) (mm yr^{-1}), compared to other archetypes, with an average value of 2985 mm yr^{-1} for archetype 9. (B) Average precipitation values for each archetype and every ecoregion are plots, archetype 9 exhibits high mean rainfall values especially in the Central African mangroves ecoregion (C).

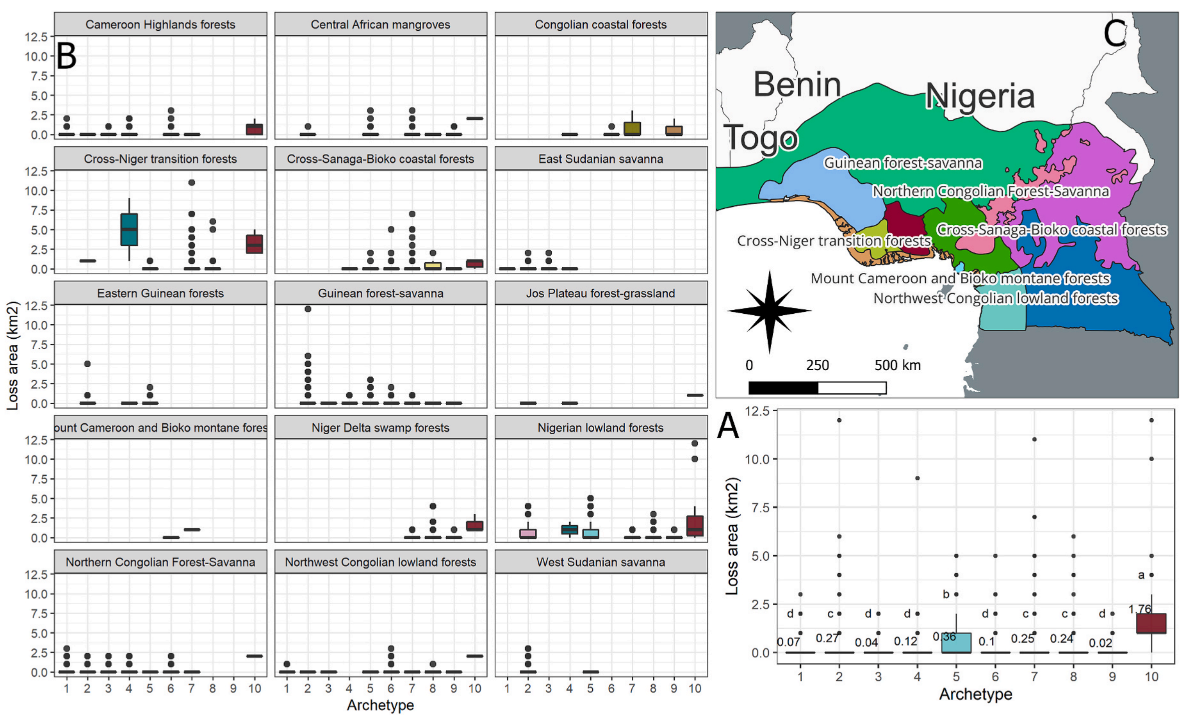

Fig. 8. (A) Significantly different (ANOVA) values (signified by letters) for Loss area (km^2) compared to other archetypes, with an average value of 1.76 km^2. (B) Forest loss is most pronounced for archetype 10 in the Nigerian lowland forests and Cross-Niger transition forests (C).

management of forests is one of the nine response options with the potential for medium to large benefits for climate change mitigation, adaptation, desertification, land degradation and food security (Shukla et al., 2019). As such, this study attempts to present an integrated view of remnant forest patches at a regional level, by considering the various dimensions of socio-ecological, proximity, land cover change and biophysical indicators, which affect them. Here, through classifying forest patches into archetypes, we identify and examine various regional patterns of underlying anthropogenic and ecological change pressures, which offer deeper insights than would an analysis based on only biophysical land cover land-use metrics. Specifically, the analysis shows that distinctive groupings of forest patches can be identified based on their social-ecological contexts. Hence, (dis)similarities between forests need to be considered when researching them or when designing policy measures. Importantly, the grouping of forest patches at regional scales allows common characteristics of major underlying anthropogenic and ecological change pressures to be identified. In turn, these may allow targeted policy actions to be developed while raising awareness among stakeholders. For instance, we suggest that remnant forest patches of Archetype 1 may comprise a high priority for conservation and sustainable use, since they lie in a landscape with little anthropogenic disturbances, show an NDVI greening trend, and are often far from any formally protected areas. Below, we discuss several additional specific examples in more detail.

4.2. Dynamic forests patches

Remnant forest patches belonging to archetype 10 (Changing forests undergoing forest and biomass loss and gain) often comprise plantations, and fragmented forest patches in arable or (semi)urban landscapes. Plantations are included in the forest patch inventory dataset since they conform to the definition of forest used, namely, a tree cover >30% and tree height >5 m (Wingate, Akinyemi, Iheaturu, & Speranza, 2022). The intentional management of shade trees with agricultural crops (agroforestry) has high potential for providing habitats outside of protected areas (PAs), by both connecting PAs and providing a buffer to natural resource use pressure; hence agroforestry plays a major part in forest conservation in human-dominated regions (Bhagwat et al., 2008). In addition, these fragments were often characterised as undergoing forest and biomass loss and/or gain. Thus, fragments of this archetype could be considered as both dynamic, changing forests, and experiencing a high degree of anthropogenic land-use change pressures, relative to other archetypes. In effect, their geographical location within the Nigerian lowland forests and Cross-Niger transition forests ecoregions, are areas which are densely populated relative to other ecoregions of the study area (i.e., mangrove), and which would therefore suggest a high degree of land-use change pressures requiring local strategies to address these.

4.3. Biomass gain

The variable Biomass Difference is prominent in characterising Archetype 8; moreover, when looking at all forest patches of that archetype simultaneously, we find that almost all exhibit positive biomass changes during the period 2010–2018. In effect, applying the Analysis of Variance (ANOVA) and Tukey's test, they show significantly different Biomass Difference values compared to other archetypes, with an average value of 56.9 Mg ha^{-1} (Fig. 9 A).

Thus, not only has the archetyping analysis identified groups of fragments which have significantly different biophysical values (in this case BiomassDiff), compared to other archetypes, but it has also allowed these to be spatially mapped and grouped into ecoregions; for instance, in Fig. 9 B, we find that positive biomass differences are most pronounced in the "Central African mangrove" and "Northwest Congolian lowland forests" (Fig. 9 C). Moreover, results from Fig. 6 B show that fragments in these two ecoregions also exhibit a positive NDVI greening trend.

Results suggest that forest fragments of these ecoregions are undergoing positive AGB changes combined with a greening trend; further research would be required since it counters findings of widespread AGB loss across forests of this region (R. Fischer et al., 2021). Further, these results imply that widespread vegetation changes are occurring which could potentially benefit targeted policy actions, such as conservation measures and carbon sequestration programs. This is illustrated in Fig. 10 (supplementary material), which shows patch archetypes overlaid on the biomass change detection analysis. In addition, a polynomial regression analysis between the natural log of average fragment size and the percentage and total biomass change per size class, is included for each archetype (Fig. 11, supplementary material). This analysis highlights how biomass change is cumulative positive for small size classes of

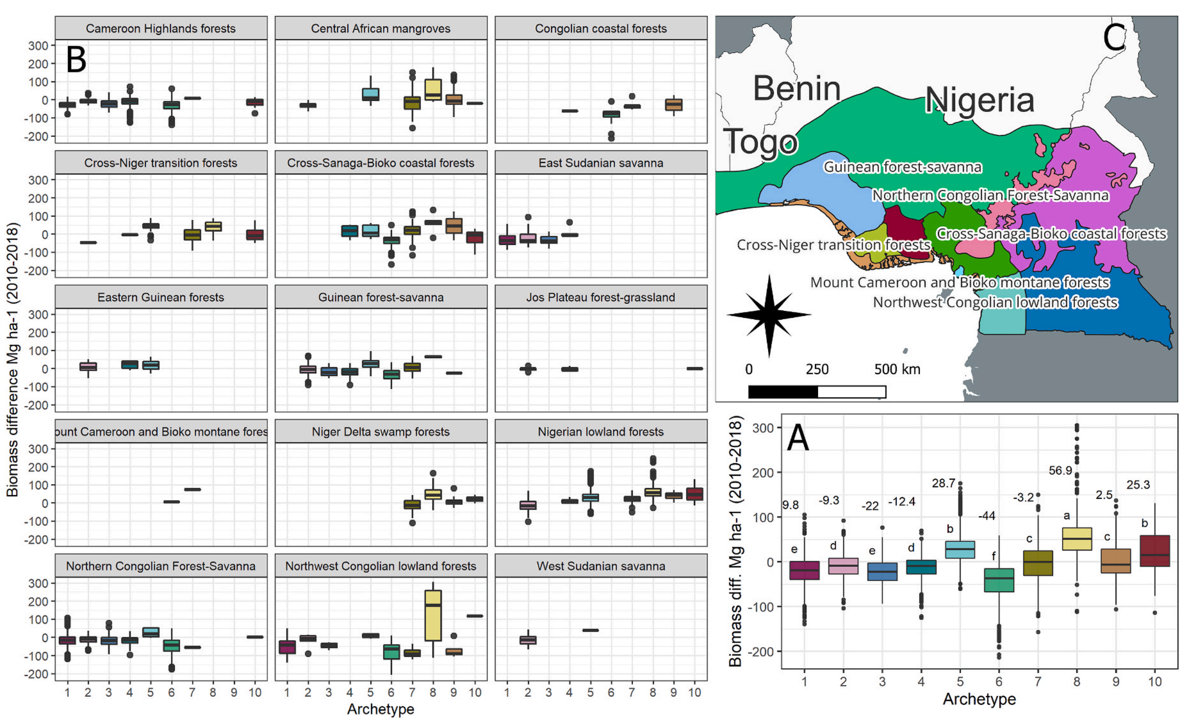

Fig. 9. (A) Significantly different (ANOVA) Biomass difference values (Mg ha^{-1}) (signified by letters) compared to other archetypes, with an average value of 56.9 Mg ha^{-1} for archetype 8. (B) A positive biomass difference is most pronounced in forests belonging to archetype 8, located mostly in the "Central African mangrove" and "Northwest Congolian lowland forests" (C).

archetype 8, but negative when taken as a percentage of total biomass change per size class.

4.4. Remote forest patches

For fragments belonging to archetype 3 (Remote from settlements and low human landscape modification), little to no visible human impacts could be identified on the landscape, and areas far from human settlements can be assumed to exhibit relatively little human landscape modification. In contrast, patches belonging to archetype 10 (i.e., Changing forests undergoing forest and biomass loss and gain), were often fragmented or comprised plantations which exhibited a high degree of change.

4.5. Synthesis

The archetypes described in this study are novel and have not been described in the literature. The key outcome of this archetyping analysis is the identification of common underlying ecological change pressures and characteristics, which may contribute to better informing targeted policy and conservation actions on remnant forest patches, for instance, such as the prioritization biomass gain forest patches for further research. Pressures on the natural resources of the study countries are rising rapidly, and the consequent alarming loss of biodiversity, which is also measure for assessing these pressures, is at a critical juncture (Beier et al., 2002; Fischer et al., 2021; Norris et al., 2010); hence, the protection and sustainable use of the widely dispersed remnant forests is increasingly urgent. Patches in Benin are often small, sacred forests, which are widely studied (Adomoui et al., 2010; Nagel et al., 2004; Neuenschwander & Adomou, 2017). In contrast, most patches in the remaining area of this study are widely scattered across a vast and generally remote area, encompassing diverse ecoregions, ranging from mangrove to montane (Wingate, Akinyemi, Iheaturu, & Speranza, 2022). They are probably rarely studied, have little or no formal or informal conservation status or management plan, are subject to multiple change pressures, and are found in a biodiversity hotspot region; as such, they present manifold opportunities for research and conservation (Myers et al., 2000).

5. Conclusions

Understanding the context and condition of remnant forest patches is critical for tailoring approaches to ensure their sustainable management; hence, this study classified remnant West African forest patches into 9 archetypes using 20 indicators and described their dominant characteristics. Importantly, the regional archetyping analysis contributed a method to identify common underlying anthropogenic and ecological change pressures and characteristics. In doing so, it may facilitate the development of local strategies and help informing targeted policy actions to address these changes. We assessed the performance of the archetype classification and find that the indicators characterising the archetypes can readily be associated with one another; for instance, moderate rainfall and reduced tree cover, while others including low gHM, can readily be visually identified using high resolution aerial imagery. This work improves our knowledge of the change pressures affecting remnant forest patches and provides a foundation for researching their multiple services and functions. In particular, this study provided novel insights into the condition of remnant forest fragments in relation to the study area ecoregions, for instance, that greening, and biomass gains occur mainly in mangrove and swamp forests. This study provides a first approximation of how remnant forest patches group into archetypes based on a set of indicators and may be improved as more accurate and pertinent data become available. Such a dataset would contribute to subsequent field studies by ensuring representative sampling of field sites, and better characterising forest patches in inventory databases.

Credit author statement

Vladimir Wingate: Conceptualization, Methodology, Software, Data curation, Formal analysis, Investigation, Writing- Original draft preparation, Visualization, Software, Validation.

Felicia O. Akinyemi: Conceptualization, Methodology, Investigation, Writing- Reviewing and Editing.

Chinwe Ifejika Speranza: Funding acquisition, Resources, Conceptualization, Methodology, Investigation, Writing- Reviewing and Editing, Supervision.

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Data availability statement

Data available upon request.

Declaration of interest statement

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apgeog.2023.103024.

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