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Two decades of land cover change and forest fragmentation in Liberia: Consequences for the contribution of nature to people

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Abstract

The Guinean forests of West Africa have been identified as a global biodiversity hotspot due to its exceptional concentrations of endemic species and exceptional loss of habitats. The majority of what remains of the Guinean forests lies within Liberia, a country whose share of total wealth is nearly equally distributed into human and natural capital. The Liberian government seeks a more inclusive development agenda that forges a path for improved human capital while sustainably managing its natural capital wealth, which requires consistent data on land cover change and forest disturbance over time. To address this need, Landsat data were used to map and quantify land cover change and forest fragmentation in Liberia between 2000 and 2018. In addition, LiDAR data from the Global Ecosystem Dynamics Investigation (GEDI) mission were applied to assess the integrity of forest remnants. Between 2000 and 2018, only 1% of all forest cover classes (i.e., dense/primary, open/secondary and sparse/degraded) were converted into non-forest classes, with the most observed change being between these three forest classes. During the study period, 27% of the dense/primary forest class transitioned to either the open/secondary or sparse/degraded canopy classes through consistent fragmentation along the edges of the last large remaining blocks of dense/primary forest located in the north-west and south-east of Liberia and more than 14% of dense/primary forest areas identified in previous studies as "essential natural capital" for either biodiversity, forest carbon storage or provision of freshwater ecosystem services were degraded. The 2018 GEDI-based measurements show that the overall average height of dense/primary forest decreases by 24% and 48%, and canopy closure decreases by 33% and 59%, when transitioned to the open/secondary and sparse/degraded classes, respectively. The information derived from this analysis will be critical for informing the development of new policies and actions, leading to more sustainable forest management in Liberia.

KEYWORDS

forest fragmentation, GEDI, Google Earth Engine, land cover change, time series

1 | INTRODUCTION

The Guinean forests of West Africa (GFWA) consist of a belt of tropical moist forests stretching from Cameroon to the east, to Liberia, Sierra Leone and Guinea to the west and they are divided by the Dahomey Gap into the Upper and Lower Guinean forests. These forests are among the most diverse regions in the world (Myers et al., 2000; Oates et al., 2005), supporting a remarkable diversity of endemic species of plants and animals (Mittermeier et al., 2004; Oates & Nash, 2011), and with above ground biomass estimates ranging from 120 to 200 tons of carbon per hectare (European Commission, 2010; Lewis et al., 2009; Lewis et al., 2013; Lindsell & Klop, 2013; Liu et al., 2017; Penman et al., 2003; Ploton et al., 2020). These forests also provide a suite of important ecosystem services that support human livelihoods in the region, including the provision of food and clean water, climate regulation, protection against natural hazards, and other benefits.

Liberia holds the largest intact tract of what remains of the Upper Guinean forests (Mittermeier et al., 2004), making it a biodiversity hotspot and one of the highest global conservation priorities. Rapid development and population growth (CILSS, 2016) in Liberia have increased the pressure on natural resources, leading to noticeable changes in the forest cover in the country. The loss of forest habitat will likely lead to the decline in endemic species such as western chimpanzees, pigmy hippopotamus, or forest elephants. Forest loss will also have an impact on the provision of a range of ecosystem services benefits that are critically important to the livelihoods in Liberia. It is estimated that Liberia holds about 106 M metric tons of total irrecoverable carbon, defined as stores of carbon in nature that are vulnerable to release from human activity and that if lost could not be restored by 2050 (Noon et al., 2021). The reduction in forest cover combined with forest degradation and fragmentation leads to the release of significant amounts of greenhouse gases emission that are detrimental toward achieving global climate goals.

The long-term survival of Liberia's forests is challenged by a myriad of factors, including historical land-use practices, commercial enterprise, demographic shifts, and recent conflicts. Liberia's forest landscapes have a 300-year history of human intervention through shifting cultivation (or "slash and burn agriculture"), which has directly contributed to deforestation and loss of biodiversity (The World Bank, 2010). Increasing demand for globally important forest commodities such as cocoa, rubber, and palm oil has also driven forest loss in the region (Ordway et al., 2017): more than half of world's exports of cocoa originate from this region (Ruf et al., 2015), and Liberia holds Firestone's largest contiguous rubber plantation in the world (Verite, 2012).

The National Forest Inventory conducted in 2019 estimated Liberia's total forest cover 6.69 million ha (69% of land area) (World Bank, 2020). This vast forest land makes significant contribution to Liberia's formal and informal economy. In 2021, agriculture, fisheries, and forestry combined represented 39.8% of the GDP, of which formal forestry sector contributed 8.8% (Central Bank of Liberia, 2021). Informal contribution of forestry is largely unmeasured and unaccounted for in national statistics. Activities associated with chainsaw milling, charcoal production, and extraction of non-timber forest products (e.g., fruits, nuts, firewood, honey, and medicine) make significant economic contribution through employment and income. The revenue contribution of chainsaw milling alone is estimated at 3%–4% of GDP (US$ 31–41 million p.a.) (World Bank, 2020). Charcoal production activities make additional contribution of similar magnitude, with the estimated value of annual demand at US$ 46 million (ibid).

West Africa has the highest fertility and population growth rates on Earth (Bongaarts, 2009) and has experienced a 5-fold increase in the population since the early 1950's (Herrmann et al., 2020). This rapid growth in population has exerted substantial pressure on natural resources and driving drastic land cover conversion. More recently, Liberia's internal migration and mining activities exploited by armed conflicts has also led to forest degradation and loss (Enaruvbe et al., 2019). Intense human intervention in the GFWA in recent years and its direct contribution to forest fragmentation and loss has been documented as one of the potential causes of Ebola virus disease outbreaks (Olivero et al., 2020; Rulli et al., 2017). The 2014–2016 epidemic was West Africa's largest Ebola epidemic in history, with Liberia being the second country with total cases and the leading country in number of deaths (Kamorudeen et al., 2020). Drought-related events are one of the few natural causes contributing to major disturbances in the moist forests in West Africa and Liberia; however, the resilience of these moist forest to droughts has been reported in the literature (Asefi-Najafabady and Saatchi, 2013). Human-driven impacts have considerably larger footprint compared to disturbances caused by natural phenomena. Population growth, global demand for palm oil and rubber, and technological development are the most significant of drivers of forest loss in the region.

The ecological importance and the concern for the long-term survival of GFWA has led to an increasing number of studies addressing a range of ecological aspects of such forests and the importance of their conservation. However, political instability and the civil conflicts of 1989–1997 and 2002–2003 severely hindered field research from being carried out in Liberia, meaning that it is one of the least studied countries, in terms of ecological and biological conservation research, in the region (Luiselli et al., 2019). This has contributed to the increasing reliance on remote sensing-derived data (i.e., satellite imagery and aerial photography) as an alternative for the lack of in situ measurements. Despite the increasing availability of large-volume remote sensing data through cloud-computing platforms (Gorelick et al., 2017), a detailed quantitative analysis of land cover change and forest loss has yet to be done. Although valuable insights about the trends of forest loss and other land cover classes in Liberia can be drawn from global datasets (Hansen et al., 2013), understanding the drivers, scale, and intensity of these disturbances remains challenging. Comprehensive estimates of land-use and land cover classes in Liberia do not provide sufficient information on extent and change; earlier estimates of the extent of other land cover classes in Liberia are likely to have been derived from existing global land cover datasets (e.g., Arino et al., 2007; Bartholomé & Belward, 2005; Bontemps et al., 2011; Friedl et al., 2010; Fritz et al., 2003; Hansen et al., 2013; Loveland et al., 2000), or from land-use land-cover (LULC) products that focused on either several west African countries or only for certain portions of Liberia (Gessner et al., 2015; Laurin et al., 2012; Mayaux et al., 2004; Vittek et al., 2013). Natural capital mapping and accounting relies on land cover products and other remote sensing-derived datasets (e.g., Neugarten et al., 2017) and the lack of current and thematically comprehensive land cover products pose many challenges for accurate natural capital reporting in Liberia. Finally, consistent, large-scale monitoring of the forest structure, namely, canopy height and canopy closure, is still lacking for Liberia. The highly dynamic nature and fine scale of land cover change and forest degradation and fragmentation that is occurring in the region warranties the use of fine resolution imagery at the annual increments.

We describe a methodology for mapping and quantifying land cover change and forest fragmentation in Liberia from 2000 to 2018. The objectives of this research are to understand: (1) To what extent has land cover changed across Liberia in the 18-year period? (2) How have the forests changed in terms of extent, fragmentation, canopy cover and structure? (3) How have these changes affected natural capital (e.g., biodiversity, forest carbon, freshwater ecosystem services, and coastal protection) in Liberia? To address these research questions, land cover change was analyzed using classified Landsat imagery at 30-m spatial resolution, and changes in forest fragmentation were calculated. The forest structure (canopy height and canopy cover) was analyzed using the waveform LiDAR data obtained from the Global Ecosystem Dynamics Investigation (GEDI) mission.

2 | DATA AND METHODS

An overview of the methodology for creating the multi-temporal classified land cover images from 2000 to 2018 and Theil–Sen nonparametric regressions to evaluate the changes in annual fragmentation is shown in Figure 1.

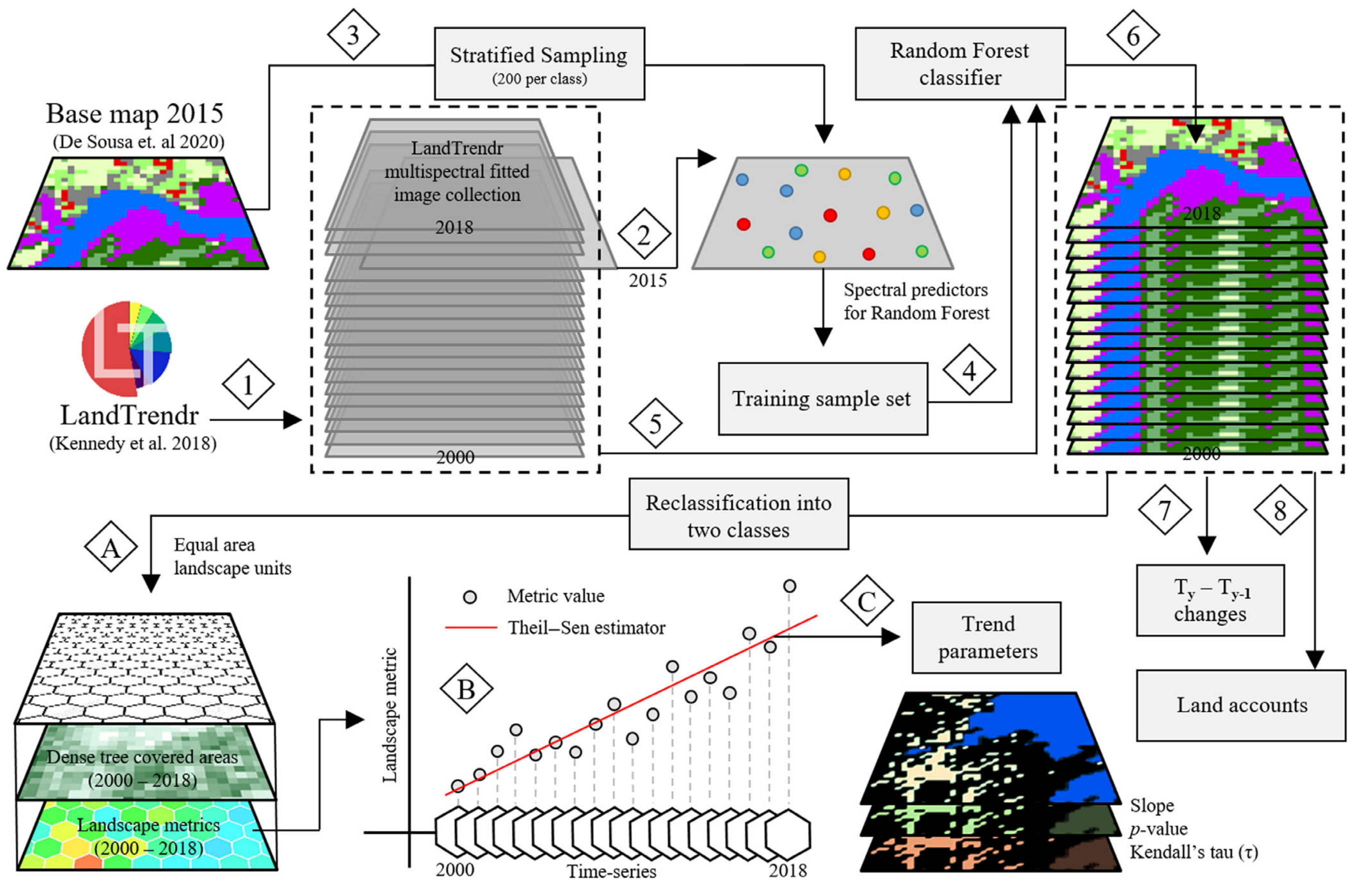


FIGURE 1 Schematic overview of the methodology. Numbers represent each step in the land cover classification and change analysis, whereas letters represent the order of each process in the forest fragmentation analysis: (1) Annual temporal consistent composites using LandTrendr. (2) 2015 fitted image to match the 2015 land cover base map. (3) Stratified sample selection based on the 10 classes from the base map. Spectral information was extracted from the 2015 LandTrendr composite at the location of each sample. (4) Training sample set was composed by each sample and its predictors, and the Random Forest (RF) classifier was trained. (5) Multispectral fitted imagery stack was classified using the trained RF model. (6) Land cover map (LCM) outputs. (7 and 8) Land cover extent area was computed for each LCM outputs. (a) Reclassification of the 10-class land cover maps into two classes: dense forest and other land cover classes and calculation of landscape metrics at the landscape unit size. (b) Landscape metric values were extracted at each landscape unit across Liberia and across the period of the time-series and the Theil–Sen nonparametric regression was used to evaluate the changes in annual fragmentation for each metric. (c) Spatial distribution of trend-parameters for each landscape metric.

2.1 | Reference satellite imagery and land cover data

The acquisition of current and thematically comprehensive baseline LULC products at the national scale for Liberia is challenging. A 30-m resolution Landsat-based land cover product, circa 2015, for Liberia that was produced with the Google Earth Engine platform (De Sousa et al., 2020) was used. The map was produced taking into consideration Liberia's recently established forest definition, and it was developed as an initial step toward Liberia's effort to integrate the value of nature into their national policies and decision-making processes through an ecosystem accounting framework. The final 2015 land cover product consists of 10 classes, including both nonvegetated (i.e., open water, artificial surfaces, bare soil, shore, and sandy beaches) and vegetated (i.e., mangroves and wetlands, woody crops, grasslands, dense tree-covered areas, open tree-covered areas, and mixed vegetation) classes, with a reported final overall accuracy of 81%. This product was used as a baseline map for a stratified training sample selection to be used for the multitemporal land cover classification step. The Landsat surface reflectance product available on Google Earth Engine was used as the main input for the land cover classification step. To ensure spectral consistency across different Landsat sensors, the Landsat collections were harmonized using the published set of coefficients (Roy et al., 2016). Annual composites from 2000 to 2018 were created with all scenes for a given year using the multidimensional median method (Flood, 2013).

2.2 | Mapping land cover extent and change

The multitemporal land cover classification approach was based on spectral trajectory segmentation using *LandTrendr* (Landsat-based Detection of Trends in Disturbance and Recovery) (Kennedy et al., 2010). *LandTrendr* is a well-known change detection algorithm that has been extensively used for forest disturbance detection (Zhu, 2017) but less to attribute disturbance change agents (Kennedy et al., 2015) and only recently to build LULC maps (Yin et al., 2018). *LandTrendr* was applied over Landsat images from 1985 to 2018. Image data from 1985 to 1999 were used to extract the spectral trajectories at the pixel scale and pass it to *LandTrendr*'s trajectory segmentation algorithms. This segmentation process is the main method to detect both abrupt and slow changes in a Landsat time series (Kennedy et al., 2010). *LandTrendr* uses nine user-defined parameters to define how the spectral-temporal trajectory segmentation is performed (see Cohen et al., 2010 for more information on each of these segmentation parameters). Random Landsat pixels were selected across the country and evaluated using different combinations of parameters that best represented abrupt and slow changes in the pixel's spectral trajectory over the 1990–2018 period.

Finally, the selected control parameters were used to fit the spectral trajectory of the Tasseled Cap Wetness (TCW) index (Crist, 1985). Tasseled cap indices have been shown to more accurately separate closed canopy forest from other LULC classes (Dymond et al., 2002; Schultz et al., 2016) and to be more accurate to show forest disturbances particularly when Landsat images are acquired less than 2 years apart (Jin & Sader, 2005). However, a single index does not describe the spectral behavior across time of different LULC types. To enhance the spectral variability and distinguish among different land cover classes, the fitted temporal trajectory detected using TCW was imposed over a set of spectral metrics:

Spectral bands: Band 1, Band 2, Band 3, Band 4, Band 5, and Band 7;

Simple ratio indices: Normalized Burned Ratio (NBR), Normalized Difference Vegetation Index (NDVI), and Normalized Difference Mangrove Index (NDMI).

Multiband indices: Tasseled Cap Wetness (TCW), Tasseled Cap Greenness (TCG), Tasseled Cap Brightness (TCB), Tasseled Cap Wetness Difference (Δ TCW), Normalized Degradation Fraction Index (NDFI), Green Vegetation Fraction (GV_NDFI), Soil Fraction (SOIL_NDFI), and Non-vegetation Fraction (NV_NDFI).

Change in tropical forests is best shown by spectral metrics (Schultz et al., 2016). A RF model was trained using a training sample set based on the 10 classes from the 2015 base map ($n = 500$ per class). The value for each spectral metric was extracted from the 2015 *LandTrendr* composite at the location of each sample. The 2000–2018 annual composites were then classified with the trained RF model. The accuracy of the latest land cover map in the time series (2018) was assessed with a reference dataset acquired across the 10 classes in Liberia. A stratified random pixel sampling design was used to attain equal representability of each class in the accuracy assessment, resulting in a total of 500 samples (50 per each class) based on the equal weight assigned to each class. Visual interpretation of very high-resolution imagery available on Google Earth was conducted, and the corresponding dominant land cover class was assigned to each sample and were compared with the 2018 land cover through an error matrix (Figure S3). Changes in the land cover extent (in km^2) across the 2000–2018 in Liberia were calculated based on the RF classification outputs.

2.3 | Calculating forest fragmentation

For this analysis, we focused on the fragmentation of dense/intact forest. We selected 500 locations across Liberia where observed conversion from dense forest in the year 2000 to another land cover class in the year 2018. We tested 100 grid sizes at each location, ranging from 0.1 × 0.1 km to 10 × 10 km at 100-meter increments. Shannon's diversity index H (Shannon, 1948; Spellerberg & Fedor, 2003) was then calculated for each grid size at each location using the base map as reference (see Figure S1 for more information on the theoretical background). The final landscape unit size (3 × 3 km, that is, 9 km^2) was chosen by computing the mean H for each grid size across all sample points and selecting the grid size in which we observed the inflection point or slope decrease in the H value curve (Figure S1b).

Once the landscape unit size was selected, the next step in the yearly analysis of forest fragmentation was to reclassify the 10-class land cover maps into two classes: dense forest and other land cover classes. The definition of dense forest, as shown in De Sousa et al., 2020, includes areas with canopy cover equal or greater than 50% within a 30-meter pixel of broadleaved trees relatively intact or with no clearly visible indication of human activity and with more than 50% canopy cover. The fragmentation analysis focused on the dense forest because their intrinsic ecological values, representing the untouched remnant of the GFWA within Liberia.

Subsequently, fragmentation metrics for the dense treed class were computed (Birch et al., 2007). Avoiding metrics that are redundant and statistically correlated, two key parsimonious fragmentation metrics were computed for each landscape analysis unit across Liberia: the number of forest patches and the average patch size (in hectares). The number of forested patches indicates the number of patches within a landscape unit: a larger number of patches is an indicator of a more fragmented forest (McGarigal & Marks, 1995). The average patch size is the average size of the forest patches within the landscape unit. In this case, smaller average sizes indicate more fragmentation (McGarigal & Marks, 1995).

Theil–Sen nonparametric regression (Sen, 1968) was used to evaluate the changes in annual fragmentation for each metric. The Theil–Sen estimator fits a line—linear regression—through the sample fragmentation metric values through time by calculating the median of all pairwise slopes for that given metric. Compared to more traditional estimators (e.g., ordinary least squares), the Theil–Sen slope is robust against outliers and, therefore, more widely applied in time-series analyses (Pickell et al., 2016; Rickbeil et al., 2018). The Theil–Sen slope will measure the magnitude (value) and direction (positive or negative value) of the trend of a given fragmentation metric through time. Slope significance was computed using the nonparametric Mann–Kendall test (Kendall, 1948).

2.4 | Assessing forest structure using GEDI data

In 2019, NASA's Global Ecosystem Dynamics Investigation (GEDI) instrument (Dubayah et al., 2020) started providing widely available nearly global scale information about the vegetation structure. This information proved to be essential for practical applications including analyzing forest degradation and condition and for mapping the diversity of canopy structure. We used GEDI-derived information to assess the current structural characteristics of forest classes in Liberia and to validate the 2018 forest extent. The GEDI data consisted of the L2B Canopy Cover and Vertical Profile metrics acquired between April 2019 and November 2020, available from the NASA/USGS Land Processes Distributed Active Archive Center (DAAC) (Dubayah et al., 2021). At each GEDI footprint (25 m diameter with estimated horizontal accuracy of 10–20 meters) within Liberia (a total of 109,525,248), we extracted the relative height metric RH100 (100th percentile of beam return height in meters relative to the ground) and total canopy cover (percent) gridded to the Landsat 30-meter pixel. The average height and percent canopy cover were calculated for the three forest classes to derive statistics on the two structural characteristics.

2.5 | Essential natural capital in Liberia

The impact of land cover change and fragmentation on natural capital in Liberia was assessed using maps of "essential natural capital" developed by Neugarten et al. (2017). "Essential natural capital" (Figure S2) is defined as a subset of natural capital that provides benefits that cannot be easily substituted or replaced (Neugarten et al., 2017). In the absence of reliable data on the amount of natural capital that is needed to support Liberia's biodiversity, people's wellbeing and the economy, the authors identified the "most important" areas for three types of natural capital instead: biodiversity, carbon storage, and provision of freshwater ecosystem services.

3 | RESULTS

3.1 | Land cover change

The overall accuracy of the most recent LULC map in the time-series (year 2018) remained close to the original base map (78.8% and 81%, respectively), and with dense and open forest classes showing high user's accuracies compared to other classes (92% and 96%, respectively) (Figure S3). We found that 96.74% (93,517.97 ± 96.14 km^2) of the Liberian territory is covered by the three classes of forests (dense, open, and sparse/degraded forests) while the remaining 3.26% (3165 ± 82.7 km^2) are divided among the other LULC classes. This proportion remained relatively constant throughout the period of 2000–2018 (Figure 2). Most of the changes observed for the forest classes in this period are mainly related to the transition among these classes, with less than 1% of their year 2000 extent being converted into different non-forest classes. The dense forests in Liberia gradually transitioned into more open tree canopy classes in the 2000–2018 period: at each of the three interval periods (that is, 2000–2006, 2006–2012, and 2012–2018 shown in Figure 2a), larger extents of dense forest transitioned to the open forest, that is, 5012 km^2, 7119 km^2 and 10,034 km^2, respectively. Similarly, larger extents of open forests transitioned to the sparse/degraded forest class, that is, 2289, 3373, and 6649 km^2, respectively. In contrast to this trend, smaller areas of open forests transitioned to the dense forest class throughout these intervals, that is, 5598, 2557, and 2081 km^2, respectively. The same pattern was observed for sparse/degraded transitioning into the open forest class, that is, 5886, 4582, and 4178 km^2. The transitions from denser to more open canopy classes occurred primarily toward the end of the period while the

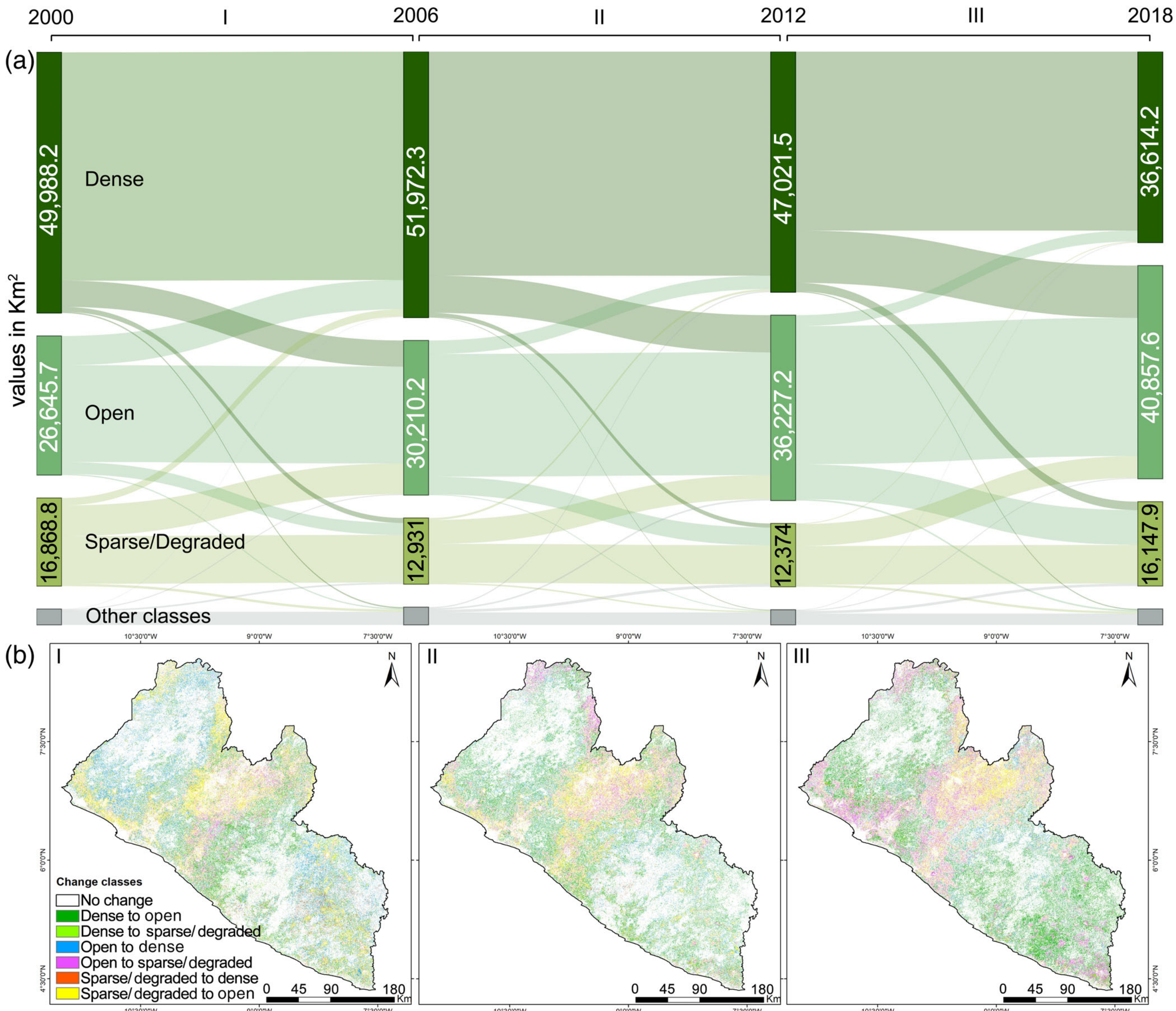


FIGURE 2 Land cover extent and change in Liberia, 2000–2018. (a) Land cover and forest extent change where columns represent the stable extent and the width of the bands between columns is proportional to the area gained and lost between classes during periods I, II, and III. (b) Spatial distribution of change in the three forest classes in Liberia for each 6-years interval.

transitions from sparser to denser forests are more evident in the early years (Figure 2b).

Other land cover classes have shown significant changes during the 19-year period (Figures S4 and S5). We observed an overall increase in nonvegetative classes, namely the 123% increase (196.5 km^2 in 2000 to 439 km^2 in 2018) in artificial surfaces and urban areas across the country, followed by 83% increase (229 km^2 in 2000 to 419 km^2 in 2018) in bare areas, which correspond mainly with the decrease of grasslands and woody crops (Figure S6). Mangroves and wetlands have shown a decreasing trend from 2005 onward, with a total change of −26% in 2018 from its original extent in 2000.

3.2 | Forest fragmentation trends

Dense forests in Liberia have shown a decline in extent and an increase in fragmentation over the 2000–2018 period. This process corroborates the observed transition of the dense forest class into more open canopy classes discussed in the previous section. The multitemporal analysis of two forest fragmentation metrics indicate that the dense forest is indeed being fragmented in Liberia at the 9 km^2 landscape unit (Figure 3 and Supplemental Materials Figure S7 and S8). We found a strong increasing 19-year trend of number of dense forest patches across Liberia (Supplemental Materials Figure S5 and S8). This increasing trend (i.e., the process of

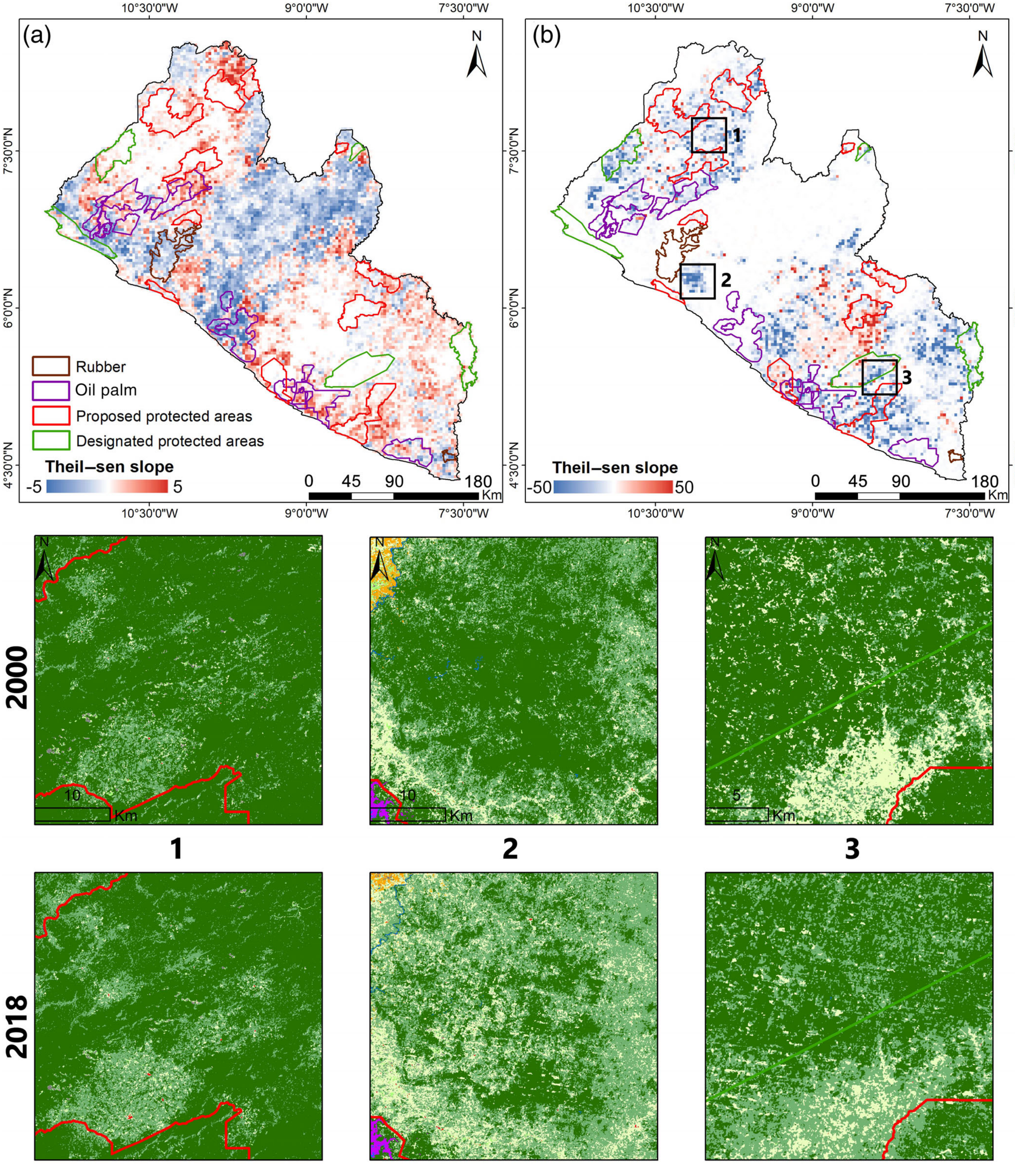


FIGURE 3 Theil–sen estimator slope values showing mature dense forest fragmentation trends in Liberia from 2000 to 2018 at each 9 km^2 landscape unit. (a) The trends in the number of patches within each landscape unit. Positive slope values (red hues) represent an increasing trend in the number of patches of mature forest, while negative slope values (blue hues) represent a decreasing trend in the number of patches. (b) The trends in the average size of the patches within each landscape unit. Positive slope values (red) highlight areas with an increasing trend in the average size of the patches while negative slope values (blue) represent a decreasing trend in the average size. Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.

continuously fractioning large patches into smaller ones) is strongest toward the surroundings of the large remaining patches of untouched mature and dense forests in the north-west and south-east (Figure 3a).

There are large areas in the central and south-west part of Liberia with a decreasing trend in the number of dense forest patches (blue areas in Figure 3a), which represent either smaller patches merging to large ones through the natural regrowth or by being converted into other land cover classes and eliminated. Since no trend in average patch size was observed for these areas (Figure 3b), the decreasing trend in the number of patches is mostly due to conversion of mature forest patches to other land cover classes (Figure 3b and Figure S8).

Increasing and decreasing trends in the number of dense forest patches were observed within areas designated as agricultural concessions for oil palm and rubber plantations. These areas are both contributing for new patches of mature forest to form as well as to the conversion of existing patches into forest plantation and other land cover classes. In contrast, designated protected areas did not show any significant increasing or decreasing trend in the number of patches (Figure 3a), which suggests that forests within these areas have been relatively intact throughout the 19-year period.

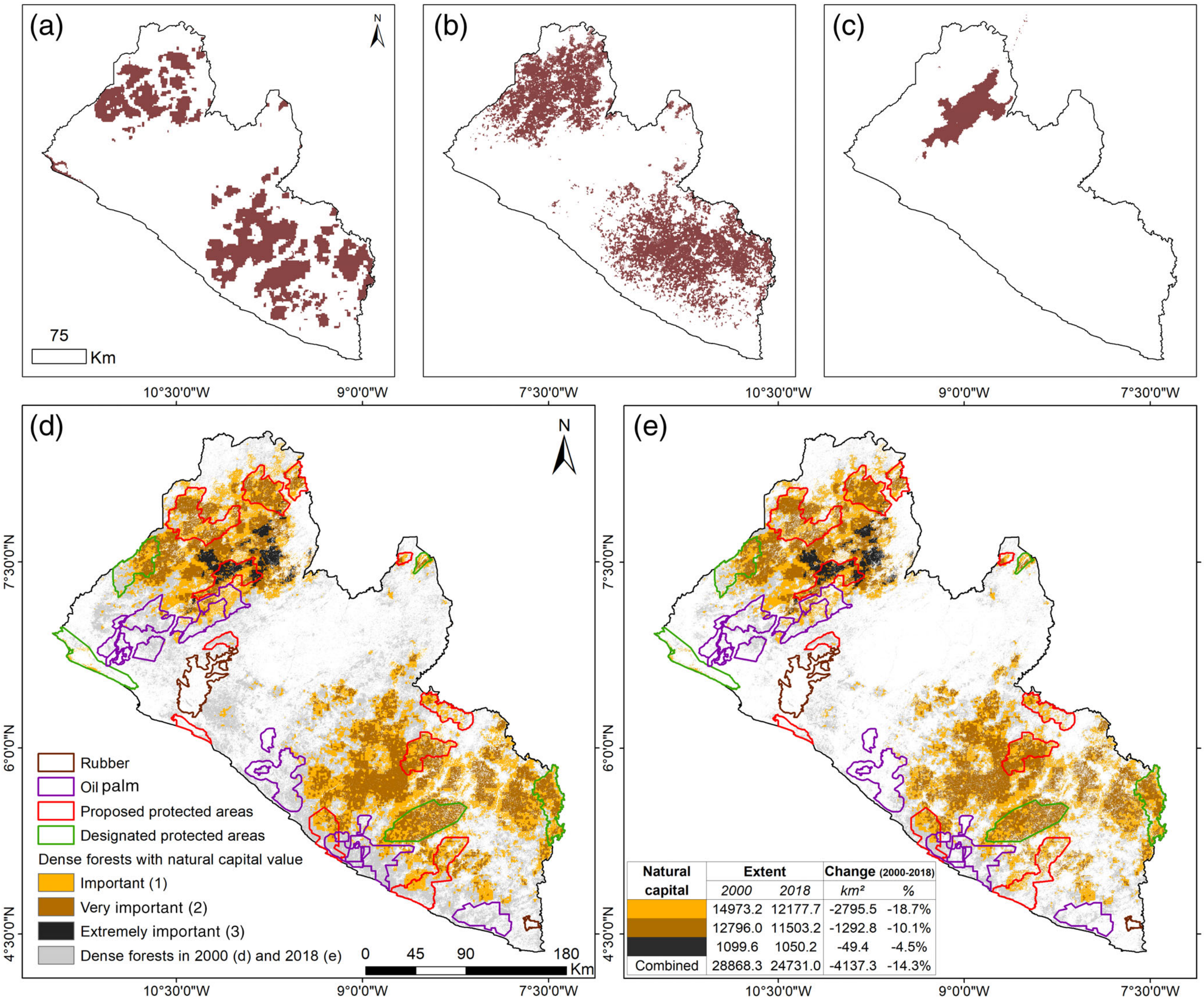
We observed some trends at the 3×3 km landscape unit that do not align with the broader trends observed on the ground. Some of these unusual trends are a result of artifacts in the classified images due to image quality, gap-filling issues, and persistent cloud cover. Figure 3.1 shows an area in the north of the country that was not affect by data artifacts, and there is an observed trend of fragmentation; increasing number of patches and decrease in the average patch size. Figure 3.2 shows an area in the south-central part of the country that is both affect by image artifacts, in the form of "striping", and fragmentation with a trend of increasing patch numbers and decreasing the patch size. Figure 3.3 shows an area in the southern part of the country near Sapo National Park where there are many artifacts in the images, leading to a decrease in the average patch size but no associated increase in the number of patches.

3.3 | Loss of essential natural capital

The overlay analysis showed that the fragmentation of areas with dense forest corresponded with a decline in the extent of areas identified as essential for biodiversity, forest carbon, and freshwater ecosystem services. An area of 13,374 km^2 of the dense forests have been degraded (i.e., converted into more open canopy classes) in Liberia in the period between 2000 and 2018 (Figure 2 & Figure S6). Approximately, 31% of this loss (4137.3 km^2) consisted of forests reported as essential natural capital (Figure 4). These forests were in the marginal areas of the larger remnants of the dense forest patches where more forest fragmentation was observed. Areas of dense forest identified as important, essential for at least one natural capital asset, lost 2795.5 km^2 (18.7% decline) of their original extent in the year 2000. Areas of dense forest identified as very important, essential for two natural capital assets, showed a decline of 1292.8 km^2 (10.1% of its original extent in the year 2000). Areas of dense forest identified as extremely important, essential for all three natural capital assets, showed a decline of 49.37 km^2 in the 19-year period. The designated protected areas in Liberia currently encompass 7.87% (2881.2 km^2) of the extent of dense forests in our latest 2018 map, and if the proposed protected areas were all formally designated, this area would increase to 22.96% (5534.2 km^2). Overlaying the map of essential natural capital with our dense forest extent map for the year 2018 (i.e., 36,614.2 km^2) revealed that 67.5% (24,731 km^2) of this area is essential to at least one natural capital, with only 10.2% (2523.51 km^2) being captured by the currently designated protected areas. Similarly, if the proposed protected areas were all formally designated, they would capture an additional 7.8% (1931 km^2), totaling 18% of Liberia's essential natural capital.

3.4 | GEDI-based vegetation structure analysis

The relative height metric RH100 (in meters) and total canopy cover (percent) at each GEDI footprint (Figure S9) was gridded to the Landsat 30-meter pixel to infer about the current integrity of forests in Liberia. The distribution of canopy height and canopy cover values over dense/primary forests in 2018 showed higher density of observations from denser (canopy cover >70%) and taller (canopy height >20 meters) trees (Figure 5a) compared to the other classes of forests. The relatively undisturbed condition of these areas led these forests to be 21 ± 0.02 m (mean $\pm$ standard error of the mean) tall and with a canopy closure of 54 ± 0.05%. As expected, forest height and canopy closure values decreased from denser to more open canopy classes: open forests in Liberia are, in average, 16 ± 0.01 m tall with a 36% $\pm$ 0.05% canopy cover while sparse/degraded forests areas had an average height of 11 ± 0.02 m and 22% $\pm$ 0.06% canopy closure. These values indicate that the ongoing fragmentation trend of dense forests in Liberia will ultimately lead to an overall loss of forest canopy closure



Natural capital	Extent		Change (2000-2018)	
	2000	*2018*	*km²*	*%*
(Important)	14973.2	12177.7	-2795.5	-18.7%
(Very important)	12796.0	11503.2	-1292.8	-10.1%
(Extremely important)	1099.6	1050.2	-49.4	-4.5%
Combined	28868.3	24731.0	-4137.3	-14.3%

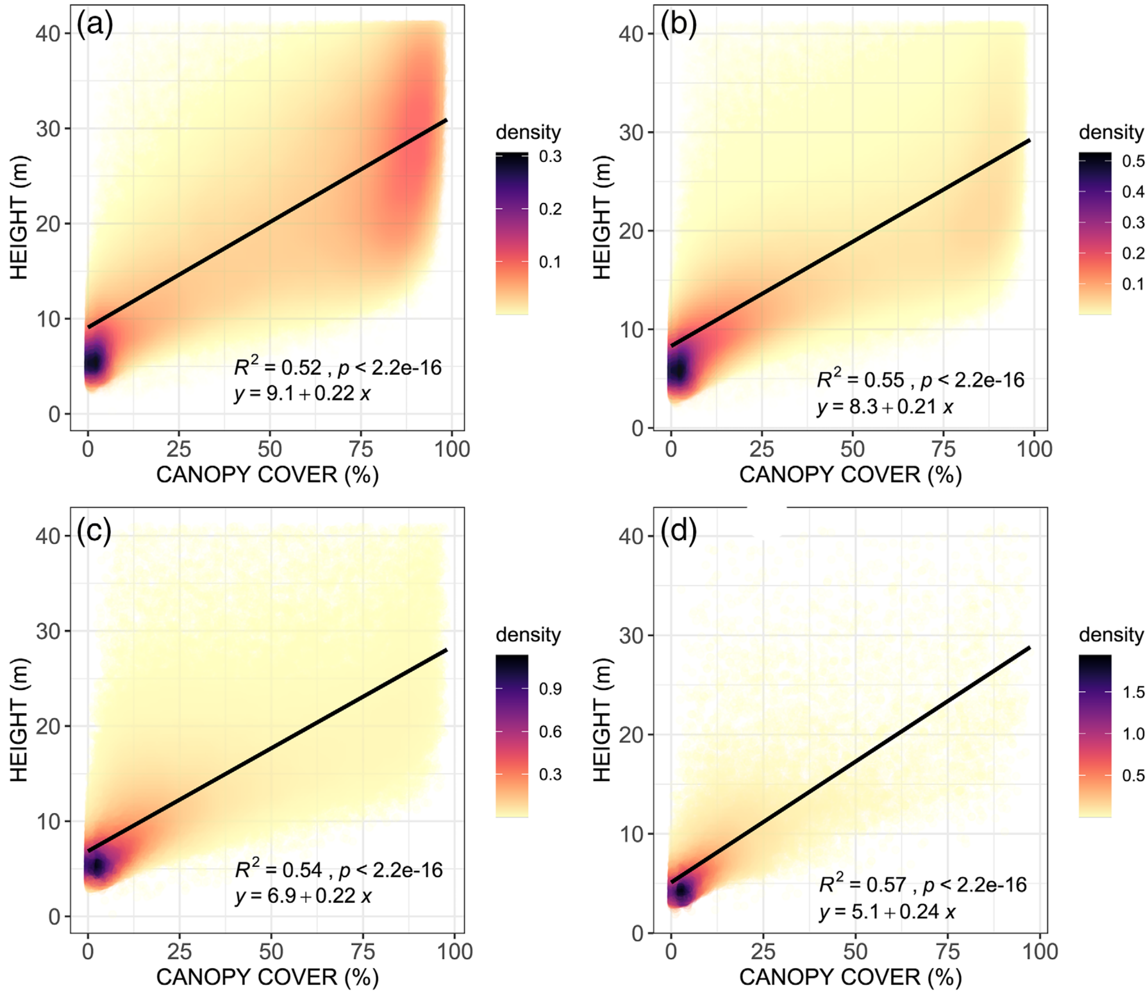
FIGURE 4 Essential natural capital of forests in Liberia. An additive “importance index” (ranging from 1 to 3, where 3 equals to extremely important) was created by combining the areas identified as essential for biodiversity (a), forest carbon, (b) and freshwater ecosystem services (c) in Liberia (Source: Neugarten et al., 2017). The combined layer was overlaid with the dense forest extent in the year 2000 (d) and 2018 (e). The loss of dense forest with natural capital value between the two periods is reported in a table inserted in (e). Areas of rubber and oil palm concessions as well as designated and proposed protected areas were included for reference.

and height, as dense forests are steadily transitioning into more open-canopy areas (see Figure 2).

4 | DISCUSSION

4.1 | Land cover mapping and change analysis

We relied heavily on map-to-map change detection, however, assessing the accuracy of a LULC time series is challenging and time consuming because each map needs to be assessed independently. Multitemporal accuracy assessment is complicated by the number of land cover land-use classes, limited resources and personnel to carry out assessments, and the lack of multitemporal reference ground data and very high-resolution imagery for these very cloudy regions, especially for the early years of the time series. Despite these challenges, the overall accuracy of the maps tends to remain close to that of the original 2015 base map for a time series where only a relatively small percent change occurs. In the case of countries like Liberia, where the relatively stable forest classes represent most of the total area, changes will likely occur within the other more variable and dynamic land cover classes, representing only a small portion of change. Most changes observed throughout the 19-year period for the forest classes represents the transition in between three



Forest class	GEDI metric	Mean	SD	N	SE	Quantiles: *min*	*25%*	*50%*	*75%*	*max*
a	Canopy cover (%)	54.13	31.37	340556	0.05	0.00	26.00	61.60	82.73	98.63
	Height (m)	21.07	9.62		0.02	0.21	13.43	21.04	28.62	40.99
b	Canopy cover (%)	36.96	30.69	401596	0.05	0.00	8.50	29.21	64.84	98.84
	Height (m)	16.13	8.75		0.01	1.63	8.97	14.56	21.62	40.99
c	Canopy cover (%)	21.88	23.63	159503	0.06	0.00	4.31	12.80	30.98	97.90
	Height (m)	11.59	6.98		0.02	0.21	6.28	9.48	14.97	40.99
d	Canopy cover (%)	16.76	20.61	21741	0.14	0.00	2.85	8.28	22.23	97.33
	Height (m)	9.19	6.63		0.04	1.89	4.55	6.71	11.59	40.97

FIGURE 5 GEDI-based measurements of forest structural characteristics, 2019–2020. Canopy height (in meters) and canopy cover (in %) was extracted from each GEDI footprint within dense forests (a), open forests (b), sparse/degraded forests (c) and all other classes (d). The summary statistics for the canopy cover and canopy height values for each class (and all other classes) is also shown (*SD* = standard deviation; *N* = count; and *SE* = standard error of the mean).

forest classes, rather than transitions from forest to non-forest classes. *LandTrendr* minimizes minor changes that may arise due to "noise," small variations in reflectance values due to atmospheric conditions and intra-annual variability that may interfere in the classification process, between Landsat measurements as a stable trajectory is being fitted throughout the multiple observations. This technique ensures that only changes in the reflectance signal that represent changes in the ground will be highlighted. A confusion matrix was produced using a 500-samples reference dataset acquired across the 10 classes in Liberia for the most recent LULC map (2018), using methods similar to De Sousa et al., 2020 (Figure S3). The overall accuracy of the most recent LULC map remained close to the original base map (78.8% and 81%, respectively), and forest classes showed the highest user's accuracy among all classes.

4.2 | Forest fragmentation patterns

Our results are consistent with reported estimates of the extent, rate of loss, and fragmentation of Liberian forests from 1986 to 2000 (Christie et al., 2007), and depict a concerning reality of the GFWA remnants in Liberia: progressive reduction in the size of fragments during the last two decades (see Figures S5 and S8). Assessing forest fragmentation is dependent on the scale of analysis and there are many metrics that can be applied. The average patch size and total number of patches were used instead of a series of complex, and often correlated fragmentation metrics. These two metrics and the landscape unit size were useful for showing how the overall Liberian forest landscape changed between 2000 and 2018 and how larger remnants of untouched dense forests have been consistently reduced to more numerous and smaller fragments. Although some of the Liberian mature forests are under protection (approximately 8% of its extent in 2018), much of the remaining forests is still unprotected and susceptible to many forms of exploitation and disturbance. It is important to note that the distinction between anthropogenic and natural causes of fragmentation in Liberia was outside the scope of this analysis. The results highlighted stronger trends of fragmentations at the edges of the larger remnants because of neighboring farmlands and, in central Liberia, where the road network is more developed.

A dramatic change in the rate of fragmentation of dense forest class was observed starting around 2015 (Figure S10). It is plausible that some of the observed increase was driven by artifacts found in several of the classified land cover maps. These artifacts, appearing as misclassified areas within the dense forest class, were most likely caused by a malfunction of the scan line corrector (SLC) of the Landsat 7 Enhanced Thematic Mapper Plus instrument (ETM+). Starting in May 2003, the Landsat imagery contained wedge-like data gaps, known as “striping.” A significant effort by the U.S. Geological Survey and NASA went to fixing this problem by “gap-filling” the affected scenes using nonaffected scenes (Storey et al., 2005). However, it appears that in regions where there is not a sufficiently large number of nonaffected scenes available, these artifacts can still be found on some of the imagery. This seems to be true in areas with prevailing cloud cover, such as the south-east of Liberia. However, despite these issues, there is still overwhelming evidence that fragmentation has significantly increased between 2000 and 2018. Our results support previous findings that deforestation and fragmentation tend to occur next to already fragmented and deforested areas (Rosa et al., 2013; Rosa et al., 2015). Therefore, the results proved to be useful for a rapid identification of potential fragmentation hotspots that could assist the development of effective land use-related policies in the proximity of areas of dense forests and around protected areas.

4.3 | GEDI-based assessment of structure in Liberia

GEDI is designed to provide 3D tree canopy structure information at global scales by sampling vertical canopy profiles within a 25-meter footprint. The standard GEDI data products have several limitations for practical applications: (1) the size of each footprint, leaving most land surface without any observations; (2) the variable transect sampling due to the International Space Station's variable orbit around Earth making it not suitable for targeting specific forest change events; and (3) its recent launch and deployment only offer a little more than 2 years of data. Despite these limitations, it is still the most suitable instrument for developing a baseline assessment of the structure of mature dense forests in Liberia. The measured laser waveform from GEDI includes signal returning from the ground, which, in turn, can be affected by steep terrains. In the case of Liberia, where its landscape ranges from flat coastal lowlands, to rolling hills and plateaus further inland, and low mountains in the northeast, disentangling the ground and vegetation canopy signals is not likely to be an issue, helping to minimize inaccurate estimates of tree canopy structure features.

The objective of this analysis was to show that forest height and canopy closure decrease from mature dense forests toward all other land cover classes. The GEDI estimates of forest structure support the validity of the land cover classification approach. Dense and open forest classes had the highest user's accuracy (>90%) among all classes for the latest land cover map in the time series (2018) based on interpretation of independent samples. The overall accuracy of our maps can be inferred by the range of values of canopy cover and forest height and quantiles (Figure 5): excessive commission and omission errors between these classes can directly affect their overall distribution of height and canopy cover values, rendering them unrepresentative of what has been documented for well-preserved patches of the GFWA, based on field measurements (Vaglio Laurin et al., 2019) and forests with different successional trajectories with shorter and more open canopies. Previous studies have shown the strong correlation between LIDAR-based canopy height estimates and above ground biomass (Drake et al., 2002; Lefsky et al., 2002). The GEDI-based estimates of forest height and canopy closure coupled with the results on fragmentation and forest conversion trends can serve as initial steps in quantifying potential loss of forest biomass and its impacts on Liberia's forest carbon storage potential and biomass and carbon-related natural capital.

4.4 | Natural capital

Understanding the value of natural capital—the world's stock of natural assets, including renewable resources, such as freshwater, marine, and terrestrial ecosystems, and their provision of ecosystem services, in addition to nonrenewable resources such as minerals—has been increasingly recognized as critically important for achieving sustainable development goals and was one of the main drivers of conducting this study. Natural capital is one of the key components of a country's wealth, alongside human and produced capital.

Natural capital accounted for 42.7% of Liberia's total wealth in 2018, having declined from 55.4% in 1995 (World Bank, 2021). The country's share of human capital wealth, in turn, increased from 29.7% 1995 to 41.6% in 2018, though such increase did not translate into per capita human capital wealth, which declined during that period.

Understanding a country's composition of wealth is critically important for the measurement of economic progress, and more robust and comprehensive natural capital accounting is a necessary step toward achieving that goal. The United Nations' System of Environmental-Economic Accounting (SEEA) is an internationally accepted framework for measuring of nature's contribution to the economy and for integrating that information into national accounts. The SEEA Ecosystem Accounting (SEEA EA) focuses on measurements of ecosystems, their condition, and the benefits they provide. To date, 39 countries (Hein et al., 2020; UNCEEA, 2021), including Liberia, have published at least some of their compiled ecosystem accounts. However, the efforts for mapping natural capital (Neugarten et al., 2017) and natural capital accounting in Liberia (including through the analysis presented here) have only recently started. For example, we have produced Liberia's first nationwide, 30-meter resolution ecosystem extent map for the year 2015. This map has been delivered to Liberia as a starting point for accounting for ecosystem extent and services nationally (De Sousa et al., 2020). Ongoing efforts are under way to provide a complete set of SEEA EA in coastal Liberia, as part of a Global Environment Facility (GEF)-funded project: Conservation and Sustainable use of Liberia's Coastal Natural Capital.

The work presented here is particularly relevant as the global community adopts the post-2020 Global Biodiversity Framework (GBF) of the Convention of Biological Diversity (CBD), with a new set of biodiversity targets toward the 2050 Vision of "Living in harmony with nature." The Monitoring Framework adopted the 15th Conference of the Parties (COP) of the CBD includes (1) headline indicators capturing the GBF goals and targets (the only set of indicators agreed upon during the COP); (2) global level indicators; and (3) optional components and complementary indicators. Importantly, the 15th COP of the CBD made a direct call for alignment between the GBF Monitoring Framework and the United Nations' System of Environmental-Economic Accounting (SEEA), noting the importance for mainstreaming environmental accounting into national statistical offices. Indeed, SEEA can provide the methodological basis for various goals and targets indicators in the Monitoring Framework, including the extent of selected natural and modified ecosystem (Goals A.). The efforts we describe here can support operationalization of such task.

5 | CONCLUSIONS

We quantified land cover change and forest fragmentation at the national level for Liberia covering 19 years from 2000 to 2018. Our study was the first of its kind for the region and an important initial step toward compiling ecosystem extent accounts in Liberia. Several important conclusions came out of this research, both in the technical application of remote sensing and in understanding the patterns of forest change in Liberia.

LandTrendr's spectral trajectory segmentation algorithm is a powerful tool that is capable of overcoming a problem of missing observations caused by prevailing cloud coverage common for tropical countries such as Liberia. The implementation of this algorithm in Liberia has been mostly successful with some exceptions.

The land cover change analysis revealed that important ecosystems, such as mangroves and wetlands have lost approximately 25% of their extent between 2000 and 2018. Mature dense forests identified as essential natural capital lost more than 14% of their original extent over the study period. The extent of secondary open forests in Liberia steadily increased during the study period, mostly driven by the transition from mature dense forest through fragmentation and growth and regeneration of sparse/degraded forests.

The GEDI analysis of the forest structure showed the remaining of dense forests maintained average canopy height that agrees with the field-measured canopy height found on the literature. Transitions from the mature dense forest class to secondary open and sparse/degraded forest classes were also reflected in the forest structure variables derived from GEDI. The overall average difference between the three forest classes was 5 meters (21, 16, and 11 meters for dense, open, and sparse/degraded forests, respectively).

The methodology described here can provide the Government of Liberia with the necessary means to measure broad changes in the extent from one ecosystem type to another over time. These trends in land cover change, forest structure, and fragmentation could be used to inform development planning and resource management and provide high level indicators on the current status of forests in Liberia. However, the method may not be suitable for the use in official statistics following the SEEA standards in Liberia, due to the challenges associated with automated time-series analysis described in the discussion. For SEEA reporting, individually generated annual maps, with associated accuracy assessments, may be more suitable as they are less susceptible to errors resulting from artifacts in the underlying imagery.

AUTHOR CONTRIBUTIONS

Celio de Sousa, Miroslav Honzák, and Timothy Max Wright: Conceptualization, formal analysis (land cover and forest fragmentation, GEDI), methodology, writing—original draft, writing—review and editing;
Lola Fatoyinbo: Project administration, resources, supervision, writing—review and editing;
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Miroslav Honzák, Trond Larsen, Rosimeiry Portela, and Daniel Juhn: Writing—review and editing (Natural Capital Accounting) and resources (natural capital datasets).

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CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

All land cover core files (2000–2018) are available from the 10.6084/m9.figshare.19617228.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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